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Household Financial Decision-Making After Natural Disasters: Evidence from Hurricane Harvey

Alejandro del Valle Therese Scharlemann Stephen Shore*

Hurricane Harvey brought more than four feet of rainfall to the Houston area in August 2017, leading to substantial flooding in many areas. Using regulatory data with detailed information on borrowing terms, we compare the borrowing response to Hurricane Harvey in parts of Houston that were more and less affected by flooding. We find that hurricane-affected households borrowed in a price-sensitive and time-limited manner, relying almost exclusively on promotional-rate credit cards and mortgage forbearance for new credit and repaying balances quickly. We find that conditional on flooding, households in FEMA-designated floodplains borrowed less. Within the floodplain, building code changes that required homes to be elevated above the floodplain dramatically reduced households' storm-related liquidity use. Flooded borrowers in homes subject to this type of physical hardening used forbearance at the same rate as borrowers who did not experience flooding, suggesting that for natural disasters, *ex ante* physical hardening is a substitute for *ex post* credit. (JEL:Q54, D14, G22, H84)

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1 Introduction

Weather provides an exogenous and unpredictable shock to the need for funds. Natural disasters, and in particular flooding events, are an increasingly relevant shock to household balance sheets. While households differ in their preparation for natural disasters (and the incidence of flooding correlates with preparation for flooding) the timing of the shock and the intensity of the treatment is observable, making it a good framework for studying how households navigate their financial options. Hurricane Harvey produced the largest rainfall event of any US hurricane on record (Emanuel, 2017). Harvey flooded coastal Texas with more than a trillion gallons of water in late August 2017, with parts of Houston receiving more than four feet of rain over just a few days (HCFCD, 2018).

How do households use credit markets to manage shocks stemming from a natural disaster? There is a large and active literature on the *magnitude* of households' financial responses to natural disasters, particularly hurricanes. Much of this literature has found limited credit response to hurricanes overall (Gallagher and Hartley, 2017; Deryugina, Kawano and Levitt, 2018; Groen, Kutzbach and Polivka, 2017; Aladangady et al., 2016; Edmiston, 2017).[1] This dampened response partly reflects robust federal aid (including Small Business Administration loans and FEMA grants), which cover the needs faced by many households (Gallagher, Hartley and Rohlin, 2021). Aggregate borrowing following storms is limited to households who need additional credit because these federal loans and grants are unavailable or are insufficient to cover their storm-related needs (Billings, Gallagher and Ricketts, forthcoming). In this paper, we explore the *nature* of households' financial responses to natural disasters, particularly how affected households meet those credit needs. We find that those driven to borrow by natural disasters act in a strategic, time-limited, and price-sensitive manner and that they use borrowing as an ex-post substitute for ex-ante "hardening" of their homes.

The finding of price-sensitive borrowing in private credit markets shows that this be-

[1] There is also an active literature focused on firms. This literature finds that disaster-related business disruptions are short-lived but costly (Agarwal et al., 2021). These losses tend to be uninsured, and firms rely heavily on credit to finance their recovery efforts (Collier et al., 2020*b*,*a*).

havior is not specific to post-disaster loans from the Small Business Administration (Collier and Ellis, 2021) and stands in contrast with the research findings on frequent credit users in non-disaster settings. This non-disaster literature shows that typical U.S. borrowers often rely on expensive, repeated sources of credit and that they routinely fail to take advantage of arbitrage opportunities. This behavior has been documented both in secured long-term borrowing arrangements such as mortgages (e.g., Woodward and Hall, 2012; Davidoff, 2015; Keys, Pope and Pope, 2016; Agarwal, Rosen and Yao, 2016; Agarwal, Ben-David and Yao, 2017) and more surprisingly, given the possibility to learn from repeated use, in unsecured short-term borrowing arrangements such as those offered by payday lenders or credit card companies (Ausubel, 1991; Agarwal, Skiba and Tobacman, 2009; Agarwal et al., 2015; Lusardi and Tufano, 2015; Ponce, Seira and Zamarripa, 2017; Keys and Wang, 2019; Hundtofte, Olafsson and Pagel, 2019). Understanding whether this observed behavior is suboptimal and whether it is being driven by consumers' biases, lack of information, financial literacy, or cognitive limitations is of crucial importance to the design of consumer financial protection regulations (Campbell et al., 2011). Hurricane Harvey provides a reason for an unlucky but fairly typical group of U.S. residents to borrow, even if they may not have been frequent borrowers in the past. These individuals induced by storm damage to borrow do not seem to use credit in the costly, recurring, and problematic ways documented in more frequent borrowers.

One reason why this price-sensitive behavior has not been documented previously in private credit markets is that the existing literature focuses heavily on the Consumer Credit Panel (CCP) (an anonymized random sample of consumer credit reports), which while extremely useful along a number of dimensions, has several disadvantages in measuring the details of particular forms of credit use. First, until 2020, the CCP was available at a quarterly frequency, so some short-term household responses may be lost. Second, it comprises a 5% random sample of households; even within a storm-ravaged area, a 5% sample may not be large enough to precisely observe responses. Third, the data do not include many details about the terms of borrowing, making price-sensitivity difficult to observe. Finally, the y14m allow us to separate purchase volumes from revolving balances, whereas the CCP shows only changes in outstanding balances. Therefore, it's difficult to know from the existing literature whether flooding or financial data are too geographically aggregated to adequately distinguish affected from unaffected households, whether hurricane damage is large but households cannot or do not use credit card borrowing to handle that damage, or whether the response to hurricane damage is uneven, with effects that are difficult to see in average data.

We are able to make headway on some of these questions by linking data on flood depth at exact locations with detailed credit card account and mortgage data containing locations identified at the ZIP+4 level. We measure hurricane severity with high-resolution flooding depth data (3-meters aggregated to the ZIP+4 location level). As a result, we are able to get extremely detailed measures of the degree to which credit card accounts and mortgages are attached to homes that were more and less affected by the Hurricane. Our data also cover far more borrowers than the CCP. We measure response to Hurricane Harvey with monthly loan-level credit card data on a majority of credit card accounts from CCAR Y-14M data. This dataset contains not only detailed information about charging, payments, balances, and revolving balances, but also information that allow us to track originations, "teaser" (promotional) loan terms, rates, and fees. This detailed dataset allows us to perform an extremely detailed analysis of borrowers' responses to hurricane Harvey. Mortgage data, which also come from monthly CCAR filings, cover about half of outstanding mortgages in our sample area. This is the first time that these credit data have been used to study in the impact of a natural disaster.

Our findings on total credit card borrowing mirror the previous literature, with flooding from Hurricane Harvey having little impact on balances overall. However, we find that while *borrowing* on credit cards in essentially unchanged, *purchases* on credit cards in affected areas increase by about $20 per foot of flooding, an effect that persists for about a year. These additional purchases are paid off immediately, leaving both the revolving and cycle-ending balances unchanged. These new charges could reflect additional spending or a shift from spending cash to spending on credit cards, but it does not reflect additional borrowing.

Additionally, we find large increases in the number of new credit card originations immediately after Hurricane Harvey in affected areas, particularly on cards with promotional (temporary zero interest) rates. These newly originated cards tended to be issued to borrowers with high credit scores who built up unusually large revolving balances immediately after origination but paid down these balances quickly before teaser rates reset (so that interest rates were near zero). In short, nearly all incremental credit card borrowing induced by storm damage is short-term on new teaser cards at an interest rate of approximately zero. These effects are less pronounced in floodplains, where homes might be designed to receive less damage for a given amount of flooding, and where households tend to carry insurance.

We also find evidence that households in impacted areas used mortgage forbearance offers as a form of bridge borrowing.[2] This finding is in line with those of Kousky, Palim and Pan (2020), who use data matching ex post flood *damages* to mortgage performance – a different exercise than looking at forbearance conditional on *flooding.* We find that households in the most impacted areas missed mortgage payments at about 4 times the usual rate. We also find that households in areas that did not flood skipped payments at far higher rates than normal: their delinquency rate roughly doubled. We saw no increased credit card borrowing activity in non-flooded areas, suggesting that these borrowers did not have the same type of liquidity need as in flooded areas, and they may have used forbearance "strategically" – i.e., they likely would not have defaulted absent the forbearance offers. This is not to say that these borrowers did not need or benefit from forbearance, and these borrowers' ability to forestall mortgage payments may have had general equilibrium benefits to the Houston area that we cannot capture.

However, while previous literature (like Kousky, Palim and Pan (2020) and Billings,

[2]This adds to a growing literature studying the use of forbearance programs, focused largely on the Covid-19 pandemic, such as Cherry et al. (2021), Kim et al. (2021), An et al. (2021), Lambie-Hanson, Vickery and Akana (2021) and Zhao, Farrell and Greig (2020).

Gallagher and Ricketts (forthcoming)) show that households in floodplains are less distressed in the long-run, and attribute that protection to insurance requirements, we show that physical hardening explains much of the reduction in borrowing in floodplain areas. For this result, we exploit a change in construction requirements which mandated that structures built after 1985 in flood hazard areas be elevated at least 1 ft above the 100-year floodplain (City of Houston, 1985). We find that mortgages attached to houses built after 1985 saw much lower forbearance rates than houses built earlier – flooded borrowers in houses subject to the new code used forbearance at about the same rate as borrowers who did not experience flooding. Outside the floodplain, we find no relationship between the year a house was built and the mortgage's forbearance propensity, ruling out generic improvements in construction as an explanation.

In summary, our results provide evidence that credit is used intensively by a small number of borrowers that use new credit cards and mortgage relief for relatively short-term borrowing. This borrowing comes at low cost because it is done on promotional cards and using mortgage forbearance, which are paid off quickly. We find attentuated effects in designated floodplains, and are able to attribute that attentuation to physical hardening. This behavior across credit products shows that, in the context of natural disasters, households induced to borrow are quite attentive to the cost of borrowing and navigates the credit space more capably than is suggested by the literature focused on frequently revolving credit-users.

2 Data

2.1 Flooding, floodplain, flood insurance, building code, and demographic data

We observe mailing address for credit cards and mortgages at the Zone Improvement Plan plus-four level (ZIP+4). These 9 digit codes used by the United States Postal Service identify small geographic segments within the ZIP code (five-digit) delivery area. To assess the severity of the flooding caused by Hurricane Harvey at the ZIP+4 level, we use the high-water-mark (HWM) depth grids created by the Federal Emergency Management Agency (FEMA).

The FEMA (2017*b*) dataset is a raster image composed of 3.2 billion grids (pixels). Each grid reports the maximum depth of Harvey flooding in feet (ft) and has an area of 3 square meters ($\approx$ 9.8 square ft). In our analsys we use the depth grids that cover Harris County (Houston) and the coastal counties of Aransas, Nueces, and San Patricio, where Harvey made landfall.

To construct HWM grid depths for Harvey, hydrographers from the U.S. Geological Survey visited the affected counties between September 2 and October 10, 2017, and recorded the height of flooding at 2755 points.[3] FEMA then interpolates these points to construct a flood surface depicting the maximum height of water. Flooding depth is derived in turn by subtracting the flooding surface from (3-meter resolution) LIDAR terrain data. Figure 1a presents depth grids for Harris County, which makes up the bulk of our sample.

We assign depth of flooding to each ZIP+4 location using a two-step process. First, we overlay the footprints of houses and buildings observed in aerial imagery (FEMA, 2017*d*) over the depth grid and calculate for every structure in our coverage area the maximum depth of flooding around the structure. This step allows us to guarantee that we are measuring flooding that directly affected the observed structures. In the second step, we use the ZIP+4 centroid coordinates provided by a private shipping company (Pitney Bowes, 2018), to locate all structures within 100 meters ($\sim$ 328 feet) of a ZIP+4 centroid. We then calculate for every structure group the average depth of flooding and assign that value to the ZIP+4. Figure 1b illustrates this calculation.

To study Harvey's heterogeneous impact on the credit market, we include in our dataset information from four additional sources. First, to measure the risk of flooding, we use data from the national flood hazard zones map, that was current at the time of Hurricane Harvey

[3]HWM provide information on maximum flooding because hydrographers record the distance between the ground and the highest mark left on objects exposed to the water.

(FEMA, 2017*c*). Specifically, we overlay our ZIP+4 centroids on the flood insurance risk maps for the counties that make up our sample and assign to each ZIP+4 the official FEMA flood zone designation. We define a ZIP+4 to be in the floodplain when it has a one percent chance of flooding each year, or when it is at high risk from storm surge, that is, FEMA flood zones types A and V. We define a ZIP+4 to be outside of the floodplain when it is at low or moderate risk from flooding, FEMA flood zones type X.

Second, while borrowers in floodplains are technically required to carry flood insurance if they have a mortgage, compliance with this rule is far from perfect (Michel-Kerjan, 2010). Instead, we measure insurance penetration directly by calculating the share of structures with an active policy at the time of Hurricane Harvey. Specifically, we divide the counts of active policies at the census tract level provided by FEMA (2017*a*) by the count of structures derived from aggregating FEMA (2017*d*) to the same level. We then assign to each ZIP+4 the calculated value of the census track share of insured structures.

Third, we measure whether a structure is subject to building code regulations that could mitigate flooding by taking advantage of the Texas ordinance (City of Houston (1985)) zoning regulations. These regulations require that structures built or substantially renovated after 1985 be raised 1 foot above the 1 in 100 years floodplain. As explained in subsection 2.3 we identify the year built for structures observed in our mortgage dataset using CoreLogic data drawn from deed records matched using the mortgaged property's address. Last, we use census block group level data from the American Community Survey (US Census Bureau, 2017) to measure median household income.

2.2 Credit Card Data

We draw credit card data from the CCAR FR Y-14M (hereafter Y-14) regulatory filing.[4] The Y-14 report collects monthly loan-level credit card, first mortgage lien, and home equity loan data from large Bank Holding Companies (BHCs) and Intermediate Holding Companies

[4] All Y-14 data was pulled in November 2020

(IHCs) subject to Capital Assessments and Stress Testing. We believe that this data set covers roughly 90 percent of credit cards in the marketplace.

Hurricane Harvey's warning was issued on August 23. Harvey made landfall on August 25th, with substantial rainfall continuing in the Houston area until August 29th. Credit card spending and payment during the late-August period would appear in the September billing cycle, so for the purposes of analyzing credit card data we define September 2017 as the first treatment month. September behavior immediately following the hurricane would show up in the October billing cycle. We monitor credit card borrowers for 2 years before Hurricane Harvey and 12 months after, so that our data span the period from September 2015 to August 2019.

We observe the ZIP+4 of the mailing address of the credit card. ZIP+4 areas are relatively small: each has on average 20 credit cards and 20.3 structures (buildings or houses). Our sample contains 259,000 ZIP+4s. We limit data to cards with mailing addresses in Harris County (Houston), and the coastal counties of Aransas, Nueces, and San Patricio where Harvey made landfall.

We evaluate credit card use on the intensive margin (spending on existing cards) and extensive margin (origination and use of new cards). Our sample of existing cards includes all cards in areas that experienced flooding. We use a 5% sample of existing cards in areas that did not experience flooding. Unflooded areas cover about 90% of our sample. For this sample, we exclude cards originated after January 2017. We also limit our sample to cards that we define as "active": cards that are carrying balances or have been used for purchases within the previous 6 months. When we evaluate new originations, our sample of new cards includes all originations observed in our sample period. We monitor these cards for 12 months following origination.

For both samples, we exclude cards for which flooding data is unavailable (less than 10 percent of cards). Additionally, we exclude cards for which we have incomplete data (missing months), or for which the pattern of reported promotional APRs is inconsistent with typical card offers and may reflect borrower negotiations or reporting errors.[5] Few cards are removed from our sample for these reasons.

We also exclude observations for which the ZIP+4 is unavailable. Often these observations occur earlier in the sample, as banks have improved reporting over time. Because we found that the accounting identities allowing us to infer the borrower's revolving balance are occasionally inconsistent for the first two months of data (both for existing cards recently purchased by a bank and for new originations), we exclude the first two observations of data from our analysis of financial outcomes. The weighted sample includes over 100 million card-months and 4.3 million unique cards.

The credit card data include a rich set of characteristics about the card utilization and the terms of credit, including monthly payment and balance information (charges, payments, balances, fees, and performance), credit card terms (current and original APR, promotional status, current and original credit limit, whether the card is co-branded, etc), and some borrower characteristics (income at origination, original and current credit score).

We track three key ongoing credit card measures: charges, payments, and revolving balance. Charges refer to the total purchase volume on that card in a given month. Payments refer to the total actual payment amount received for that card in a given month. The revolving balance is the cycle-ending balance from the previous month minus payments in the current month; for interest-bearing cards, the revolving balance reflects the amount on which any interest is owed.

For new cards, we additionally evaluate whether the card is under promotion at origination (i.e., whether new purchase and transfer balances are carried at market or discounted interest rates). The card's promotional status is a calculated field. Banks are required to report the promotional status and promotional APR only for cards where borrower has a balance on the card at the end of the billing cycle (the balance can be non-revolving; carrying a balance indicates only that the card was used during the billing period). We infer that a

[5] For example, if the enters and exits promotional status several times over a short period of time.

card has been originated with a teaser rate if the card is observed to carry a promotional rate within the first 12 months of origination. About 95% of the cards we classify as promotional cards show an interest rate of 0% during the months they are under promotion.

Table A1 in the appendix shows origination characteristics for cards issued during our observation period from June 2016 through April 2018. Table A2 in the appendix shows the same origination characteristics for cards issued in the 3 months before the hurricane separately for each category of observed flooding intensity. No clear differences emerge in the origination characteristics of affected and unaffected borrowers.

2.3 Mortgage Data

Like the credit card data, mortgage data are drawn from the CCAR FR Y-14M regulatory filing, which requires filers to report on the performance and characteristics of loans in their mortgage servicing portfolio. Our sample includes 34 unique Y14 filers, which together service about half of mortgages in the Houston area. Because the sample consists of large bank servicers, it is not completely representative of all outstanding mortgage loans. Y14M filers' servicing portfolios include fewer FHA loans and more portfolio-held loans than average.

The data include granular geographical information (ZIP+4), monthly performance (delinquency status, prepayment, servicing transfer, modification status), updated credit score, and detailed origination information.

We merge information about the build year of the structure at the property level using CoreLogic data drawn from deed records. While these data offer high match rate with the mortgage data, they end in 2014, so properties built or substantially renovated in the intervening 3 years will not have updated records.

Table A3 in the appendix shows the distribution of these characteristics during our sample period. Table A4 in the appendix shows how these characteristics vary by flood depth in the 3 months before the storm hits.

3 Empirical Strategy

We estimate a two-way fixed effects model that relates credit market outcomes to the level of flooding created by hurricane Harvey. Our preferred specification is the following:

$$\mathbf{Y}_{czt} = \sum_{\tau=-24}^{12} \beta_\tau \cdot D_{ct}^{\tau} \times \mathbf{F}_z + \alpha_c + \alpha_t + \varepsilon_{czt}, \tag{1}$$

where Y_{czt} denotes the outcome of credit line c in ZIP+4 z and month t, α_c is a credit line fixed effect, α_t is a year-month fixed effect, $D_{ct}^{\tau} = 1\{t - \tau^* = \tau\}$ is an indicator variable for being τ months away from August 23 2017 (τ^*) when the National Weather Service issued the first Hurricane watch for Texas. The variable F_z measures the depth of flooding in feet (ft) created by Harvey at ZIP+4 level.[6]

For continuous outcomes (purchases, payments, balances), we estimate equation 1 using ordinary least squares. For delinquency (forbearance), use a linear probability model. For new card originations, for which we construct a binary outcomes (with predicted probabilities outside the unit interval) we use a logit model. Our results are robust to our model choice for binary outcomes.

We cluster standard errors at the ZIP+4 level. Because the hurricane watch occurred at the end of August ($\tau = 0$), we interpret the β_τ coefficients for $\tau \leq 0$ as corresponding to the pre-Harvey period (leads of treatment). Accordingly, the β_τ coefficients for $\tau > 0$ correspond to the post-Harvey period (lags of treatment). We normalize the coefficient on the coefficient on ($\tau = 0$) to be equal to zero.

We argue that the β_τ coefficients for $\tau > 0$ have a causal interpretation and that they describe the evolution over time of the average causal response to flooding under the assumptions of no anticipation effects and parallel trends. In our application, both assumptions are likely to hold.

Regarding the anticipation assumption, we can rule out that ZIP+4s changed their pre-

[6] Note that $\sum_{\tau=-24}^{12} \beta_\tau \cdot D_{ct}^{\tau}$ is subsumed by the time fixed effects, and F_z is subsumed by the credit line fixed effects.

treatment outcomes in response to Harvey because households could not have foreseen the timing or distribution of the flooding it created.

The parallel trends assumption in our application is that the average change in outcomes that would have been observed if ZIP+4s had not experienced flooding of a given intensity is the same as the average change in outcomes observed among ZIP+4s that experienced that intensity of flooding. Two pieces of supporting evidence indicate that this is a reasonable assumption. First, we test and are unable to reject, for almost every outcome, that treatment leads $\tau \leq 0$ are statistically different from zero. Note that this test is valid because our event date is common (no differential timing) and because we can rule out anticipation effects. Accordingly, the contamination effects described in Sun and Abraham (2020) for this type of test are not present in our application. Second, we show in tables A2 and A4 in the appendix that in terms of pre-Harvey credit outcomes, households are similar across levels of flooding. The lack of gradients with the depth of flooding indicates that in the case of a major storm like Harvey, households could not sort into particular flooding intensities.

While we conduct our initial analysis using specification 1, this specification reports 34 β_τ coefficients of interest. To provide readers with a concise summary of the impact of Harvey, we report results in table format using a modified version of specification 1, where we bin the D^τ_{ct} indicator variable. The combined lags are τ = 1-3, 4-6, 7-9, and 10-12. The combined leads are τ = -24 to -3, -2 to 0. We normalize the last bin before Harvey (τ= -2 to 0) to be zero.

Additionally, because our preferred specification (equation 1) may not always provide a good summary of the impact of Harvey, for example, in cases where there is substantial treatment effect heterogeneity by level of flooding. We also present coefficient plots derived from a modified version of specification 1 where we discretize F_z into two groups (more and less than 1 foot of flooding), or in the case of substantial heterogeneity into four groups: less than 0.1 foot; 0.1 to 1 foot; 1 to 3 feet; and over 3 feet of flooding.

4 Results

4.1 Purchases, Payments, and Balances on Existing Cards

We begin by studying the impact of hurricane Harvey on the use of existing credit lines. The outcomes are credit card charges, payments, and revolving balances. Figure 2 plots the differential impact of Harvey over time between those exposed to more and less than 1 ft of flooding. The figure reveals that consumers used existing, market-rate cards to spend but not to borrow. Specifically, we observe that while Harvey leads to an increase in credit card charges consumers are able to avoid expensive borrowing by immediately matching the increase in charges with credit card payments [7]. Figure 2 additionally provides strong supporting evidence for the causal interpretation of these coefficients because it shows that pre-trends for charges and payments are very similar between more and less flooded areas. Consistent with the previous results we also find small negative effects on revolving balances. One important caveat with this result is that the figure reveals a downward pre-trend for revolving balances.[8]

To give a better sense of the magnitude of Harvey's impact table 1 summarizes the previous results and investigates whether these effects are driven by credit lines that were frequently used to borrow. Specifically, we extend specification 1 and include an interaction with an indicator variable that takes the value of one for credit lines that carry a revolving balance before Harvey.

The coefficients on the main effects Columns 1 and 2 show that among cards without a pre-Harvey revolving balance, charges and payments move in lock step with the largest increase, roughly $ 70 per ft of flooding being observed 4 to 6 months after Harvey's landfall. Because average flooding among flooded areas is about 1.5 ft these coefficients imply that Harvey increased charges and payments by roughly $100 on average among cards in flooded

[7] Payments lag purchases by one period. The initial jump in payments observed in period 2 more-than-offsets the increase in purchases observed in period 1, reducing revolving balances

[8] The revolving balance is calculated as the cycle ending balance of the previous period less payments. If the indicated balance is negative, the revolving balance is 0.

areas. Consistent with these results column 3 reports effects of Harvey on revolving balances that are small and statistically indistinguishable from zero.

The coefficients on the interaction with the indicator variable *revolves*, in columns 1 to 3, show that the response in charges, payments, and balances is not driven by cards with pre-Harvey revolving balances. Accordingly, the marginal effects for all outcomes is much smaller for these cards. Interestingly, however, even among these cards, we still find the same pattern of results with no effect on balances and charges and payments moving in lock-step. We interpret these results as indicative of Harvey leading to increased use of credit cards for purchases but not borrowing. These results also suggest that households use different cards for borrowing and for purchasing, or that Harvey increased the use of cards for purchases among households that seldomly use their cards for borrowing.

On the whole our findings extend those of Gallagher and Hartley (2017), who find small, transient impacts of hurricane Katrina on credit card balances, but who cannot distinguish between spending and borrowing. Specifically, we show that the muted effect in balances is the result of charges and payments surging together in affected areas. Additionally, we show that these effects are driven by the use of existing credit lines that are infrequently used for borrowing.

4.2 Origination and Subsequent Use of New Cards

Although the previous section found no average increase in intensive borrowing (carrying additional balances on existing credit cards) borrowers may have increased borrowing on the extensive margin; that is, affected borrowers may have originated new cards and carried balances on those cards.

To study the impact of Harvey on the number of credit card originations and their use, we use the Y-14 dataset to create a panel of credit card originations at the ZIP+4 month level. The panel includes the count of promotional cards, that is, cards with temporary, low interest rates; the count of standard cards; and the total number of originations both promotional and standard. Because less than 5 percent of ZIP+4 report more than one card origination in any given month, we code every ZIP+4-month unit as either reporting zero or at least one origination. The dataset also allow us to observe other attributes of these credit lines including their revolving balances.

Figure 3 plots point estimates and 95 percent confidence intervals derived from a logit specification where the outcome is observing at least one origination in a ZIP+4-month unit.[9] Consistent with the findings of the previous section the figure reveals that consumers are also sensitive to the price of credit in the extensive margin. Specifically, we see that in the months after Harvey in affected areas the odds of a new card origination increases, with this increase being particularly notable among promotional cards. By showing that there is no evidence of a pre-trend in originations for either type of card, the figure also provides supporting evidence for the parallel trend assumption .

Table 2 present results from an analogous logit specification where the results are summarized using quarter bins. Column 1 shows that Harvey lead to a 6 percent per ft of flooding temporary increase in the odds of observing a card origination. Columns 2 and 3 highlight, that consistent with the result of figure 3, the temporary increase is driven by a large spike in promotional card originations, which experience an increase of 9 percent per ft of flooding. By comparison, we find that standard card originations experience a smaller 4 percent increase per ft of flooding.

To study how these new promotional cards are used Figure 4 plots average revolving balances over time by 3 month cohort of origination, type of card, and level of flooding. Panels A and B presents results for promotional cards in areas affected by more and less than 1 ft of flooding. Panels C and D presents analogous results for standard cards. In the figures triangle markers correspond to origination cohorts after Harvey, circle markers correspond to origination cohorts before Harvey. The figures show that balances on these new promotional originations in hurricane-affected areas following Hurricane Harvey are

[9] This specification does not include ZIP+4-level FE. We have also tested a linear probability model that includes ZIP+4-level fixed effects and produces nearly identical results.

much larger than is typical at other times and in other areas, and that they are paid off faster. Specifically, Panel A shows that average revolving balances on new promotional cards in hurricane-affected areas are much higher immediately after Harvey than before it (approximately a \$650 increase in average new balances on promotional cards). We also find that revolving balances on promotional post-Harvey originations in the most affected areas fall precipitously over the first 12 months, and the additional, storm-induced balance is paid off within the first year. By comparison cards originated before Harvey, in less affected areas (panel B), or in cards that charge standard interest rates (panel C and D) report effectively no storm-induced change in balances during the first year of the loan. This implies that incremental borrowing on new cards induced by the storm was short-term and on promotional cards, so that borrowers paid an interest rate of approximately zero.

This card-utilization pattern is also apparent in regression form in Tables A5 and A6 in the appendix. Specifically, table A5, shows that among promotional cards originated after Harvey, each additional foot of flooding leads to revolving balances that are \$221, \$131, and \$87 higher 2, 4, and 6 months after origination, respectively. By comparison, in table A6 we find no evidence of increased borrowing on standard cards. Accordingly, we conclude that this pattern of borrowing is unique to promotional cards.

Overall the results of this section indicate that consumers are sensitive to the price of credit. They take advantage of the least expensive borrowing option available to them, and they are sophisticated in the sense that they are able to pay down their additional balances before the promotional period expires so that they pay an interest rate of approximately zero.

4.3 Borrowing by missing mortgage payments

Among homeowners with mortgages, the forbearance offers made by mortgage lenders and servicers in response to hurricane Harvey provided financial relief in two ways. First, they suspended foreclosures. Second, it allowed homeowners to skip mortgage payments for 3 months, with the possibility of skipping payments for up to an additional 9 months after establishing contact with their servicer. At the end of this period, borrowers could make up any skipped payments over a short period of time (a repayment plan) or Fannie Mae, Freddie Mac, and FHA offered modification options for borrowers to recapitalize the missed payments and pay them back over a longer time period. As a result, most homeowners could borrow the value of any skipped payments for up to one year at their mortgage rate. Eligibility for this forbearance depended only on the borrower's home or place of employment being located within the Harvey major disaster declaration area; no evidence of damage was required.

We are unable to observe forbearance directly in our data, because forbearance is not a field reported by Y14M filers. When a mortgage borrower uses forbearance, the loan appears delinquent. However, we infer that much of the surge in delinquency is driven by forbearance for several reasons. First, based on the policies at Fannie Mae, Freddie Mac, and FHA, most borrowers who miss payments immediately following the storm are automatically granted short-term forbearance. Second, we document that the payment behavior of borrowers following the first missed payment is quite different during the storm than during non-storm years. This is true even outside the storm area, where the nature of the economic shock likely resembled the type of non-storm shocks that normally drive missed payments. Lastly, we show below that borrowers who missed payments did not see their credit scores fall, whereas normally, missing a mortgage payment causes a 10-20 point decline in a borrower's credit score.

Figure 5 shows that the use of this forbearance offers was widespread. Specifically, the figure plots the coefficients from four separate regressions of the form in Equation 1 where paused mortgage payments (delinquent when not in forbearance) is the dependent variable. Each set of coefficients reflects the results of the regression using a sample with different flooding intensity. The figure reveals that, consistent with the idea that individuals borrowed by pausing mortgage payments, there is a sharp increase in missed payments just after Harvey that returns to pre-Harvey levels roughly within one year. The figure also reveals that use of forbearance grew monotonically with the level of flooding. Among those that experience extreme flooding (3 feet or more) nearly one in six mortgages paused their payments. Equally notable, among those that experience no flooding, roughly one in twenty paused their payments. The widespread use of forbearance including in non-flooded areas is perhaps unsurprising, as our entire sample falls within Harvey's major disaster declaration and is therefore eligible for forbearance.

While it is generally expensive to borrow by missing payments because of the financial penalties and damage to credit scores, forbearance does not entail these downsides. Specifically, during the forbearance plan, servicers are prohibited from charging late fees and are required to suppress reporting to credit bureaus. As previously mentioned, to verify that borrowers where not adversely affected by missing payments, Figure A1 in the appendix plots the 6-month change in credit score following a missed mortgage payment. The figure reveals that missing payments just after Harvey has no impact on credit scores but that missing payments outside of forbearance leads to a reduction in credit score of roughly 20 points. As a result, skipping mortgage payments in the region affected by Harvey was a low-cost (at the mortgage interest rate), low-hassle (no need to apply for a loan) way to borrow moderate sums (up to one year of mortgage payments).

To what degree did borrowers take advantage of this straightforward and low-cost form of credit? To gauge the extent to which individuals borrowed using forbearance offers, Figure A2 in the appendix plots the average number of missed payments by level of flooding among homeowners using forbearance. While use of credit increases monotonically with the level of flooding, the amount borrowed is relatively limited for all levels. Specifically, we find that even those most affected by Harvey miss only 2 of 12 possible payments on average, while those least affected miss only 1.5 payments on average. These results suggest that these homeowners are borrowing between \$1,300 and \$2,300 by missing payments. The fact that the majority of borrowers did not miss 3 or more payments also suggest that the there may have been a substantial transaction cost in extending the forbearance offer by establishing contact with the servicer. Also consistent with the idea that transaction costs are important we observe that the majority of borrowers (about 95%) repay their debt within a year, either by selling their house or becoming current. Only about 5% of borrowers record mortgage modifications - a fraction that is roughly invariant to flooding intensity.

4.4 Substitution and complementarity with other risk management tools

Households have several tools at their disposal to mitigate risk from flooding. These tools include taking self-protection measures to reduce the probability of damage from flooding (e.g., sandbags, water pumps, or structure elevation) and the use of self-insurance and NFIP insurance to reduce the value of the losses. In this section, we investigate the relationship between households borrowing and these risk management tools.

We measure the extent to which households engaged in risk management against flooding before Harvey in several ways. First, we use an indicator variable for location in the floodplain (FEMA zones A and V). Because risk from flooding is more salient in these areas, we hypothesize that these households are more likely to undertake self-protection and self-insurance actions. Additionally, mortgage lenders require mortgages in flood zones to carry flood insurance. Second, we construct an elevated structure indicator taking advantage of City of Houston (1985), which mandated elevating new structures at least one foot above the 1 in 100 years floodplain. From an engineering perspective elevating a structure is one of the most effective, albeit expensive, ways to harden a structure against flooding. Accordingly, we expect those residing in an elevated structure to experience much lower direct damage. Third, we proxy insurance penetration by computing the share of insured structures at the census tract level.

Table 3 studies how the borrowing response varies in relation to the level of self-protection and self-insurance by augmenting our baseline econometric specification (equation 1) with an interaction term between the flood measure variable F_z and an indicator variable for being in the floodplain. The table shows that borrowing using credit cards and by missing mortgages payments (using forbearance) is substantially muted among those in the floodplain.[10] Column 1, presents results when the outcome is observing at least one promotional card origination in a ZIP+4 month unit. We focus on promotional cards because as discussed in section 4.2 credit card borrowing after Harvey takes place primarily through this type of credit card. The coefficients on the interaction reveal that the odds of observing a promotional card origination are more sensitive to flooding outside than inside the floodplain. In fact, inside the floodplain, new promotional card originations are not increasing in flood depth. This result may reflect the fact that households inside of the floodplain are more likely to have used self-insurance and self-protection tools. Columns 2 and 3 report results where the outcome is the revolving balance on these promotional cards at 2 and 4 months after origination. The columns show that short term borrowing on these cards is concentrated among those outside of the floodplain. Specifically, the coefficients for the main effect reveal that balances on these cards are quickly built up before starting to decline 4 months after origination. The coefficients on the interaction with floodplain reveal a similar pattern of short term borrowing but of a much smaller magnitude. Taken together the result of columns 1 to 3 indicate that the use of promotional cards in both the extensive and the intensive margin was driven by households outside of the floodplain who were unlikely to have engaged in self-protection and self-insurance actions before Harvey.

Next in Column 4, we present results when the outcome is a binary variable for mortgage delinquency, that is, in the majority of cases during our time period equivalent to taking advantage of the forbearance programs. Consistent with our previous results we find that borrowing by missing mortgages payments occurs primarily among those outside of the floodplain. To see whether the documented decrease in borrowing among those in the flood-

[10]Table A7 in the appendix further shows that among existing credit lines charges and payments are also muted for those in the floodplain, but as in section 4.1 these lines of credit are not used to borrow in the aftermath of Harvey

plain is driven by structure hardening, we further augment our econometric specification and include an interaction with an indicator variable for residing in an elevated structure, which we identify using a regulation change in 1985 that required new structures in flood plains to be elevated. The results are reported in column 5. We find that those subject to the new building code use substantially less forbearance. For example, we observe that immediately after Harvey those residing in an elevated structure in the floodplain are 1.4 percentage points per ft of flooding less likely to use forbearance than those in the floodplain. In fact, flooded borrowers in the floodplain subject to the new building codes use forbearance at roughly the same rate as borrowers who did not experience flooding. We do not find that households living in structures built after 1985 *outside* the floodplain are less sensitive to flooding, ruling out generic improvements in construction as an explanation. We also observe decreased borrowing among those in the floodplain but not residing in elevated structures. This results suggest that the response of these household may be moderated by other factors, such as market insurance or other forms of self-protection.

Lastly, we explore the relationship between credit use and flood insurance penetration. Unlike physical hardening, flood insurance does not reduce damages from the storm, so it may not reduce liquidity needs, at least in the short run. And in fact, we do not find evidence that insurance affected households' new borrowing through newly-originated credit cards or forbearance following the storm. Table A9 in the appendix repeats the exercise of Table 3 but interacts a dummy variable indicating high insurance in place of the floodplain dummy.

Although insurance does not reduce the need for liquidity, it may protect households financially. For example, insurance does appear to support household consumption after the storm. Figure 6 [11] shows that households in areas with high-insurance penetration increased

[11] This figure shows how purchases, payments, and revolving balances differ in areas with high and low insurance penetration, defined as above- and below-median coverage rates. The figure plots the coefficients from three regressions with the basic structure of Equation 1, with charges, payments, and revolving balances as dependent variables. The coefficients are the interaction between a dummy variable indicating the card is in a census tract with above-median insurance coverage and a dummy variable indicating an area that experienced more than 1 ft of flooding. The coefficients can be interpreted as the difference in the response among those with above- and below-median insurance coverage. The regression controls separately for the relationship between household income and flooding before and after Hurricane Harvey.

charges more than households in lower-insurance areas. We also see an unexpected pattern: two months after the hurricane, payments in high-insurance, flooded areas increased even more than charges, and revolving balances declined, suggesting that part of the insurance payments paid down existing expensive credit card debt. Appendix Table A8 corroborates this story. This table shows purchases, payments, and revolving balances separately for cards with and without pre-existing revolving balances at the time of the storm. Purchases and payments on cards without pre-existing revolving balances moved in tandem. On cards with pre-existing revolving balances, in high-insurance areas, purchases did not increase with flooding, but payments did, and revolving balances fell – consistent with high-insurance borrowers paying off credit card balances.

These results come with some caveats. First, our measure of National Flood Insurance Program (NFIP) insurance is imprecise at the ZIP+4 level, because the publicly-available NFIP insurance data are aggregated to the much-coarser census tract. Therefore, our point estimates may be attenuated. Second, we find that flood insurance at the tract level is highly colinear with household income, which we measure at the census block-group. To account for this colinearity, we control for income in levels and interacted with time and flood depth variables. This approach generates high standard errors as we cannot clearly distinguish the effect of household income from the effect of insurance on household behavior. For both of these reasons, we do not place great weight on the magnitudes of our findings and instead view these results as suggestive.

5 Conclusion

In this paper, we create a new dataset that provides detailed information on the use and origination of credit cards and mortgages for small geographic units (ZIP+4 locations) affected by varying levels of flooding from Hurricane Harvey. We use this dataset to describe the financial decisions of households in the aftermath of Harvey. Our estimates are derived from a difference-in-differences design that exploits the flooding gradient created by Harvey.

We find that households drawn into borrowing following the Hurricane Harvey are generally sensitive to the price of credit, and quickly repay new loans. Three pieces of evidence show that the borrowing response to Harvey is concentrated in low-cost credit options. First, we find that while households respond to the need for funds created by Harvey by increasing purchases in their credit cards, they avoid this expensive form of credit by increasing payments in lockstep. Second, we find that originations of promotional (zero interest) cards spike in affected areas, enabling households to avoid expensive borrowing. Specifically, we find that while households generate large balances on these newly or so that the rate on incremental borrowing is approximately zero. Third, we find that homeowners took advantage of forbearance programs to borrow at their mortgage interest rate by missing payments on their mortgages. Consistent with our previous results, we also find that most homeowners repay their debt without incurring any penalties.

We additionally exploit flood zone designations and a 1985 building code revision which mandated the elevation of new structures above the floodplain to study the degree of complementarity between borrowing and other risk management tools. Consistent with the idea that ex-post borrowing operates as a substitute for ex-ante risk management, we find a muted borrowing response (across all types of credit lines) in the floodplain (where residents are more likely to self-insure and self-protect) and in particular among those residing in elevated structures. We present suggestive evidence that insurance did not reduce households' need for credit, on average.

Our findings are important because policy-makers routinely face a choice about how much credit to encourage or provide after natural disasters. Policymakers may be concerned that additional borrowing after storms may lead to an ongoing cycle of expensive borrowing and default, or that the newly-issued credit will generate large losses for banks. We show that these concerns are not well-founded, as post-storm borrowers generally use credit in a cost-conscious and time-limited manner. This suggests that policy-makers may want to encourage the extension of credit following natural disasters, particularly to homeowners in non-hardened homes, for whom credit may be particularly necessary.

During Hurricane Harvey, credit was relatively abundant and Houston was booming. Had the storm occurred during another point in the business and/or credit cycle, private credit might not have been available as a tool to help affected individuals manage storm damage; government provision of credit (e.g., forbearance policies) might have been even more important, but losses may also have been higher. This paper shows that regulations to encourage physical hardening substantially reduce households' reliance on credit following the flood, potentially reducing a source of overlapping climate and macroeconomic risk.

Climate scientists expect that the frequency and severity of tropical cyclones will increase in the decades to come (IPCC, 2021), and storms may come to affect areas previously thought to be low-risk. Whereas flood insurance can expand with flood risk, physical hardening is capital-intensive and slow-moving. Policy-makers will need to develop forward-looking hardening strategies as well as ex-post credit policies to help households manage the financial impact of storm damage as these risks change.

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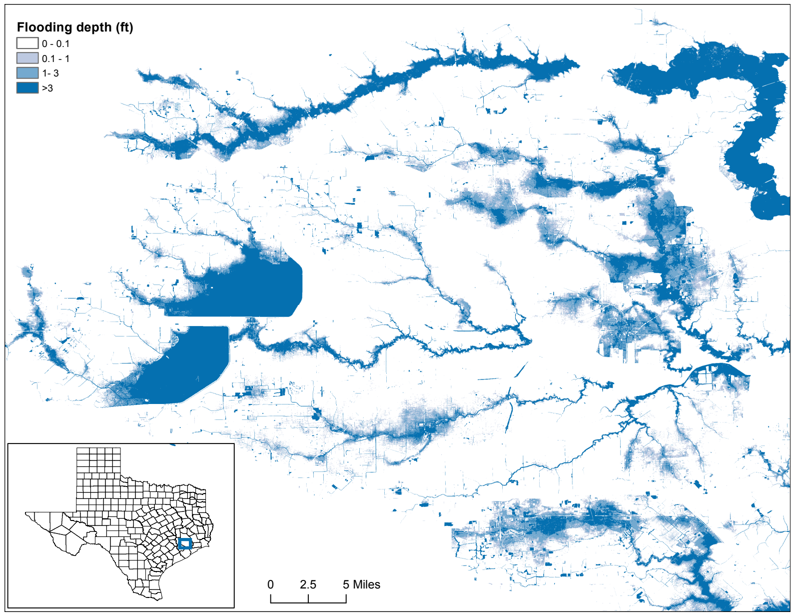
Figures and Tables

(a) Flooding from Hurricane Harvey in Harris County, Texas



(b) Illustration of flooding calculations for a ZIP+4

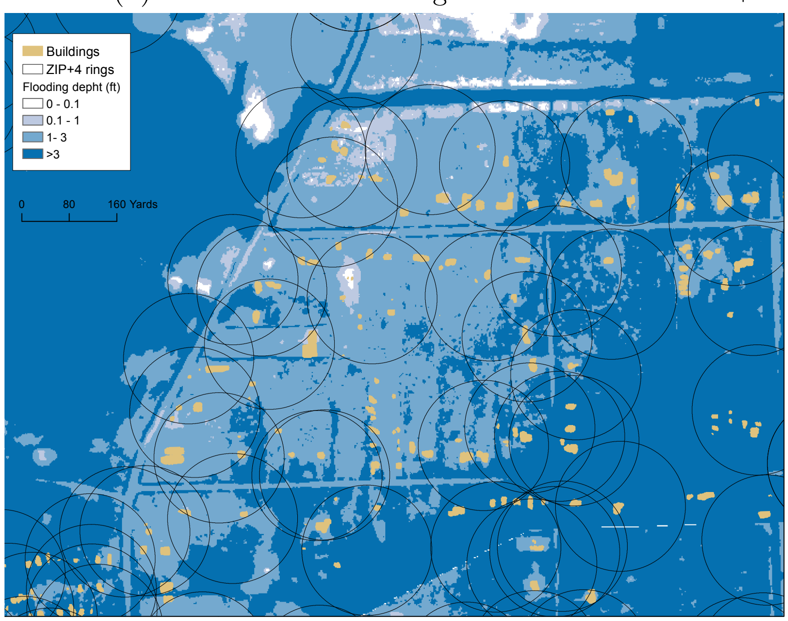


Figure 1: Flooding Maps and Calculation

Notes: Sub-figure (a), Map of Harris county Texas. The map shows the flooding created by hurricane Harvey. The darker the shade of blue the greater the depth of flooding. Sub-figure (b), plots flooding caused by Hurricane Harvey in Redwood Estates, Houston, TX 77044. It also plots a 100 meter (328 feet) ring around each ZIP+4 centroid, and structure footprints shaded in yellow. ZIP+4 average flooding is calculated by determining the maximum flooding that each structure experienced and then averaging among all structures that are located within a ZIP+4 ring.

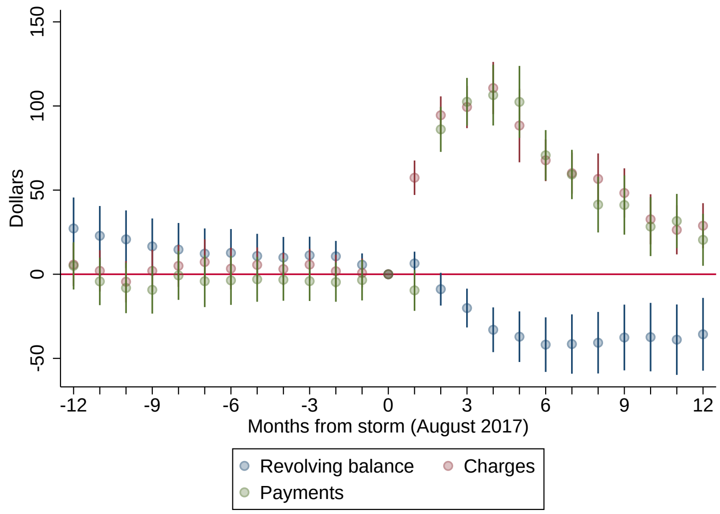


Figure 2: Purchases, Payments, and Revolving Balances on Active Cards

Notes: This figure plots point estimates and 95 percent confidence intervals of the differential impact of Harvey between those exposed to more and less than 1 ft of flooding. Specifically, the coefficients are derived from three separate OLS regressions of specification 1 (for revolving balances, charges, and payments as dependent variables, respectively) where we discretize $F_{z\tau}$ into two groups (more and less and 1 foot of flooding). Displayed coefficients show increase in balances (or charges, or apyments) in the high-flood area relative to the low-/no-flood area (in a given month for a given ZIP+4), relative to the immediately-pre-storm benchmark month. All regressions include credit line and month-year fixed effects. Confidence intervals are derived from robust standard errors clustered at the ZIP+4. Specification 1 reports 36 coefficients, that is β_{-24} to β_{12}. To avoid multi-collinearity we normalize β_{24} and β_0 to be equal to zero. Unless is informative, we provide provide more concise results by only plotting coefficients for β_{-12} to β_{12}. Definitions of all dependent variables can be found in subsection 1.2. Regression results are weighted according to the sampling framework described in Section 1.2.24.

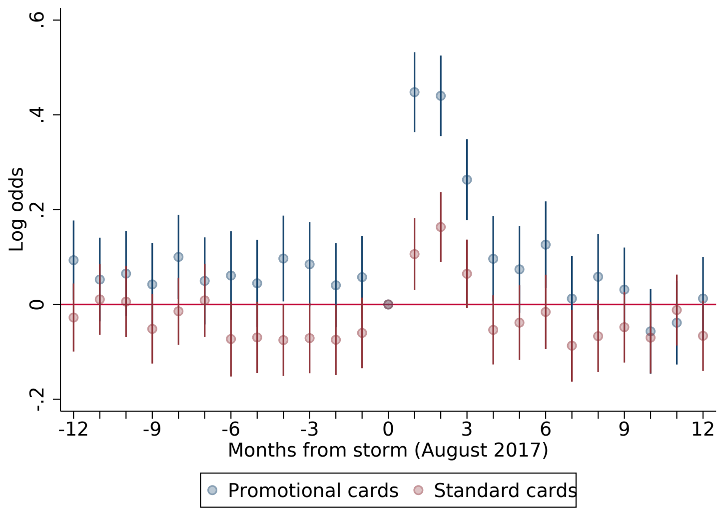
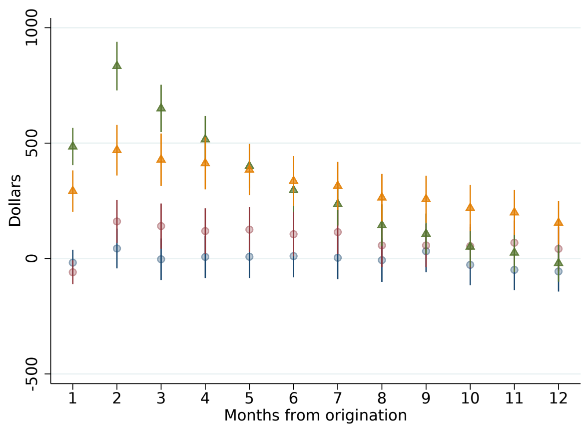
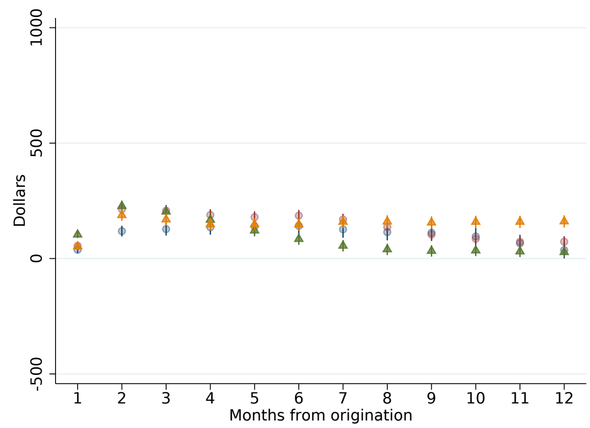


Figure 3: New card originations

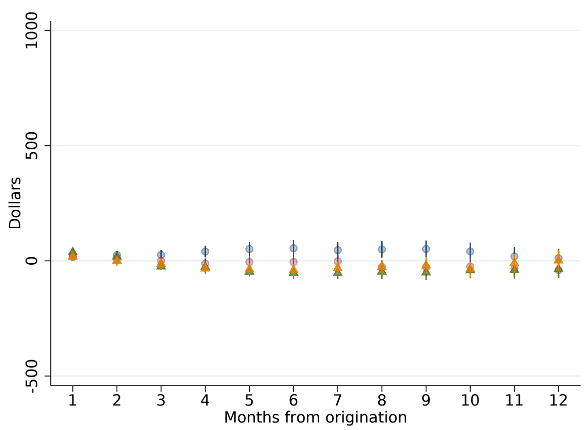
Notes: This figure plots point estimates and 95 percent confidence intervals of the differential impact of Harvey between those exposed to more and less than 1 ft of flooding. Specifically, the coefficients are derived from two separate logit estimatations of specification 1 (for promotional cards and standard cards, respectively) where we discretize $F_{z\tau}$ into two groups (more and less and 1 foot of flooding). Displayed coefficients show increase in log odds of a new origination in the high-flood area relative to the low-/no-flood area (in a given month for a given ZIP+4), relative to the immediately-pre-storm benchmark month. All regressions include month-year fixed effects. Confidence intervals are derived from robust standard errors clustered at the ZIP+4. Specification 1 reports 36 coefficients, that is β_{-24} to β_{12}. To avoid multi-collinearity we normalize β_{-24} and β_0 to be equal to zero. Unless is informative, we provide provide more concise results by only plotting coefficients for β_{-12} to β_{12}. Definitions of all dependent variables can be found in subsection 1.2.



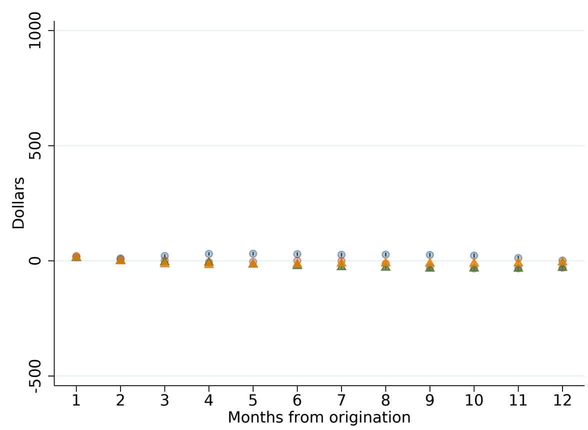
(a) Promotional card, flood depth >= 1 ft



(b) Promotional card, flood depth < 1 ft



(c) Standard card, depth >= 1 ft



(d) Standard card, flood depth < 1 ft

Figure 4: Average revolving balance by cohort of origination, type of card and flood level

Notes: These figures plot coefficients representing the difference in monthly average revolving balance relative to a pre-period spanning June 2015 - February 2017. Each series is comprised of a 3-month cohort of originations. Triangle markers correspond to origination cohorts after Harvey (green is September to November 2017, yellow is December 2017 to February 2018). Circle markers correspond to origination cohorts before Harvey (blue is March to May 2017, red is June to august 2017). Results are shown separately for areas that experienced over 1 ft of flooding and areas that experienced less than 1 ft of flooding or no flooding. These results are implemented in a regression, with coeffients for months-from-origination for each origination cohort, with the pre-period group used as a baseline. Robust standard errors are clustered at the ZIP+4.

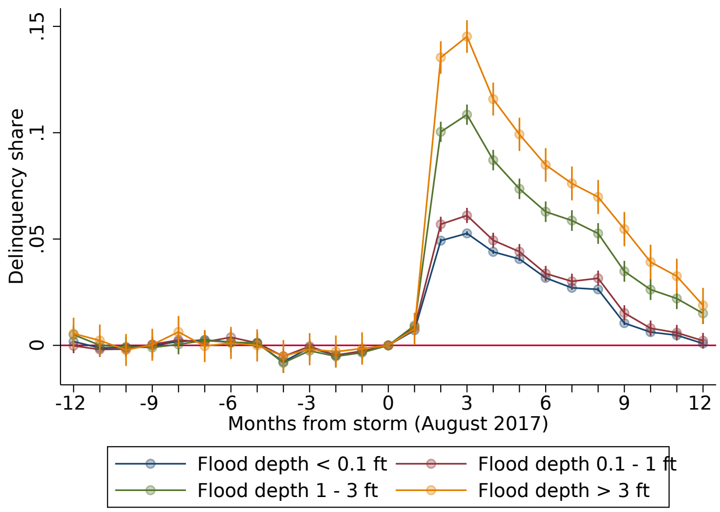


Figure 5: Share of mortgage loans in delinquency

This figure plots the coefficients from a linear probability model to predict the delinquency status of the mortgage loan (0 for not delinquent, 1 for 30+ days delinquent). Specifically, results are derived from four separate OLS regressions of specification 1, for each category of flooding intensity. Displayed coefficients show the delinquency share in each category of flooding intensity, relative to an immediately-pre-storm benchmark. All regressions include mortgage line and month-year fixed effects. Confidence intervals are derived from robust standard errors clustered at the ZIP+4. Specification 1 reports 36 coefficients, that is β_{-24} to β_{12}.

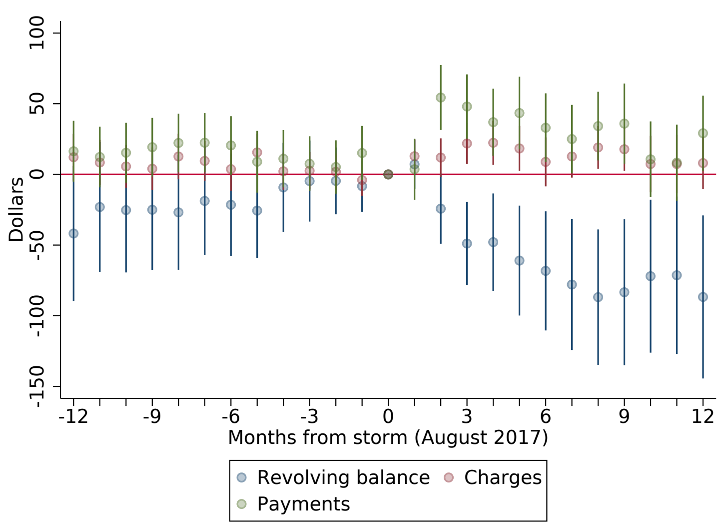


Figure 6: Charges, payments, and revolving balances: insurance interaction

This figure plots the coefficients from a three OLS regressions, where card-level charges, payments, and revolving balances are the respective dependent variables. The coefficients show interaction between a dummy variable indicating that a card is located in an area with above-median insurance coverage and a dummy variable indicating that the borrower experienced at least 1 ft of flooding. The coefficient can be interpreted as the difference (in revolving balances, charges, or payments) among flooded borrowers between areas with high and low insurance. All regressions include credit card and month-year fixed effects. Confidence intervals are derived from robust standard errors clustered at the ZIP+4. Specification 1 reports 36 coefficients, that is β_{-24} to β_{12}.

Table 1: All active cards

	Charges (1)	Payments (2)	Revolving balance (3)
1-3 mth post x depth	58.151***	38.578***	4.148*
	(4.824)	(4.302)	(1.763)
4-6 mth post x depth	70.198***	73.438***	0.942
	(11.347)	(11.774)	(2.591)
7-9 mth post x depth	40.346***	40.142***	1.549
	(7.384)	(7.276)	(3.111)
10-12 mth post x depth	19.932**	25.870***	-0.617
	(7.492)	(7.747)	(3.378)
1-3 mth post x depth x revolves	-47.988***	-28.902***	-12.097***
	(4.858)	(4.381)	(2.604)
4-6 mth post x depth x revolves	-59.597***	-59.607***	-22.397***
	(11.377)	(11.786)	(3.948)
7-9 mth post x depth x revolves	-33.423***	-33.712***	-28.268***
	(7.424)	(7.346)	(4.900)
10-12 mth post x depth x revolves	-15.987*	-22.363**	-28.422***
	(7.600)	(7.888)	(5.393)
N	15501407	15501407	15501407
R^2	0.638	0.569	0.811

Note: This table presents estimates from three separate OLS regressions (for charges, payments, and revolving balances, respectively) that interact the specification described in equation 1 with the indicator variable equal to one if borrower had a revolving balance in July 2017. The depth variable measures the average ZIP+4 level of flooding created by Harvey in feet. All regressions include credit line and month-year fixed effects. Robust standard errors clustered at the ZIP+4 level are presented in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Definitions of all dependent variables can be found in subsection 2.2. Regression results are weighted according to the sampling framework described in Section 2.2.

Table 2: New card originations (logit)

	All cards (1)	Promotional cards (2)	Standard cards (3)
1-3 mths post x depth	0.0585***	0.0853***	0.0415***
	(0.00515)	(0.00730)	(0.00651)
4-6 mths post x depth	0.00543	0.0151	-0.00101
	(0.00578)	(0.00867)	(0.00737)
7-9 mths post x depth	-0.00774	-0.00738	-0.00547
	(0.00574)	(0.00837)	(0.00727)
10-12 mths post x depth	-0.0147**	-0.0219*	-0.00665
	(0.00568)	(0.00856)	(0.00706)
N	12096717	12096717	12096717
pseudo R^2	0.003	0.003	0.003

Note: This table presents three separate logit estimates from specification 1. The depth variable measures the average ZIP+4 level of flooding created by Harvey in feet. All regressions include month-year fixed effects. Robust standard errors clustered at the ZIP+4 level are presented in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.The sample includes all originations between January 2016 and April 2018, for borrowers with mailing addresses in Harris, Aransas, Nueces, and San Patricio counties in Texas at the time of hurricane Harvey. Definitions of all dependent variables can be found in subsection 2.2.

Table 3: All borrowing, floodplain interaction

	Promotional card originations (logit) (1)	Revolving balance 2 months (2)	Revolving balance 4 months (3)	Mortgage delinquency (4)	Mortgage delinquency (5)
1-3 mth post x depth x fp	-0.097***	-168.6**	-74.8	-0.013***	-0.0083**
	(0.016)	(57.6)	(56.0)	(0.0020)	(0.0027)
4-6 mth post x depth x fp	-0.039*	-125.9*	-105.7	-0.0100***	-0.0061*
	(0.019)	(52.3)	(56.4)	(0.0018)	(0.0024)
7-9 mth post x depth x fp	-0.045*	-114.6*	-35.7	-0.0082***	-0.0048*
	(0.018)	(50.1)	(54.5)	(0.0016)	(0.0023)
10-12 mth post x depth x fp	-0.0019	-47.4	-17.2	-0.0042**	-0.0021
	(0.018)	(47.5)	(51.7)	(0.0013)	(0.0019)
1-3 mth post x depth x post-1985					0.0014
					(0.0026)
4-6 mth post x depth x post-1985					0.00091
					(0.0026)
7-9 mth post x depth x post-1985					0.0012
					(0.0023)
10-12 mth post x depth x post-1985					0.00072
					(0.0018)
1-3 mth post x depth x post-1985 x fp					-0.014***
					(0.0037)
4-6 mth post x depth x post-1985 x fp					-0.011**
					(0.0035)
7-9 mth post x depth x post-1985 x fp					-0.0098**
					(0.0032)
10-12 mth post x depth x post-1985 x fp					-0.0056*
					(0.0026)
N	11005162	861654	861845	16067039	15723040
R^2		0.018	0.017	0.515	0.516
pseudo R^2	0.003				

Note: This table presents the results from five separate regressions, of the structure noted in Equation 1. The depth variable measures the average ZIP+4 level of flooding created by Harvey in feet. All regressions include month-year fixed effects and interactions of median household income with flood depth and post-period x flood depth. Columns 4 and 5 include credit line fixed effects. Robust standard errors clustered at the ZIP+4 level are presented in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The sample for credit card originations and revolving balances after origination includes all originations between January 2016 and April 2018, for borrowers with mailing addresses in Harris, Aransas, Nueces, and San Patricio counties in Texas at the time of hurricane Harvey.

NOT FOR PUBLICATION

ONLINE APPENDICES

A Appendix Figures and Tables

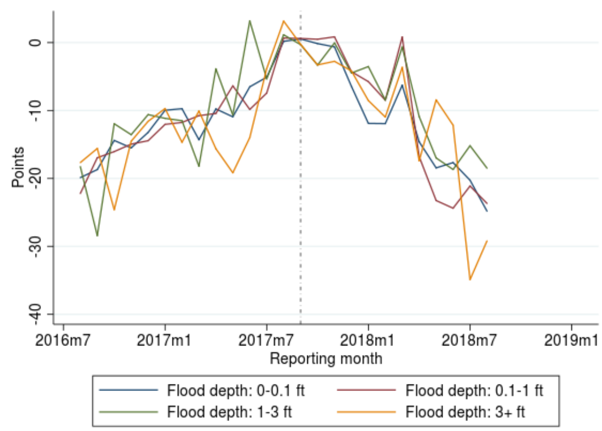


Figure A1: 6-month change in credit score following new mortgage delinquency

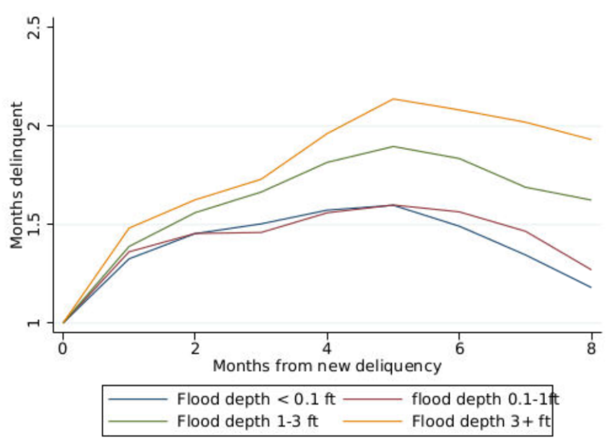


Figure A2: Average delinquency (in months) for storm-induced new delinquencies

Note: Figure A1 shows the 6-month change in the borrower's credit score following a new mortgage delinquency, for borrowers in areas that experienced varying flooding intensities. Figure A2 shows the average number of missed payments among borrowers who became delinquent in September through November 2017 *less* the average number of missed payments among borrowers who became delinquent during the same calendar months in non-storm years (2016, 2018, and 2019).

Table A1: Summary statistics: Active Cards

	N (thousands) (1)	Mean (2)	Median (3)	Std. Dev (4)	1st percentile (5)	99th percentile (6)
Charges ($)	17,521	383	23	1,633	0	5,361
Payments ($)	17,521	412	90	1,719	0	5,750
Revolving balance ($)	17,521	1,577	400	3,131	0	15,444
Delinquency(30+ days)	17,521	.045	0	.207	0	1
Updated credit score	16,883	696	700	92	464	862
Current credit limit ($)	17,520	5,721	3,000	7,004	200	30,000
Household income ($1,000)	17,392	75	68	38	22	213
Share in flood plain	16,601	.082	0	.274	0	1
Flood depth (ft)	16,968	.2	0	.7	0	3.6
Share with insurance	17,521	.182	.142	.142	.015	.706

Note: This table shows summary statistics for all card-months in the sample. Definition of variables can be found in the data section. All values are nominal dollars. Means and distributions reflect our sampling framework (described in Section 2.2). Counts are unweighted and reflect unique card-months in the data.

Table A2: Means by flooding intensity, 3 months before Hurricane Harvey (June-August 2017)

	Flood depth			
	Less than 0.1ft (1)	0.1 to 1 ft (2)	1 to 3 ft (3)	More than 3 ft (4)
Charges ($)	370	408	420	462
Payments ($)	398	438	449	496
Revolving Balance ($)	1,726	1,600	1,566	1,661
Delinquency(30+ days)	.069	.066	.066	.067
Updated credit score	690	696	697	699
Current credit limit ($)	5,598	5,910	5,946	6,312
Household income ($1,000)	66	64	66	71
Flood plain	.046	.305	.408	.435
Flood depth (ft)	0	.4	1.8	4.7
Share with insurance	.169	.263	.271	.267
Card-months (thousands)	6,595	444	314	129
Unique 9-digit ZIP codes	88,658	17,567	12,145	5,680

Note: This table shows summary statistics for all card-months in the sample during the 3 months before the storm, broken out by category of observed flooding intensity. Definition of variables can be found in the data section. All values are nominal dollars. Means and distributions reflect our sampling framework (described in Section 2.2). Counts are unweighted and reflect unique card-months in the data.

Table A3: Summary statistics: Mortgages

	N (thousands) (1)	Mean (2)	Median (3)	Std. Dev (4)	1st percentile	99th percentile
Monthly payment ($)	17,536	945	732	749	0	4,410
Principal balance ($1,000)	17,536	141.1	102.0	145.7	0	848.7
Property value ($1,000)	17,316	289.5	205.0	272.6	72.7	1,648.9
Delinquency(30+ days)	17,853	.07	0	.255	0	1
Updated credit score	17,036	724	749	91	479	479
Household income ($1,000)	17,708	87	77	43	25	250
Flood plain	16,284	.07	0	.255	0	1
Flood depth (ft)	17,446	.2	0	.7	0	3.5
Share with insurance	17,863	.203	.157	.158	.023	.778
Built after 1985	17,111	.564	1	.496	0	1

Note: This table shows summary statistics for mortgages. Definition of variables can be found in the data section. All values are nominal dollars.

Table A4: Means by flooding intensity, 3 months before storm (May-July 2017)

	Flood depth			
	Less than 0.1ft (1)	0.1 to 1 ft (2)	1 to 3 ft (3)	More than 3 ft (4)
Monthly payment ($)	903	1,061	1,077	1,166
Principal balance ($1,000)	134.6	159.5	162.9	175.8
Property value ($1,000)	274.9	336.3	348.3	384.6
Delinquency(30+ days)	.064	.057	.061	.058
Updated credit score	721	728	727	732
Household income ($1,000)	86	94	95	94
Flood plain	.039	.269	.381	.408
Flood depth (ft)	0	.4	1.8	4.6
Share with insurance	.189	.321	.312	.315
Built after 1985	.57	.489	.474	.416
Mortgages	306,748	19,433	13,482	5,382
Unique 9-digit ZIP codes	128,440	8,403	5,999	2,589

Note: This table shows summary statistics for mortgages in the sample during the 3 months before the storm, broken out by category of observed flooding intensity. Definition of variables can be found in the data section. All values are nominal dollars.

Table A5: Revolving balance on promotional originations

	2 months after origination (1)	4 months after origination (2)	6 months after origination (3)
1-3 mths post x depth	221.0***	131.2***	87.21***
	(21.69)	(19.94)	(18.47)
4-6 mths post x depth	117.4***	111.0***	83.37***
	(20.68)	(21.77)	(21.06)
7-9 mths post x depth	36.05*	11.00	-12.54
	(18.15)	(19.06)	(16.73)
10-12 mths post x depth	12.80	4.472	3.704
	(16.47)	(17.30)	(17.13)
N	934039	934123	931948
pseudo R^2			

Note: This table presents estimates from three separate OLS regressions to predict revolving balances on originations of promotional credit cards 2, 4, and 6 months after origination. The specification is described in equation 1. The time period in the far left column reflects the origination period of the credit card. So, for example, the coefficient in row 1 of column 2 indicates the difference in the average balance at 2 months for cards originated in the 3-months after the storm relative to the balance at 2 months for cards originated immediately before the storm. The depth variable measures the average ZIP+4 level of flooding created by Harvey in feet. All regressions include ZIP+4 and month-year fixed effects. Robust standard errors clustered at the ZIP+4 level are presented in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Definitions of dependent variables can be found in subsection 2.2.

Table A6: Revolving balance on standard originations

	2 months after origination	4 months after origination	6 months after origination
	(1)	(2)	(3)
1-3 mths post x depth	4.719	-7.499*	-10.99
	(3.174)	(3.729)	(5.723)
4-6 mths post x depth	4.381	2.971	-2.595
	(3.623)	(5.359)	(5.285)
7-9 mths post x depth	11.96*	14.25*	8.070
	(5.776)	(6.641)	(7.129)
10-12 mths post x depth	1.375	8.026	6.691
	(3.170)	(5.883)	(6.505)
N	1275000	1272457	1270900
pseudo R^2			

Note: This table presents estimates from three separate OLS regressions to predict revolving balances on originations of standard credit cards 2, 4, and 6 months after origination. The specification is described in equation 1. The time period in the far left column reflects the origination period of the credit card. So, for example, the coefficient in row 1 of column 2 indicates the difference in the average balance at 2 months for cards originated in the 3-months after the storm relative to the balance at 2 months for cards originated immediately before the storm. The depth variable measures the average ZIP+4 level of flooding created by Harvey in feet. All regressions include ZIP+4 and month-year fixed effects. Robust standard errors clustered at the ZIP+4 level are presented in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Definitions of dependent variables can be found in subsection 2.2.

Table A7: All active cards, floodplain interaction

	Charges (1)	Payments (2)	Revolving balance (3)
1-3 mth post x depth x floodplain	-27.860**	-30.257***	-1.450
	(9.310)	(8.836)	(4.016)
4-6 mth post x depth x floodplain	-6.682	-10.310	1.765
	(23.680)	(24.632)	(5.198)
7-9 mth post x depth x floodplain	-12.208	-11.978	5.673
	(14.243)	(14.201)	(5.869)
10-12 mth post x depth x floodplain	-10.332	-8.836	4.696
	(14.033)	(14.834)	(6.975)
1-3 mth post x depth x fp x revolves	14.336	25.170**	3.542
	(9.253)	(8.909)	(5.691)
4-6 mth post x depth x fp x revolves	-8.280	-7.450	4.496
	(23.346)	(24.258)	(7.546)
7-9 mth post x depth x fp x revolves	2.019	0.664	0.951
	(14.079)	(14.000)	(8.831)
10-12 mth post x depth x fp x revolves	9.206	4.768	0.748
	(13.802)	(14.648)	(10.025)
N	14579252	14579252	14579252
R^2	0.635	0.567	0.833

Note: This table presents estimates from three separate OLS regressions (to predict charges, payments, and revolving balances, respectively) that interact the specification described in equation 1 with an indicator variable revolves. This variable takes the value of one for credit lines that carry a revolving balance before Harvey. The depth variable measures the average ZIP+4 level of flooding created by Harvey in feet. This specification also includes an interaction with a floodplain indicator, equal to 1 if the mailing address ZIP+4 is located in a floodplain. Because floodplain designation is highly colinear with income, this specification also includes interactions of household income with flood depth and flood depth x post period. All regressions include credit line and month-year fixed effects. Robust standard errors clustered at the ZIP+4 level are presented in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Definitions of all dependent variables can be found in subsection 2.2. Regression results are weighted according to the sampling framework described in Section 2.2.

Table A8: All active cards, insurance interaction

	Charges (1)	Payments (2)	Revolving balance (3)
1-3 mth post x depth x high insurance	38.659***	21.236*	-2.521
	(9.727)	(8.940)	(4.639)
4-6 mth post x depth x high insurance	50.640**	62.546***	-5.576
	(15.866)	(16.357)	(6.280)
7-9 mth post x depth x high insurance	20.616	22.444	-5.832
	(13.200)	(12.778)	(7.616)
10-12 mth post x depth x high insurance	20.614	15.070	-6.423
	(12.652)	(12.891)	(8.574)
1-3 mth post x depth x high ins x revolves	-32.919***	-11.894	-6.893
	(9.929)	(9.310)	(6.366)
4-6 mth post x depth x high ins x revolves	-43.506**	-52.543**	-17.742
	(16.056)	(16.536)	(9.377)
7-9 mth post x depth x high ins x revolves	-15.061	-13.626	-27.897*
	(13.405)	(12.968)	(11.707)
10-12 mth post x depth x high ins x revolves	-17.313	-14.088	-27.038*
	(13.055)	(13.481)	(13.184)
N	15392057	15392057	15392057
R^2	0.638	0.570	0.811

Note: This table presents estimates from three separate OLS regressions where we interact the specification described in equation 1 with the indicator variable revolves. This variable takes the value of one for credit lines that carry a revolving balance before Harvey. The depth variable measures the average ZIP+4 level of flooding created by Harvey in feet. This specification also includes an interaction with an indicator for high insurance, equal to 1 if the mailing address ZIP+4 is located in a census tract with above-median insurance coverage. Because insurance is highly colinear with income, this specification also includes interactions of household income with flood depth and flood depth x post period. All regressions include credit line and month-year fixed effects. Robust standard errors clustered at the ZIP+4 level are presented in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Definitions of all dependent variables can be found in subsection 2.2. Regression results are weighted according to the sampling framework described in Section 2.2.

Table A9: All borrowing, insurance interaction

	Promotional card originations (logit) (1)	Revolving balance 2 months (2)	Revolving balance 4 months (3)	Mortgage delinquency (4)
1-3 mth post x depth x high ins.	0.018	61.4	25.1	-0.0020
	(0.018)	(53.9)	(54.3)	(0.0023)
4-6 mth post x depth x high ins.	-0.041*	-7.21	-19.1	0.00064
	(0.020)	(56.1)	(58.2)	(0.0020)
7-9 mth post x depth x high ins.	-0.0054	51.9	22.6	-0.00078
	(0.020)	(49.3)	(50.7)	(0.0018)
10-12 mth post x depth x high ins.	0.0026	-21.7	-25.4	-0.0012
	(0.020)	(48.6)	(51.4)	(0.0014)
N	11943293	924892	924979	17292853
R^2		0.018	0.017	0.515
pseudo R^2	0.003			

Note: This table presents the results from four separate regressions, of the structure noted in Equation 1. The depth variable measures the average ZIP+4 level of flooding created by Harvey in feet. All regressions include month-year fixed effects. This specification also includes an interaction with an indicator for high insurance, equal to 1 if the mailing address ZIP+4 is located in a census tract with above-median insurance coverage. Because insurance is highly colinear with income, this specification also includes interactions of household income with flood depth and flood depth x post period. Robust standard errors clustered at the ZIP+4 level are presented in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The sample for credit card originations and revolving balances after origination includes all originations between January 2016 and April 2018, for borrowers with mailing addresses in Harris, Aransas, Nueces, and San Patricio counties in Texas at the time of hurricane Harvey.