Household Financial Behavior After Hurricane Harvey

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Do credit markets mitigate idiosyncratic shocks?

Difficult to differentiate unexpected shock from expected changes.

- Weather can be used as a clean exogenous shock to need for funds
- Context: developed economy affected by a very large weather shocks (Harvey)
- Relevant shock in the context of climate change (Emanuel, 2017)
- Credit market with relatively fewer imperfections (best case scenario for adaptation)

What we know

A bit puzzling

- Recent literature finds limited credit response to storms (Justin Gallagher and Daniel Hartley, 2017; Tatyana Deryugina, Laura Kawano, and Steven Levitt,2018)
- Why?
  - Hurricane too small to see response?
  - Hurricane is large enough but people don't/can't respond?
  - Hurricane creates very uneven need for funds so hard to see among averages?

We exploit a nearly ideal research environment

Harvey is the largest rainfall event recorded in US history (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 (1.2 meters) of rain over just a few days (HCFCD, 2018).

High resolution credit card and flooding data

- Response to Harvey measured with monthly loan-level (credit card) data
  - Nearly the universe of credit cards (CCAR Y-14 data)
  - Location measures using zip+4 account mailing address
  - Detailed information for each card: charges, payments, balance, rate, FICO, etc.
- Harvey severity measured with 3 meter resolution flooding depth maps, aggregated to zip+4 (think of groups of about 20 houses)

Credit card data

Credit card data are from regulatory collection used for the Comprehensive Capital Analysis and Review (CCAR). (Also known as the Y14-monthly data.)

- Banks with >$50 billions in assets submit to CCAR.
- These banks account for 90% of outstanding credit card accounts.

Data include detailed monthly account information, including:

- 9-digit zip code of the mailing address of the primary card-holder.
- Purchase volume, payment, balance, APR, updated credit score, original credit score, whether the balance is under promotion (if balance positive), credit limit, borrower income at origination, delinquency, etc.
- Information is at the card level, not the household. We have no identifying information to link cards to individuals or households.

Flooding in Houston

A flooded residential neighborhood near interstate 10 in Houston, Texas (Marcus Yam / Los Angeles Times)

Measuring severity of Harvey (Illustration Jacinto City, Harris, TX)

FEMA's building footprints

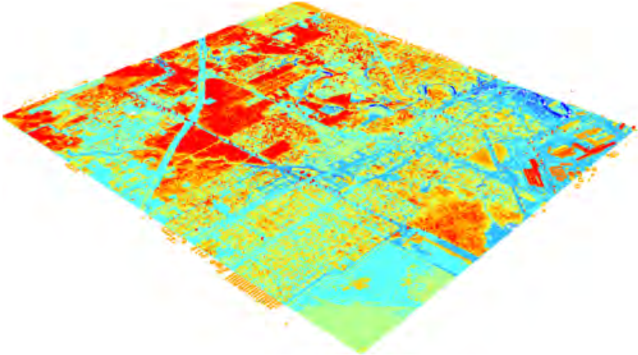
(a) Jacinto City, TX

(b) Neighborhood in Jacinto City
(Los Angeles Times photo)

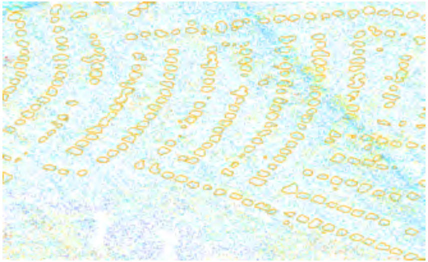
Measuring severity of Harvey (Illustration Jacinto City, Harris, TX)

LiDAR data is used to map elevation

(c) Jacinto City, TX



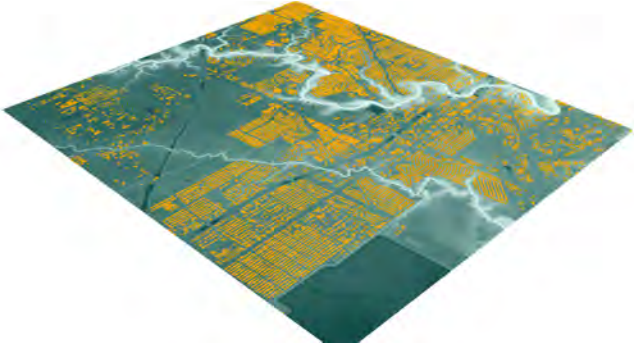
(d) Neighborhood in Jacinto City
(Los Angeles Times photo)



Measuring severity of Harvey (Illustration Jacinto City, Harris, TX)

Digital elevation model based on LiDAR data (3 meter resolution)

(e) Jacinto City, TX

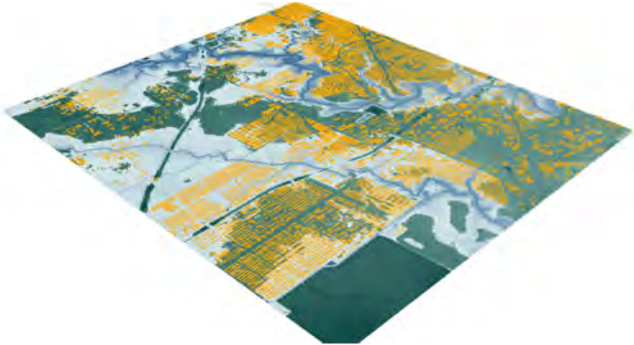


(f) Neighborhood in Jacinto City
(Los Angeles Times photo)

Measuring severity of Harvey (Illustration Jacinto City, Harris, TX)

FEMA's Harvey depth grids (High watermark surface minus elevation)

(g) Jacinto City, TX

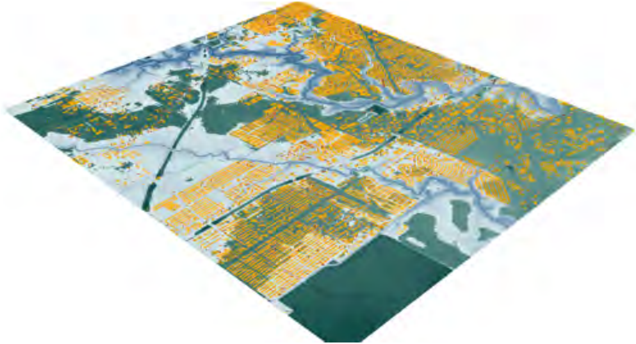


(h) Neighborhood in Jacinto City
(Los Angeles Times photo)

Measuring severity of Harvey (Illustration Jacinto City, Harris, TX)

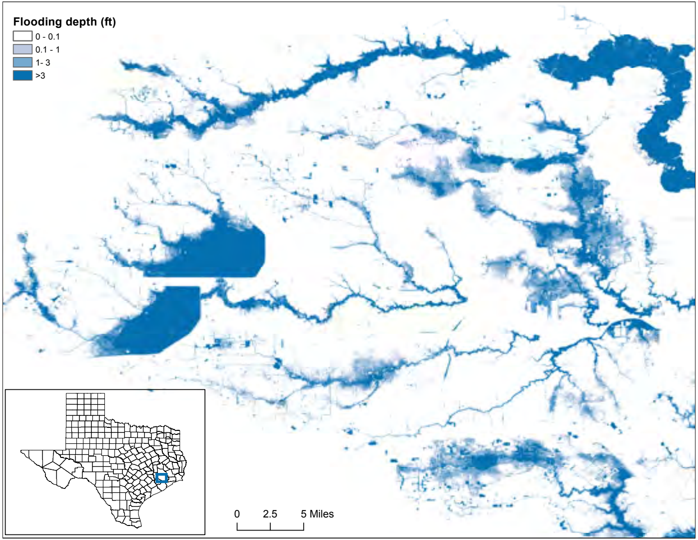
Zip+4 mean building flooding

(i) Jacinto City, TX (red dots depict Pitney Bowes centroid coordinates for zip+4 in August 2017)



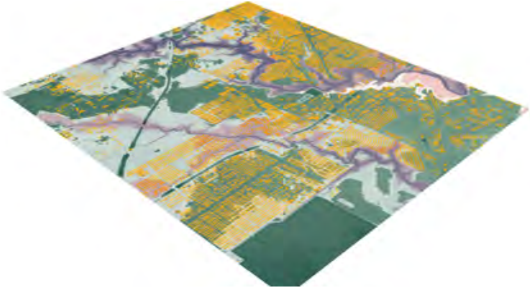
(j) Neighborhood in Jacinto City (Los Angeles Times photo)

Harvey depth grids Harris county TX (Houston)

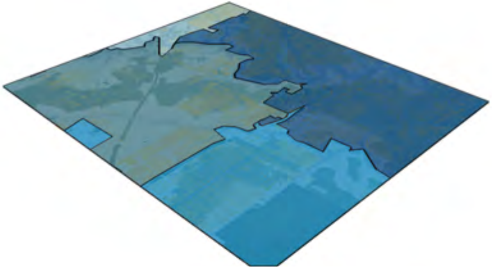


Other datasets used (Illustration Jacinto City, Harris, TX)

(k) Flood hazard: FEMA Flood Insurance Rate Maps (FIRM) available in Texas on March 2017. (Red areas denote a floodplain)



(l) Buildings covered by the National Flood Insurance Program at five digit zip code level



Flooding and ex-ante flood risk: Flooding severity in floodplain and non-floodplain areas

	Flooding			
	Less than 0.1 ft	0.1 to 1 ft	1 to 3 ft	More than 3 ft
Flood Plain	177,987	78,547	76,211	33,399
	4.7 %	30.8 %	41.2%	43.6%
Not flood plain	3,619,222	176,286	108,930	43,207
	95.3 %	69.2 %	58.8 %	56.4 %
Total	3,797,209	254,833	185,141	76,606
	100.0 %	100.0 %	100.0 %	100.0 %

Note: This table shows the count and the share of credit cards in the Y-14 data observed during our sample period (June 2016 - April 2018) by ex-ante exposure to flooding (floodplain and not floodplain) and observed flooding intensity. Columns add to 100%.

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

	Flooding			
	Less than 0.1 ft	0.1 to 1 ft	1 to 3 ft	More than 3 ft
Charges ($)	305	349	342	396
Payments ($)	329	381	360	411
Cycle ending balance ($)	1,506	1,515	1,446	1,632
Revolving balance ($)	1,218	1,196	1,136	1,261
Fees ($)	21	21	20	21
Delinquency	1.4%	1.3%	1.4%	1.5%
Updated credit score	717	719	721	723
Current credit limit ($)	5,506	5,809	5,826	6,315

Note: All values are nominal dollars. Counts are unweighted and reflect unique card-months in the data.

Approach: Difference in difference estimator

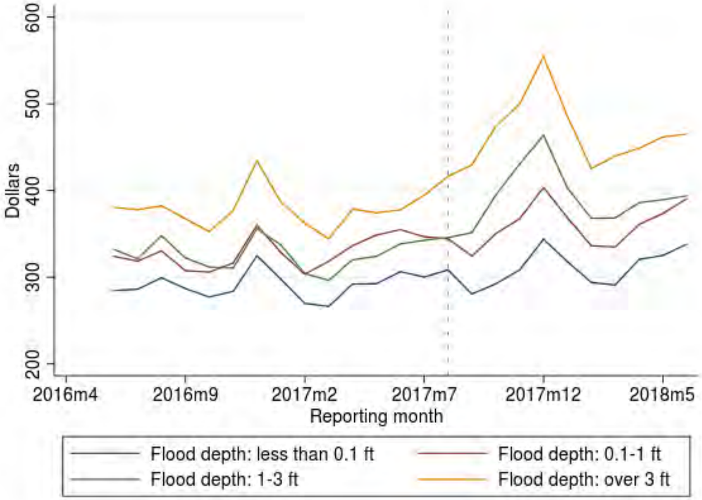
- Compare the pre-hurricane period in areas more-and-less affected by Harvey with the period immediately after the hurricane
  - “shortly after”: September - November
  - “well after”: December - February
- All regressions include month-year time dummies.
- Robustness tests for zip fe, zip-month fe, zip+4 fe, clustering at zip+4, zip, additional regressors.

$$\begin{aligned} y_{i,t} =& \alpha + \beta_1 \times \textit{flood depth}_z + \beta_2 \times \textit{shortly after}_t \times \textit{flood depth}_z \\ &+ \beta_3 \times \textit{well after}_t \times \textit{flood depth}_z + \gamma \times M_t + \varepsilon_{i,t} \end{aligned} \tag{1}$$

Where $y_{i,t}$ is a particular outcome in time period t for loan (card) i located in zip+4 z.

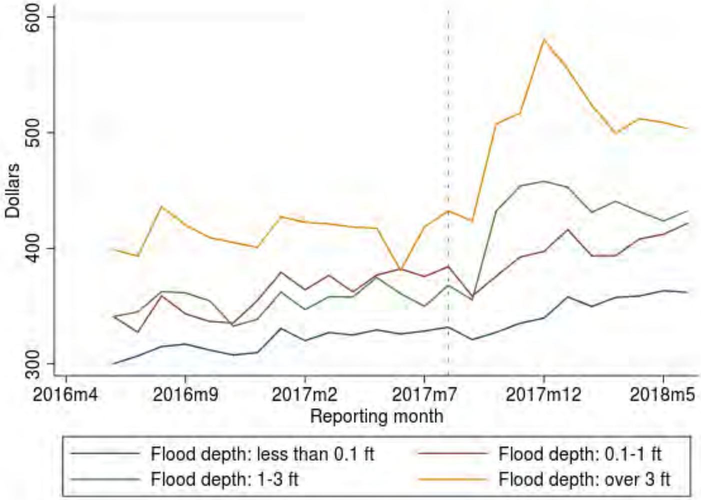
Credit card charges (purchase volume) by flood depth

Those in affected areas increase charges on their cards



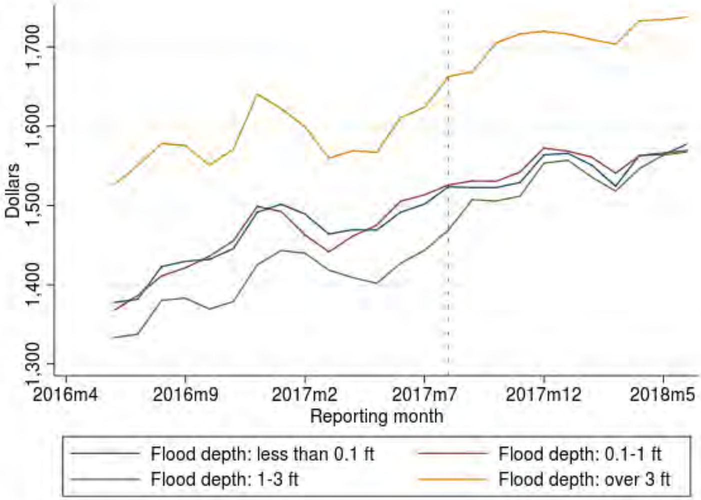
Credit card payments by flood depth

Charges and payments move up in lock-step due to storm.



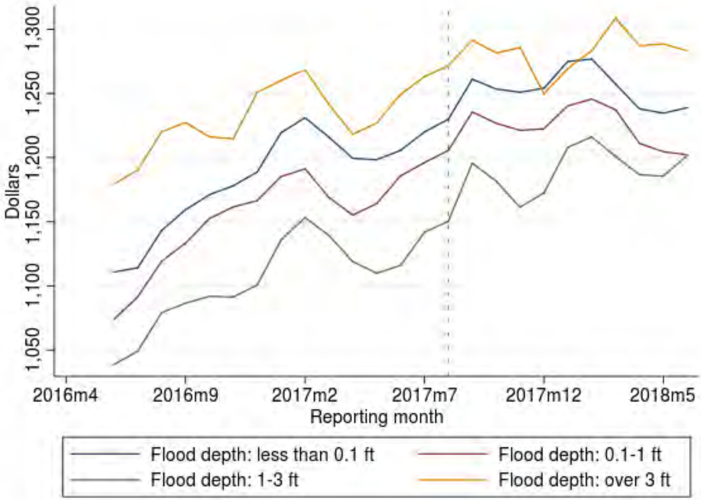
Balances (cycle ending)

We can replicate zero (small) changes in balances



Balances (revolving)

Credit cards are an expensive form of financing Table



Heterogeneity in charges, payments, and balances

- No impact on balances but more pronounced effects for charges and payments among:
  - Those outside of designated floodplain areas (structures less prepared to withstand flooding) Floodplain
  - Those in areas with high penetration of flood insurance. Flood insurance
- Low-credit-score borrowers in affected areas increased their revolving balances. Credit Score

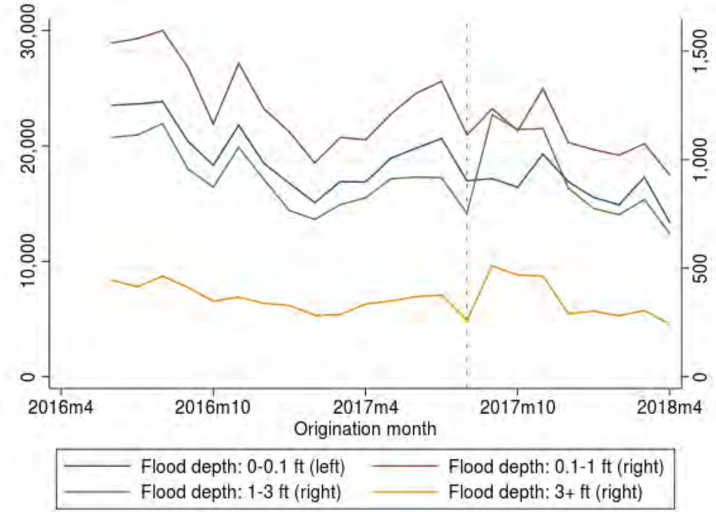
Origination characteristics for new cards originated in 3 months before Hurricane Harvey, by flooding intensity

	Flooding			
	Less than 0.1 ft	0.1 to 1 ft	1 to 3 ft	More than 3 ft
Borrower income	87,343	83,341	75,837	82,998
Original credit score	704	705	707	707
Cobrand	0.1	0.1	0.1	0.1
Promotion	0.4	0.4	0.4	0.4
Credit limit	3,992	4,041	4,158	4,364
Retail APR	20.13	20.04	20.06	20.18
Effective APR	13.09	13.10	12.84	13.05

Note: All values are nominal dollars.

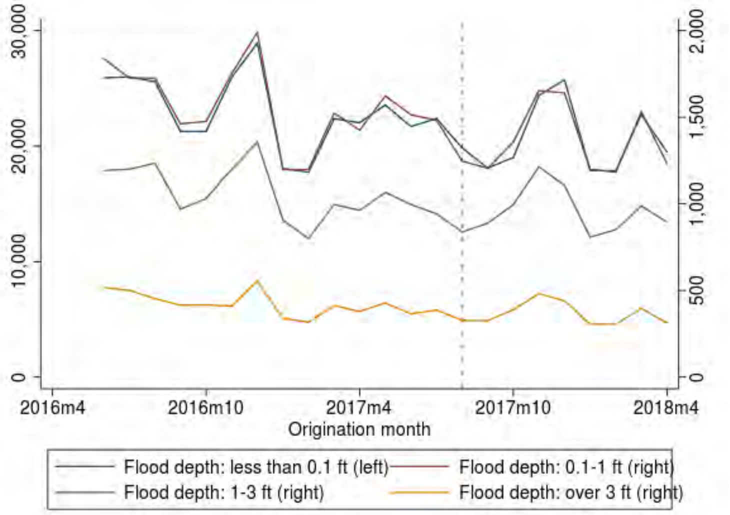
Extensive margin: New cards

Teaser cards (zero interest promotional cards) large increase ≈ 10% per foot of flooding Table



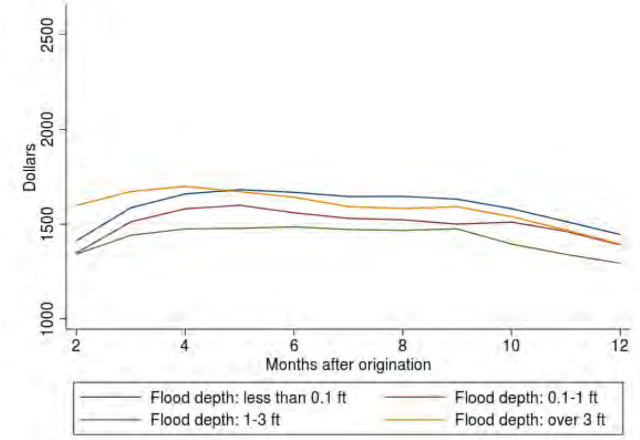
Extensive margin: New cards

Muted response among non-teaser cards Table



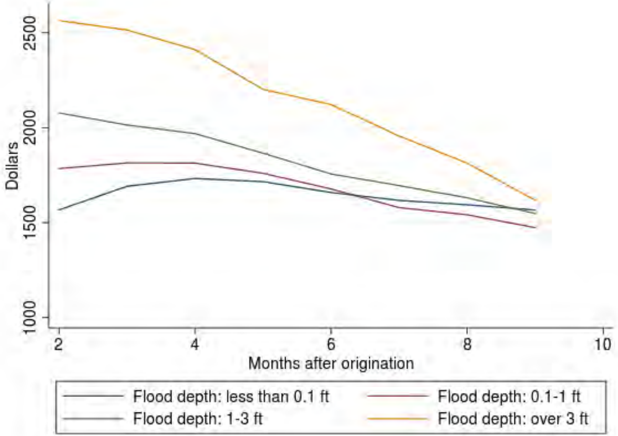
Revolving balances on teaser cards

No change in balances on recently-issued (pre-storm) teaser cards in storm-affected areas immediately after storm.



Revolving balances on teaser cards

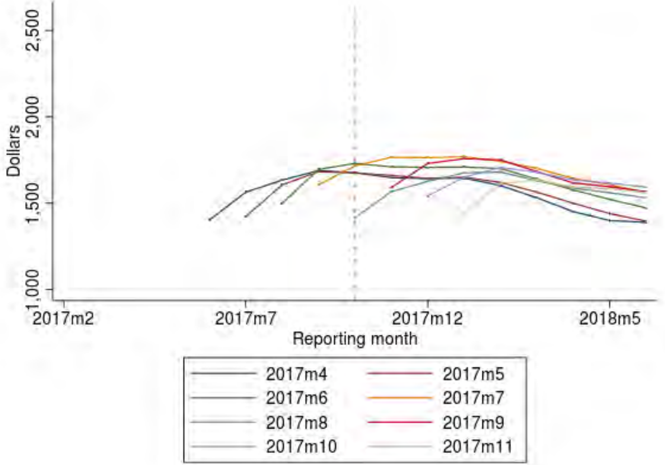
Balances on these teasers are [much higher] than pre-storm originations.Balances are paid off unusually quickly.



Table

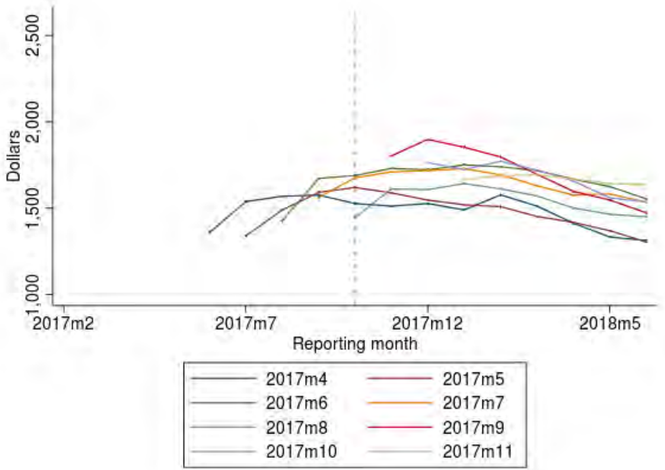
Teaser cards: revolving balance by origination month for flood depth group <0.1 ft

The jump in revolving balances is sharp and does not reflect an underlying trend in the data



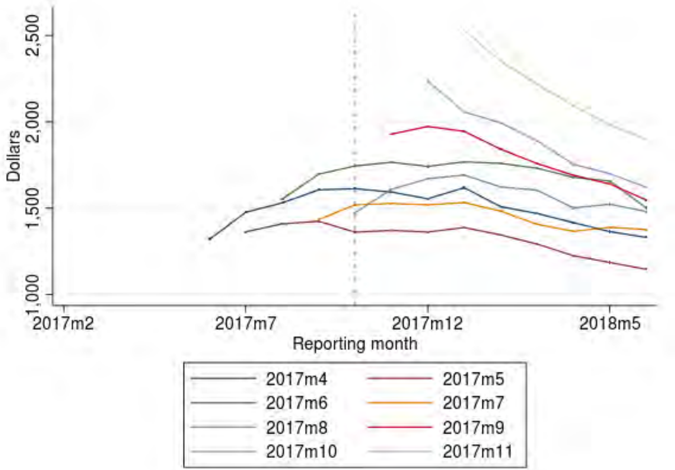
Teaser cards: revolving balance by origination month for flood depth group 0.1-1 ft

The jump in revolving balances is sharp and does not reflect an underlying trend in the data



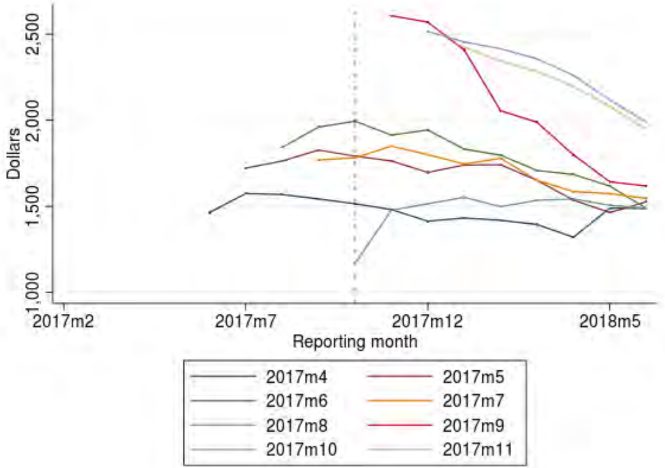
Teaser cards: revolving balance by origination month for flood depth group 1-3 ft

The jump in revolving balances is sharp and does not reflect an underlying trend in the data



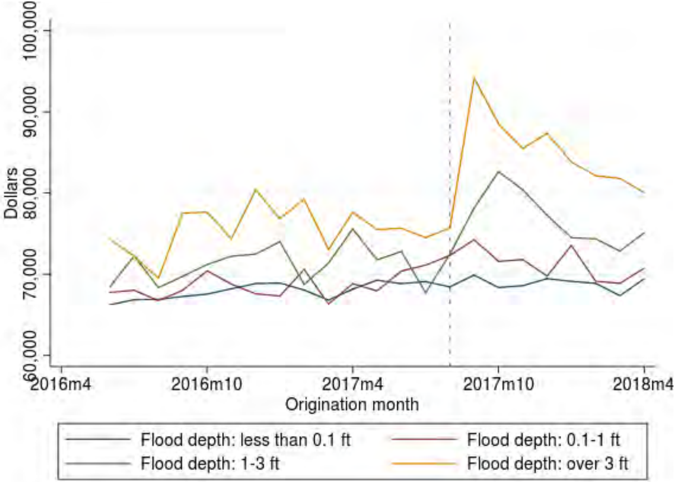
Teaser cards: revolving balance by origination month for flood depth group > 3 ft

The jump in revolving balances is sharp and does not reflect an underlying trend in the data



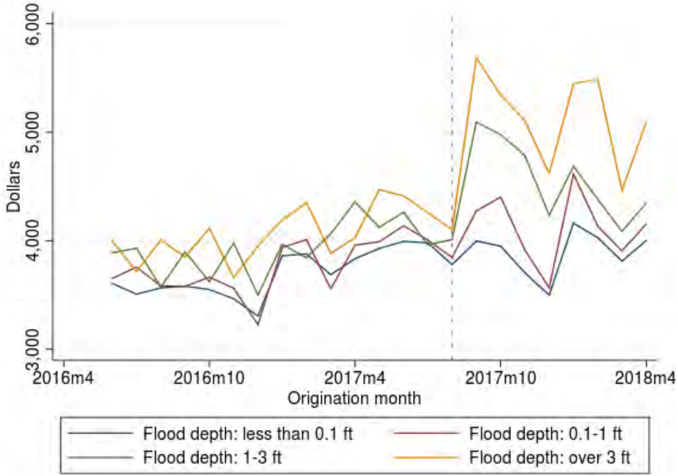
Higher-income borrowers are taking out teaser cards in storm-affected areas

Borrower income



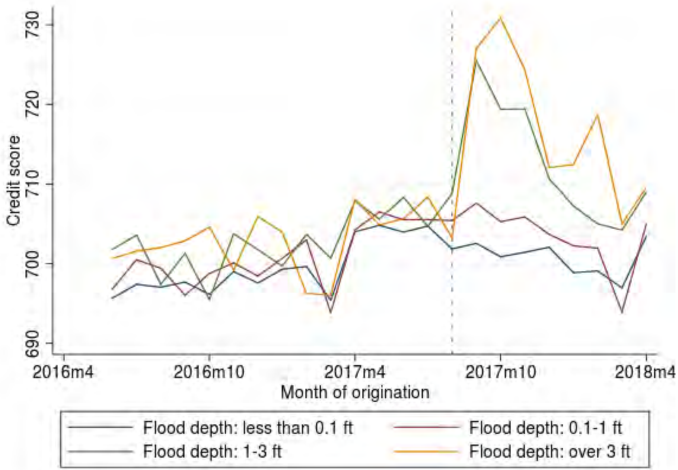
Post-storm teaser cards have higher credit limits in storm-affected area

Initial credit limit



Post-storm teaser cards are going to borrowers with higher credit scores in storm-affected areas

Initial credit score



Heterogeneity

- Among those in areas with high penetration of flood insurance
  - No difference in the number of new cards Table
  - Much larger revolving balances on new cards Table
- Among those in floodplains (structures better prepared to withstand flooding)
  - Significantly fewer new card originations Table
  - Lower revolving balances on these new cards Table

Conclusion

- We can replicate zero (small) changes in balances (revolving and end-of-cycle) for existing loans and all cards
- Large increases in new credit cards in affected areas with:
  - Teaser cards (temporary zero) rates
  - High balances, paid off quickly
  - These borrowers have higher income/credit scores
- Among those with access to these credit lines, our results provide supporting evidence consistent with the idea of complementarity between financial markets and government provided flood insurance.
- Suggests need for funds (or at least use of credit) unevenly distributed even within worst-affected areas
- Intensive use of credit by some (at low credit cost) to manage shocks