Online Appendix for

"Mortgage Finance and Climate Change"

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1 The Impact of Natural Disasters on Current Mortgages' Default and Prepayment

A key empirical question is whether natural disasters affect households' payment behavior, and whether disaster trigger either defaults or prepayments. In both cases, increases in either defaults or prepayments affect the profit of a lender that held the mortgage. Expectations of default risk should lead to greater securitization probabilities, while expectations of prepayment are less likely to affect securitization behavior as an agency MBS typically "passes through" mortgage prepayments. In other words, the agency MBS insures the lender against default risk but does not insure the lender against prepayment risk.

We estimate the impact of natural disasters on payment history by considering a dataset made of (i) the universe of individual loans in zip codes affected by the billion-dollar disasters of Table 1, regardless of the specific timing of the origination of these loans, and (ii) a 1% random sample of the universe of loans in the control group. The dataset has a total of 3.68 million loan-month observations.

The following specification controls for zip code and year fixed effects and estimates the impact of a natural disaster relative to the specific year t_0 of that event:

$$\mathbf{1}(\text{Default})_{it} = \sum_{k=-K}^{+K} \delta_k \cdot \mathbf{1}\left[t = (t_0(i) + k)\right] + \text{ZIP}_{j(i)} + \text{Year}_t + \text{Residual}_{it} \tag{1}$$

where $\delta_0, \delta_1, \ldots$ are the coefficients of interest, which measure the impact of the disaster on default. $t_0(i)$ is the year of the natural disaster of mortgage loan i. $j(i)$ is the zip code of mortgage i at origination. The effect of a natural disaster is identified as disasters occur over a period a 8 years. Year and zip code fixed effects are identified by observations both in the treatment and the control groups. Residuals are two-way clustered at the zip code and year levels.

The results are presented graphically in Appendix Figure C. The solid lines in each graph present the coefficients δ_{-2} to δ_{+5}. The dotted lines are the 95% confidence intervals. The results suggest that a natural disaster has a statistically significant negative impact on the probability that a loan is current, by about 4 percentage points. A natural disaster increases the probability that a loan is in foreclosure by 1.6 percentage points. In contrast, the impact on the probability of prepayment is marginally significant at 5%.

These results suggest that insurance payments and other transfers post-disaster may not mitigate the impact of natural disasters on delinquencies and foreclosures. This is consistent with recent work such as that of Kousky (2018) suggesting a decline in the number and dollar amount of properties insured through the National Flood Insurance Program. Section 4.4 assesses whether lenders tend to bunch mortgages at the conforming loan limit in areas where Fannie and Freddie require flood insurance.

2 Credit Risk Transfers

2.1 Regulatory Framework and Policy Implications

Credit Risk Transfers can potentially alleviate concerns about the climate risk borne by Fannie Mae and Freddie Mac as they allow a transfer of risk from Fannie and Freddie to private sector investors such as investment banks, hedge funds, and other third parties (Finkelstein, Strzodka & Vickery 2018). CRTs also provide a pricing of agency MBS risk independently of the guarantee fees set every year by the Federal Housing Finance Agency that regulates Fannie and Freddie. The policy implications of this paper are significantly different (a) when mortgage credit risk can be transferred and priced by the private sector, and (b) when credit risk is retained by the agencies thus leading to a liability for the US Treasury and the American taxpayer.

In the former case, the agencies act as an intermediary between mortgage lenders and other private sector investors. Fannie and Freddie facilitate risk sharing between mortgage lenders and investors with heterogeneous risk preference and beliefs about risk. Fannie and Freddie also provide the benefit of risk diversification by packaging loans into agency Mortgage Backed Securities and then Real Estate Mortgage Investment Conduits (REMICs), thus spreading risk across a large number of pools. Third parties can thus get exposure to a diversified pool of mortgage investments. In this case, the transfer of risk from lenders to buyers of CRTs may be efficient, allowing an equilibrium closer to the Pareto-optimal Arrow-Debreu risk sharing. In this sense Credit Risk Transfers may be a financial innovation that enables risk sharing (Allen, Gale et al. 1994).

In the latter case, credit risk is retained by the agency. The agencies are under conservatorship by the Federal Housing Finance Agency since the Housing and Economic Recovery Act of 2008

(HERA) in its Section 1311, paragraph (b), (2). Such conservatorship does not have a specified end date (Fannie Mae's 10K Report, 2010). The U.S. Treasury was issued one million shares of senior preferred stock and a warrant to purchase 79.9% of the total number of shares of common stock outstanding. Further, the Treasury has a funding commitment; holders of agency debt securities may claim for relief from the Treasury in the U.S. Court of Federal Claims (Fannie Mae's Annual Report, 2010). This institutional arrangement implies that without CRTs, the risk of default and prepayment is likely borne by the Treasury.

The Credit Risk Transfer program was initiated in 2012 and implemented starting in 2013. The first transaction was completed in the 3rd quarter of 2013.[1] The program's goal is to "transfer credit risk on at least 90 percent of the unpaid principal balance (UPB) of newly acquired single-family mortgages targeted for credit risk transfer (CRT)." Not all mortgages are part of the set of mortgages targeted for CRT. Such mortgage are non-HARP, fixed-rate mortgages with LTVs greater than 60 percent and original term greater than 20 years. The volume of CRT issuances grew from 90 billion dollars in 2013 to 709 billion dollars in 2019.[2] While sizable, this volume is only a part of the $3.5 trillion outstanding unpaid principal balance. Another potential concern is the non-random selection into Credit Risk Transfers: if CRTs are riskier than retained mortgages (negative selection into CRTs), private investors are more exposed to risk than Fannie and Freddie; yet if CRTs are less risky than retained mortgages (positive selection into CRTs), private investors may be less exposed to risk than the agencies. We use data from Fannie Mae to understand which scenario is at play.

2.2 Geographic Distribution of Loans in CRT Issuances

We use Fannie Mae's loan-level Credit Risk Transfer data to analyze the amount of USD mortgage risk purchased by (and thus transferred to) private counterparties. This allows us to assess whether climate risk is transferred to such private counterparties or retained by the agencies. To assess the exposure of individual mortgages to hurricane risk, we combine our decennial hurricane probabilities built from the National Hurricane Center's Atlantic Hurricane Date (HURDAT) to see whether CRT transfers are more or less likely in areas affected by higher hurricane frequency. To compare the volume of CRT transfers to the volume of mortgage originations in a given area, we divide the

[1] Statement of FHFA Acting Director, Edward J. DeMarco, on Freddie Mac Risk-Sharing Transaction, July 2013. Statement of Edward J. DeMarco on Fannie Mae Risk-Sharing Transaction, October 2013.

[2] CRT Progress Report, 2019Q4.

CRTs' unpaid principal balance by the volume of mortgage originations from the Home Mortgage Disclosure Act for the same area.[3]

Figure D displays three panels. The upper panel (Figure Da) presents a map of the spatial distribution of the ratio of CRTs' UPB over the volume of mortgage originations, for the Atlantic states and the states of the Gulf of Mexico. It shows substantial spatial heterogeneity in CRT transfer activity, with the largest relative volumes in Northern Louisiana, the New York tristate area, and the southern tip of Delaware. Figure Dc presents a histogram of the distribution of such ratios as of August 2020, suggesting a mode around 30% and a large heterogeneity from very low levels below 10% up to 95 to 100% for a few ZIPs.

Figure Db suggests that there is a negative correlation between the ratio of CRTs' UPBs to the volume of mortgage originations and hurricane frequency, measured as the probability that a ZIP code is in a hurricane's 64kt wind path. Visually, the graph shows that areas with no hurricane history have CRT/origination ratios sometimes in the 90-100% range. This is not the case in areas typically affected by hurricanes. In areas with very frequent hurricanes the ratio falls to 30%. This negative correlation between CRT issuances and hurricane frequency can be seen in the following regression:

$$\text{(CRT UPBs / Originations)}_j = \underset{(0.002)}{0.342^{***}} - \underset{(0.013)}{0.112^{***}}\text{Hurricane Frequency}_j + \underset{R^2=0.084}{\varepsilon} \tag{2}$$

where j is the 3-digit ZIP code. The historical hurricane frequency is taken over the 1851-2017 period. The estimated coefficient -0.112 is significant at 1% and suggests that a one standard deviation increase in hurricane frequency (6.6 percentage points) is correlated with a 0.7 percentage point decline in the ratio of CRT issuances over originations. This simple regression with only the hurricane frequency as an explanatory variable has an R-squared of 8.4 percent. This suggests evidence of some positive selection into CRTs, as the agencies may be more likely to retain mortgages exposed to hurricane risk.

[3] Fannie Mae's CRT data provides 3-digit ZIP code information, which is not as coarse as the paper's main data, at the 5-digit ZIP code level.

2.3 Remaining Challenges of Credit Risk Transfers

Recent evidence suggests that CRT issuances have dropped substantially during 2020.[4] In particular, Fannie Mae did not issue CRTs during 2020 Q2 and 2020 Q3, down from an average of 2 billion dollars per quarter. This happened even as the rate of mortgage delinquencies increased modestly, from 2.34% in the fourth quarter of 2019, to 2.81% in the third quarter of 2020. While the decline in CRT issuances may not have been caused by the rise in mortgage delinquencies but rather by new capital rules, this suggests that CRT issuances may not be positively correlated with mortgage default rates and thus are consistent with the evidence that there is negative selection into credit risk transfers.

3 Placebo Tests

3.1 The Role of Interest Rates in Bunching

The amount of bunching of loans on the left side of the conforming loan limit may be due to a decline in interest rates. Mortgage lenders may be adjusting their menu of interest rates to account for the lower cost of funds in the conforming segment. In this segment, the interest rate on mortgages could simply reflect the risk free rate plus the guarantee fee charged by the agencies. In the jumbo segment, the interest rate may reflect the risk of default and prepayment as well as the lender's market power.

Two potential complementary scenarios are at play. In the first, bunching is not due to the looser lending standards in the conforming segment, but rather to the lower interest rates caused by the ability of lenders to sell their loans to the GSEs at a fixed rate. In this world, bunching still causes a transfer of risk to the GSEs, but is not caused by more lenient screening of default and prepayment risks by lenders. In an alternative scenario, bunching is not caused by a decline in interest rates in the conforming segment but rather by lenders' less stringent screening of the borrower's ability to repay. Bunching is then a sign of a transfer of risk to the GSEs, and potentially of the lender's ability to take into account a range of observable predictors of default and prepayment risks.

We can use the McDash data to assess the extent to which interest rates are responsible for the

[4] Hannah Lang, "Why is Fannie Mae abandoning a practice that shields it from risk?", *American Banker*, December 3, 2020.

bunching of loans at the conforming loan limit. Such a regression estimates the impact of billion dollar disasters on the discontinuity in interest rates at the conforming loan limit. The regression is identical to the paper's main specification (1), with the exception that the interest rate is the dependent variable. The results of such estimation are presented in Table C. The regression also looks at other dimensions of mortgage structure, such as loan-to-value, combined loan-to-value, and whether there is a 2nd mortgage on the same property.

The table suggests no clear or statistically significant impact of a billion dollar disaster on the discontinuity in interest rates. None of the coefficients pre- or post-billion dollar disaster are significant at 10%; they also have no clearly predictable signs. This is also true when focusing on the 1st observed rate, which is the first rate observed by the servicer who reported to Black Knight. There is also no evidence that LTV, combined LTV and second mortgage are significantly affected. Yet, the paper's results suggest that billion dollar disasters lead to (i) an increase in the discontinuity in approval, origination, and securitization rates at the conforming limit, and to (ii) an increase in adverse selection in credit score, delinquency rates, and default rates.

3.2 Prices and Bunching

House prices could be a potential confounder for this paper's identification strategy. Indeed, if lenders do not alter their lending standards but rather originate more loans below the conforming limit because of declining prices; then this paper's results will be due to the decline of prices rather than to a loosening of lending standards in the conforming segment. We perform a test of this hypothesis first by estimating the paper's main lending standards regression (specification (1)) while controlling for house prices. In this specification, the dependent variable is either the approval rate for mortgage applications, the origination rate, or the agency securitization rate. Prices are measured at the 5-digit Zip-level using Zillow's Home Value Index. This Zip-level index is a repeat sales index built using a similar methodology as the Case Shiller index. The results of the lending standards specification with a control for the percentage change in the price are presented in Table D . To the extent that the regression compares the approval, origination, securitization rates of mortgages below and above the conforming limit *within the same ZIP code*, the regression thus controls for the confounding impact of prices, independently of the shift in lending standards due to the natural disaster. Results are similar to the paper's main table 2.

4 Definition of the Treatment Group

In the paper, the treatment group is obtained by estimating the impact of wind and topographical features on damages. The paper uses data from inspections of housing units by the department of Housing and Urban Development (HUD) in the New York MSA after hurricane Sandy.

An alternative way to define the treatment group is to rely on the federal National Oceanic and Atmospheric Administration's model of hurricanes. The *Sea, Lake, and Overland Surges from Hurricanes* (SLOSH) is a publicly available[5] and broadly used model of storm surges that provides granular estimates of storm surges for past, present, and potential future hurricanes. One benefit of using the SLOSH local storm surge estimates for each of our 15 billion dollar events is that this enables a straightforward replication of the paper's findings with publicly available data. Such a definition of the treatment group does not involve modeling choices by the authors of this paper.

In this section, we thus define the treatment group as the set of 5 digit Zip codes for which (i) the average storm surge height during the hurricane is above 1 foot, and (ii) within the 64kt wind speed radius. Figure F presents the approach in the case of hurricane Katrina and hurricane Sandy. The red radius is for the 64kt radius, obtained from the publicly available Atlantic Hurricane Data set. The blue area is for the area with a minimum of 1 foot of storm surge according to the SLOSH model.

Table E compares the treatment groups obtained with the paper's initial definition and with NOAA's storm surge definition. A majority of ZIP codes are both in this simple storm surge-based definition and in the paper's initial definition: for hurricane Katrina, 83.6% of the ZIPs of the storm surge definition were also in the paper's initial treatment group; for hurricane Sandy, that proportion is 93.9%.

Table F presents the estimates of the impact of a billion dollar event on approval, origination, and securitization probabilities (the "lending standards specification") in columns (1)–(3). The econometric approach is identical to the paper's main specification, with the exception of the treatment group definition. The same Table F's columns (4)–(7) presents the results of the estimation of the "bunching" specification with this new treatment group definition.

Together these tables suggest a very similar pattern compared to the paper's results: (i) securi-

[5] Accessible by all here https://www.nhc.noaa.gov/surge/slosh.php, with hurricane-specific simulations here https://www.nhc.noaa.gov/surge/HistoricalRuns/?large&parm=2005_katrina.

tization rates (column (3)) and numbers (column (7)) increase significantly in the 4 years following a billion dollar event; (ii) approval and origination probabilities (columns (1) and (2)) experience a bump in years +1 and +2, then a decline, due to the increasing number of applications (column (4)); (iii) approval, origination, securitization numbers experience a new plateau 4 years after the billion dollar event (columns (4)–(7)).

The probability of approval and origination increase significantly by between 1.9 and 5.4 percentage points. The securitization probability increases by up to 16 percentage points in year +4 (column (3)). The bunching regression results suggest that the number of mortgage applications increases significantly, by up to 10.7 percentage points in the 4th year post-disaster in the conforming segment relative to the jumbo segment. This likely explains the decline in the approval *rate* in the 4th year post-disaster in the conforming segment (column (1)). The bunching regression also suggests a substantial increase by up to 11.8 percentage points in the number of approvals, originations, and securitizations in the conforming segment relative to the jumbo segment (columns (4)–(7)).

Overall, results suggest that the paper's results are robust to the use of an alternative treatment group definition that uses publicly available data and transparent methods.

5 The Structure of Guarantee Fees: Regulatory Framework

Section 1601 of the Housing and Economic Recovery Act of 2008 (HERA) mandates FHFA to report about guarantee fees every year to Congress. The HERA specifies in Section 1601 (12 US Code 4514a) that "—The reports required under subsection (c) shall identify and analyze— (1) *the factors considered* in determining the amount of the guarantee fees charged;" Nine reports from 2009 to 2018 are publicly available, with one report on 2009-2010, and then one annual report after that. For instance the 2014 reports states the factors used:

> "In addition to the macroeconomic scenarios, the main risk characteristics included in the models that determine the estimated cost of guaranteeing a single-family mortgage are: — Borrower credit history — Debt-to-income ratio — Loan-to-value (LTV) ratio – Mortgage insurance coverage — Loan purpose (purchase, rate-term refinance, cash-out refinance) — Occupancy status (primary home, investor) — Property type

(single-family, condominium, 2-4 unit, manufactured housing) — Product type (fixed, adjustable rate, maturity term) — Mortgage interest rate."

There are some marginal variations from report to report: for instance the 2018 report includes the target return on capital rather than the mortgage interest rate. None of the reports mention "natural disasters", "climate risk", "flood risk", "hurricane", "storm surge", or associated concepts.

The evidence suggests that the enterprises rely on the flood insurance mandate to protect themselves against defaults and prepayments due to climate risk. On October 3rd 2017, Melvin L. Watt, FHFA's director stated in front of the U.S. House of Representatives Committee on Financial Services that "flood insurance is an important and necessary component to the Enterprises' risk management." Further Melvin L. Watt adds that "it is important to preserve Enterprise contractual requirements that protect against collateral risk and help protect neighborhoods." This reliance of the enterprises on flood insurance requirements rather than the g-fees is also reflected in the absence of a pass-through of geographic risk into interest rates (Hurst, Keys, Seru & Vavra 2016).

6 Modeling: Comparative Statics on the Price Impact ρ of Disasters

The paper's Section 5.2.1 performs out-of-sample comparative statics of increasing disaster risk from $\pi = 0$ to $\pi = 1\%$. The price impact ρ is set to $\rho = 20\%$. One question is whether lenders' origination and securitization responses to increasing disaster risk is sensitive to the recovery value. The recovery value affects the value of the foreclosure sale. This is the term $E_j\left[\phi(\delta)\right]$ in the lender's profit. Defaults due to the occurrence of a disaster cause a loss of interest payments for the lender independently of the recovery value. Hence we should expect a response of lenders' approval rates and securitization rates even with a full recovery value $\rho = 1$. As a significant share of the lender's loss is the foregone interest payment, and as the gain of a foreclosure sale is capped by the unpaid balance, results are not sensitive to the recovery value for values of ρ in the 70-100% range. In contrast, Figure G present the out-of-sample comparative statics in the case when the value of the land is wiped, $\rho = 1$. Results are qualitatively similar to the paper's main structural simulation.

7 Securitization and Wildfires

Other types of natural disasters may affect the performance of mortgages purchased by the Government Sponsored Enterprises Fannie Mae and Freddie Mac. Recent literature has estimated the impact of wildfire risk on the mortgage market.

Issler, Stanton, Vergara-Alert & Wallace (2019) finds a substantial increase in mortgage delinquencies and foreclosures after a wildfire. This is consistent with this paper's finding that delinquencies and foreclosures increase after a hurricane. As for hurricanes, the location of a wildfire is informative about the location of future wildfires. Figure H presents a map of historical wildfire perimeters from the National Interagency Fire Center, which suggests that wildfires tend to be located in specific areas of the West and the Midwest rather than happening in an idiosyncratic way across US land. Issler et al. (2019) point out that this increase in mortgage delinquencies and foreclosures may cause losses for lenders and insurance companies; these have led to declining supply of insurance rather than an adjustment of premia. The authors indeed mention that over 340,000 rural homeowners' policies were dropped between 2016 and 2020. This bears resemblance to the challenges faced by private insurance companies in providing affordable flood insurance policies: the large majority of such flood insurance policies are sold through the National Flood Insurance Program, funded by the federal government. This allows the supply of policies below the actuarially fair premium, i.e. below the break-even point of NFIP profitability. In contrast with flood insurance, fire insurance is part of standard home insurance policies.

We provide descriptive evidence of the fire risk purchased by Fannie Mae and Freddie Mac. These descriptive statistics suggest that (i) a substantial share of mortgages originated in wildfire perimeters is also securitized, (ii) there is little evidence that, in wildfire areas, the share of mortgages securitized is declining. To get these findings, we match data on wildfire perimeters between 2000 and 2018. Such fire perimeter data are matched to the census tracts of the coterminous US in their Census 2010 boundaries. At the census tract level, Home Mortgage Disclosure Act origination volumes and the volume purchased by the GSEs Fannie Mae and Freddie Mac is also available. The amount originated in areas with at least one past wildfire was 54 billion dollars, of which 27.2 billion dollars were purchased by Fannie Mae or Freddie Mac, or about 50.52%. Across census tracts, the distribution of securitization rates has a mode of 78%. This suggests that purchases of mortgages by

Fannie and Freddie in wildfire risk areas is common, and may be a potential risk factor for Fannie Mae and Freddie Mac in the absence of a significant amount of Credit Risk Transfers.

8 Data Appendix

8.1 Data Sources

The paper uses the following 13 sources of data:

1. Black Knight Financial's McDash data set with 5-digit zip code information and payment history. Typical McDash files used in other research only include the 3-digit zip code. This paper uses the complete 5-digit zip code McDash data. Figure I at the end of this data appendix shows that 5-digit counts are well distributed.

2. Normalized Hurricane Damage for the Continental United States 1900-2017, in Nature Sustainability. The authors provide an Excel spreadsheet.

3. Public files collected according to the Home Mortgage Disclosure Act (HMDA). Older files are obtained from the National Archives, with identifier 2456161. 2014-2016 flat files of the Loan Application Registers are available through the FFIEC's HMDA website. Recent files are provided by the Consumer Financial Protection Bureau.

4. Commercial Banks' Reports of Income and Condition, provided by the Federal Reserve of Chicago.

5. The Federal Deposit Insurance Corporation's (FDIC) Summary of Deposits provides the geolocation of bank branches for each commercial bank. This can be freely obtained at the FDIC's Branch Office Deposits data download website.

6. Census Shapefiles for ZCTA5s, blockgroups, census tracts, counties, and states, obtained through the University of Missouri's National Historical Geographic Information Survey.

7. The National Oceanic and Atmospheric Administration's (NOAA) National Hurricane Center dataset. This dataset is called the Atlantic Hurricane Database (HURDAT2) for 1851-2018.

8. The United States Geological Survey's Digital Elevation Model. This is obtained using the National Map Viewer, by zooming in on each billion-dollar event and downloading all elevation tiles. The tiles are merged, and average elevation by blockgroup is computed.

9. The United States Geological Survey's Land Cover dataset. We use the 2001 National Land Cover Dataset provided as a single Tiff file. Zonal statistics provide the share of each blockgroup in open water or wetland.

10. Hurricane Sandy's damage estimates by Blockgroup. This is provided by HUD: "A FEMA housing inspection for renters is used to assess personal property loss and for owners to assess damage to their home as well as personal property. This inspection is done to determine eligibility for FEMA Individual Assistance. For both rental and owner inspections, if the property has flood damage the inspector measures the height of the flooding. They indicate the highest floor of the flooding (for example, Basement, 1st floor, 2nd floor, etc...) and the height of the flooding in that room. In addition for the units without flooding, HUD has estimated minor/major/severe damage based on the damage inspection estimates for real property (owner) and personal property (renter). "

11. Zillow's zip-code-level Home Value Index. This is freely accessible here. Zillow's zip code data are matched with the Census ZCTA5s.

12. FEMA's National Flood Hazard Layer of 2017, which includes Special Flood Hazard Areas. This ESRI Shapefile has been removed from FEMA's website but is freely available through the corresponding author.

8.2 Crosswalks

In addition we built the following crosswalks (available through the corresponding author):

- Relationship files between ZCTA5s and Counties.
- Relationship files from HMDA Tracts to ZCTA5s.
- Relationship files from 2000 Blockgroups to ZCTA5s.
- Relationship files from ZCTA5s to CBSAs.

- Relationship files between 2000 and 2010 Blockgroups.

Each of these relationship files was built using GDAL's ogr2ogr intersection tool, with a North America Albers Equal Area Conic Coordinate Reference System (CRS). Such projected CRS allows the computation of areas and distances. When needed, counts were apportioned on the basis of the squared meter surface area of the intersections of two overlapping geographic areas. Means were computed using weighted means, where the weights are the surface areas of the intersections. Similar statistics obtained when using housing counts as weights.

HMDA uses census tracts of the 1990 census for all years prior to 2003 in our data. HMDA uses census tracts of the 2000 census for its 2004 to 2012 editions. HMDA uses census tracts of the 2010 census for its 2013-2016 editions. The success rate of the match between HMDA tracts and Census data is about 95%.

- Relationship files from HMDA's Respondentid to the Report of Income and Condition's RSSDID.

This is built using HMDA's Transmittal Sheet. This crosswalk is only available for bank lenders.

8.3 Software

- The classifier for damage is built using the *tree* function in the tree package developed by Prof. Brian Ripley of Oxford University.

- The share of each blockgroup in open water or wetland is computed using gdalwarp and rasterstats developed by Frank Warmerdam of Planet Labs (formerly University of Waterloo), Silke Reimer.

- Regressions use the lfe R package developed by Simen Gaure (Ragnar Frisch Centre for Economic Research), Grant McDermott (University of Oregon), Karl Dunkle Werner (Berkeley's Department of Agricultural and Resource Economics), Matthieu Stigler (post-doctoral Fellow at Stanford's Center for Food Security and the Environment), Daniel Lüdecke (University Medical Center Hamburg).

- McDash data were processed using PostgreSQL 9.6, JetBrains' DataGrip.

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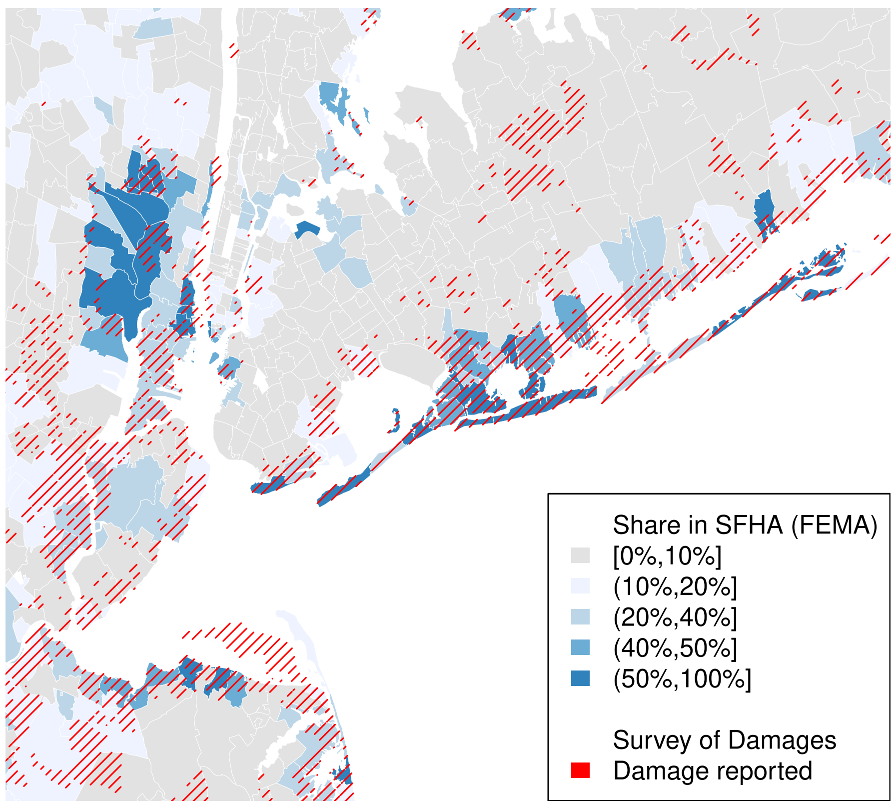
Kousky, C. (2018), 'Financing flood losses: A discussion of the national flood insurance program', *Risk Management and Insurance Review* **21**(1), 11–32.

Appendix Figure A: Comparing FEMA's Special Flood Hazard Areas and Damages – An Example for Hurricane Sandy

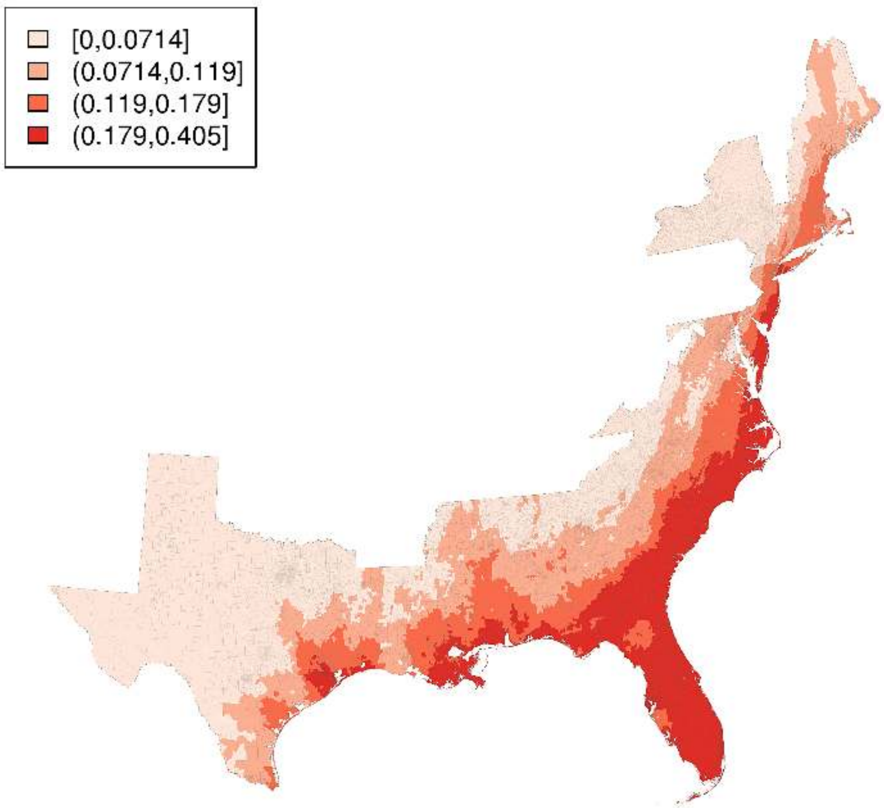
For parts of the metropolitan of New York, this map compares (a) areas of the Special Flood Hazard Area maps (blue areas), where flood insurance purchases are mandated for agency-backed mortgages†, with (b) areas where Hurricane Sandy caused damage (red areas) according to Department of Housing and Urban Development's (HUD) inspection data and released by FEMA in its IA Registrant Inspection Data‡. The unit of mapping is the zip code tabulation area (ZCTA5), and the gradient of blue colors indicates the share of a zip code that falls within the 1% flood probability area ("100-year floodplain"). The paper uses such data for all zip code tabulation areas of the Atlantic states and states of the Gulf of Mexico.



†: Fannie Mae's Selling Guide, Section B7-3-07, Flood Insurance Coverage Requirements. ‡: Sandy Damage Estimates Based on FEMA IA Registrant Inspection Data, released by data.gov.

Appendix Figure B: 168-Year Probability of Hurricane Occurrence

This map presents, for each of the 86,455 blockgroups of the states of the Atlantic coast and the Gulf of Mexico, the number of hurricane paths intersecting the blockgroup divided by 167 years. The time period is 1851-2017. For instance, a probability of 0.10 implies that there were between 16 and 17 hurricanes going through the blockgroup over 168 years. The hurricane path is the 64 kt wind speed path. 64kt corresponds to a category 1 hurricane in the Saffir-Simpson scale.

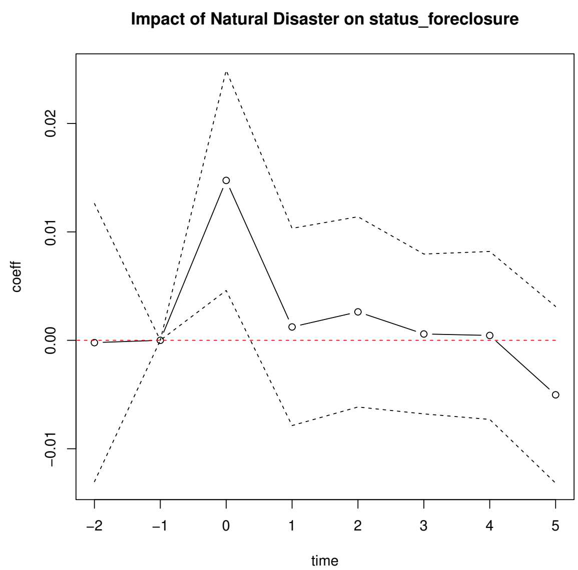


Source: NOAA's Atlantic Hurricane Data Base.

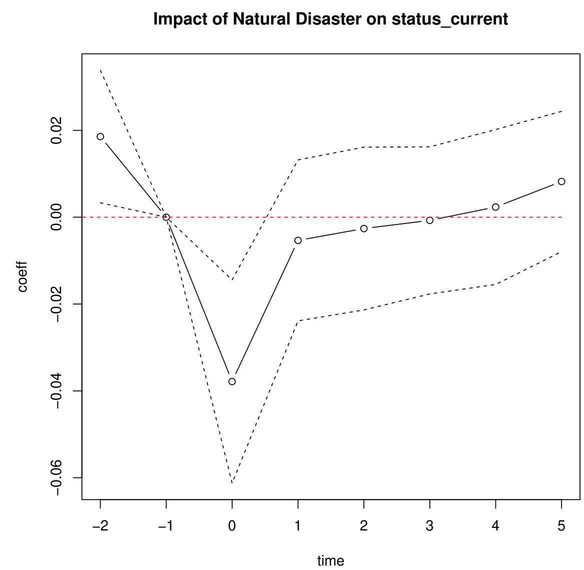
Appendix Figure C: The Impact of Billion-Dollar Events on the Default and Prepayment of Mortgages

These figures present the coefficients of a regression of payment history dummies on a set of pre- and post- natural disaster indicator variables. Regressions control for both zip code and year fixed effects.

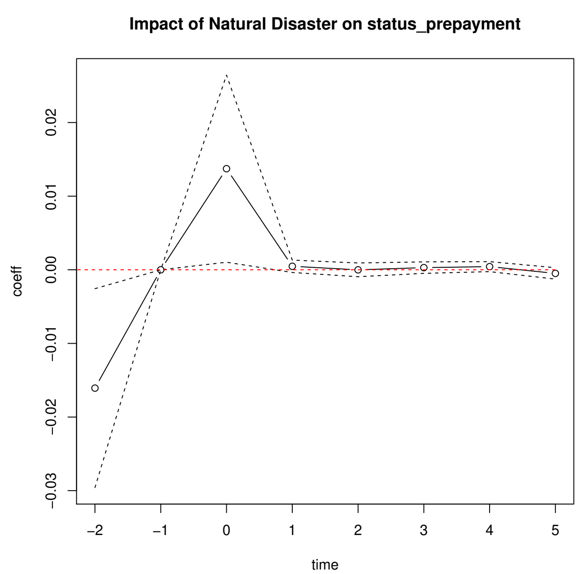
(a) Foreclosure



(b) Mortgage is Current



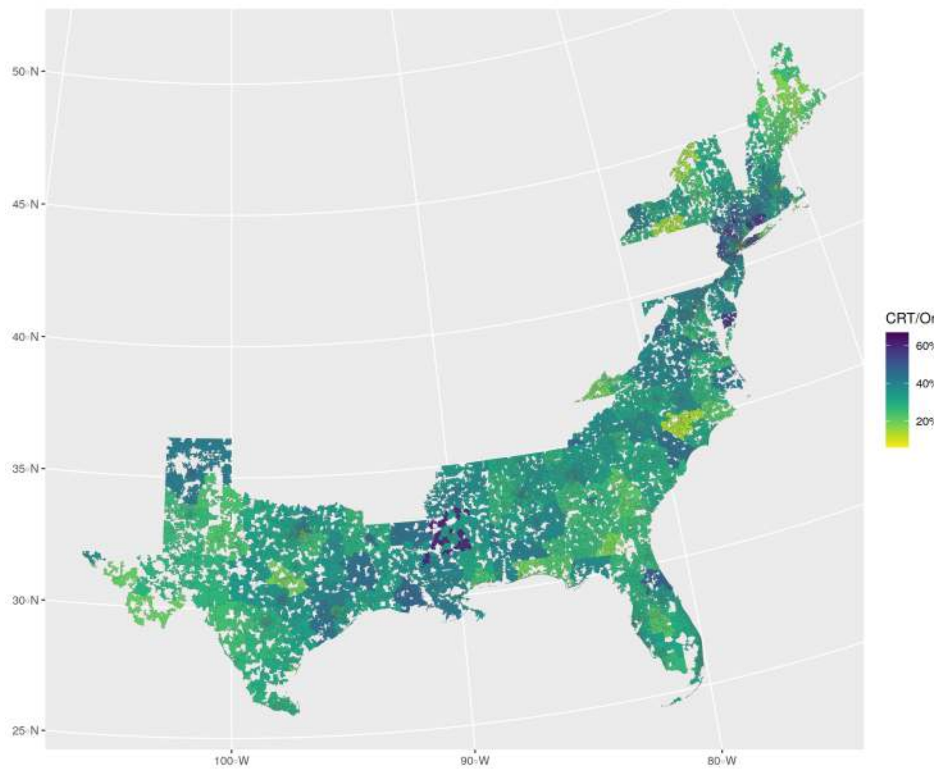
(c) Prepayment



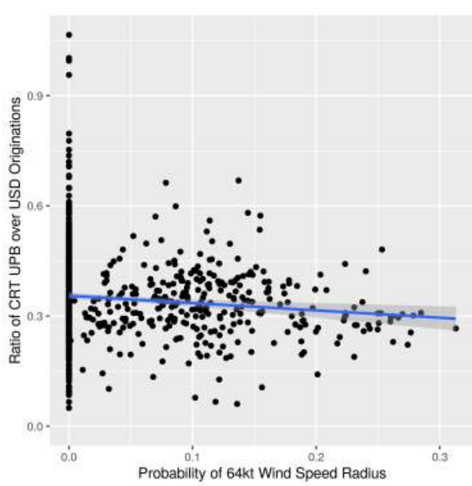
Appendix Figure D: Credit Risk Transfers and Hurricane Risk

These figures present the spatial distribution of the ratio of Credit Risk Transfers' unpaid principal balance over the dollar volume of mortgage originations. Data of CRT UPBs from the Connecticut Avenue Securities' data from Fannie Mae's data dynamics. Data on mortgage originations from the Home Mortgage Disclosure Act, aggregated to the ZIP code level, for mortgages originated and securitized.

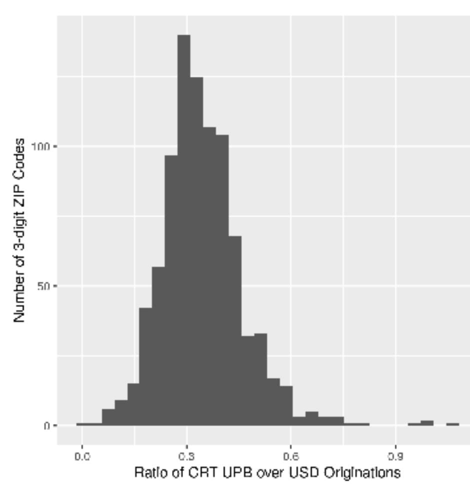
(a) Spatial Distribution of CRTs



(b) CRTs and Hurricane Frequency



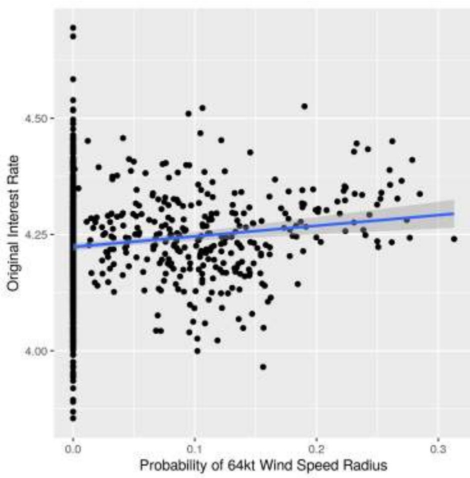
(c) CRT Volumes/Originations



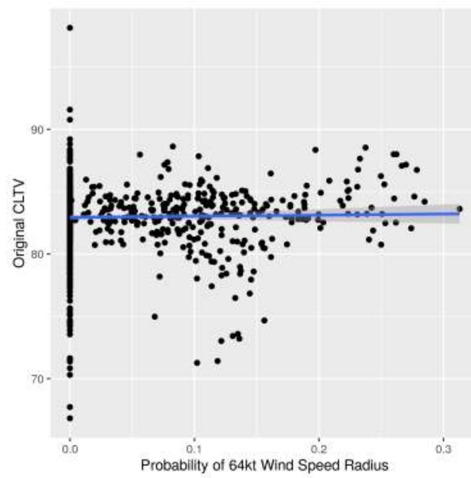
The regression of the ratio of CRTs UPBs over originations on the historical probability yields a coefficient of -0.112 *with a s.e. of* (0.013) *significant at* 0.1%.

Appendix Figure E: Credit Risk Transfers and Historical Hurricane Frequency – Loan Characteristics

(a) Interest Rate



(b) Combined LTV



Appendix Figure F: Defining the Treatment Group using the Publicly Available NOAA Storm Surge Model

These two maps describe an alternative approach to define the set of treated 5-digit ZIP codes. These present the case of hurricanes Katrina and Sandy, and a similar method is used for the other 13 billion dollar events. This approach considers the set of ZIP codes (i) within the 64kt wind radius (in red, from NOAA's publicly available Atlantic Hurricane Dataset) and (ii) whose storm surge height is above 1 foot (in blue, from NOAA's Sea, Lake, and Overland Surges from Hurricanes (SLOSH) *model, MOM forecast). The gray borders are for the 5-digit ZIP code boundaries.*

(a) Katrina 2005

(b) Sandy 2012

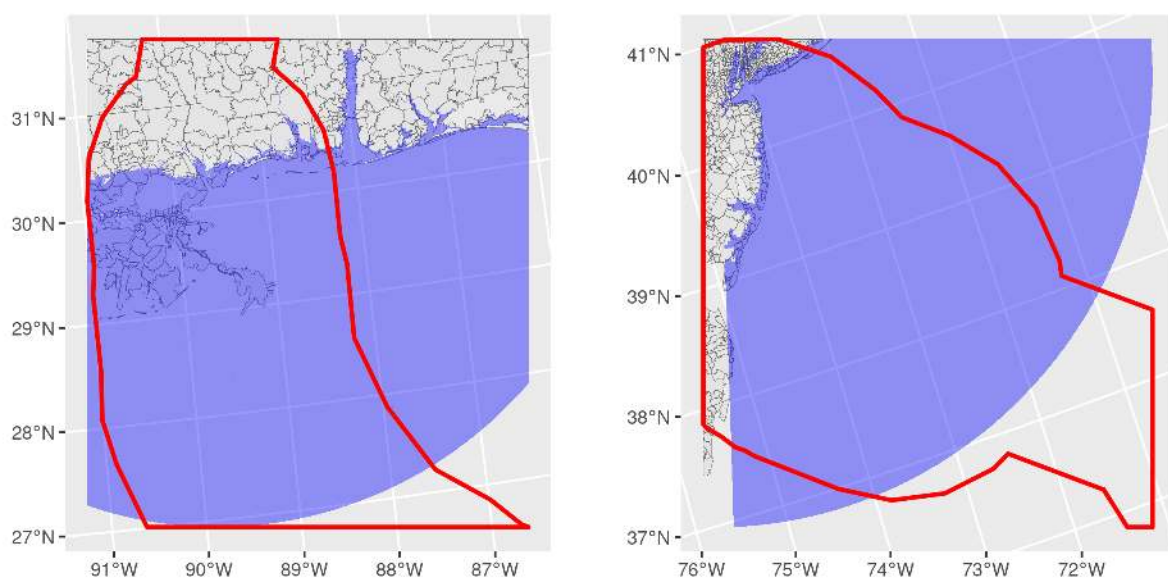


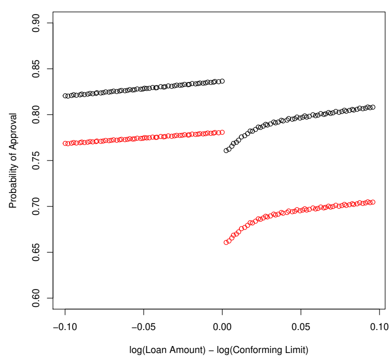
Table E compares the treatment group thus obtained with the treatment group used in the paper.

Appendix Figure G: Structural Modeling – Impact of Increasing Disaster Risk on the Equilibrium of the Mortgage Market when the Price Impact is $\rho = 1$

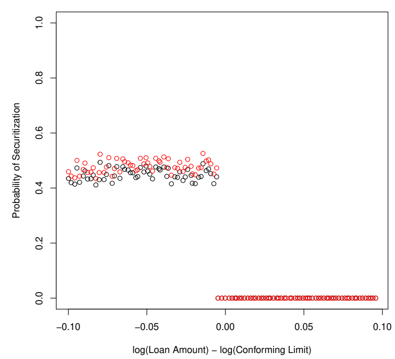
Keeping the cost of capital, neighborhood amenities, household preferences, and the dynamics of default constant, these figures present the simulation of an increase in disaster risk π *on the equilibrium of the mortgage market. This is described in Section 5.2.1. The black points correspond to* $\pi = 0\%$*, and the red points are for* $\pi = 1.0\%$.

(i) with the GSEs' Securitization Activity

(a) Probability of Approval

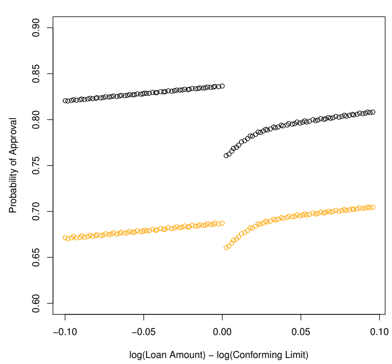


(b) Probability of Securitization

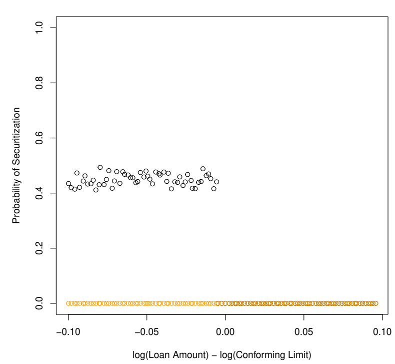


(i) without the GSEs' Securitization Activity

(c) Probability of Approval



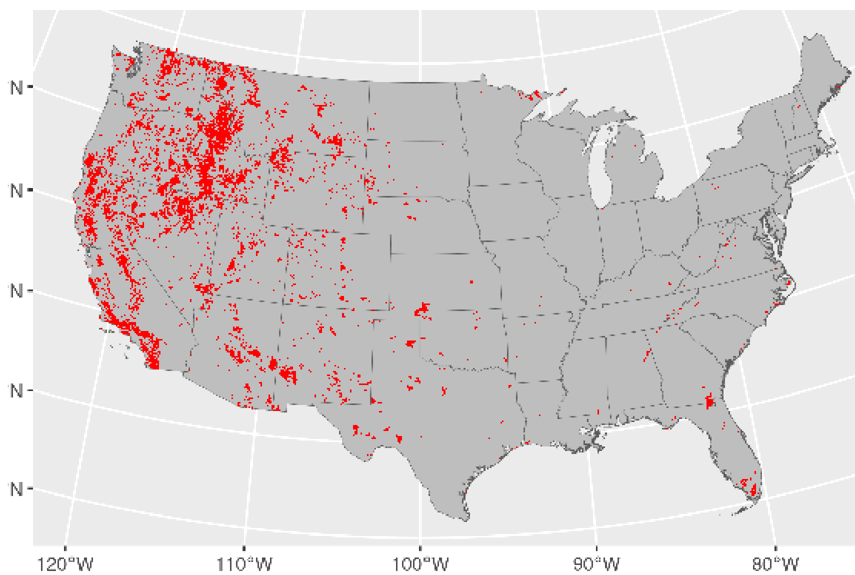
(d) Probability of Securitization



Appendix Figure H: GSE Securitization and Wildfires

The figure presents the geographic distribution of wildfires in the coterminous United States between 1835 and 2019, with consistent coverage starting in 1910. The table presents aggregate statistics on mortgages originated in areas with at least one recorded wildfire during this time period.

(a) Fire Perimeters



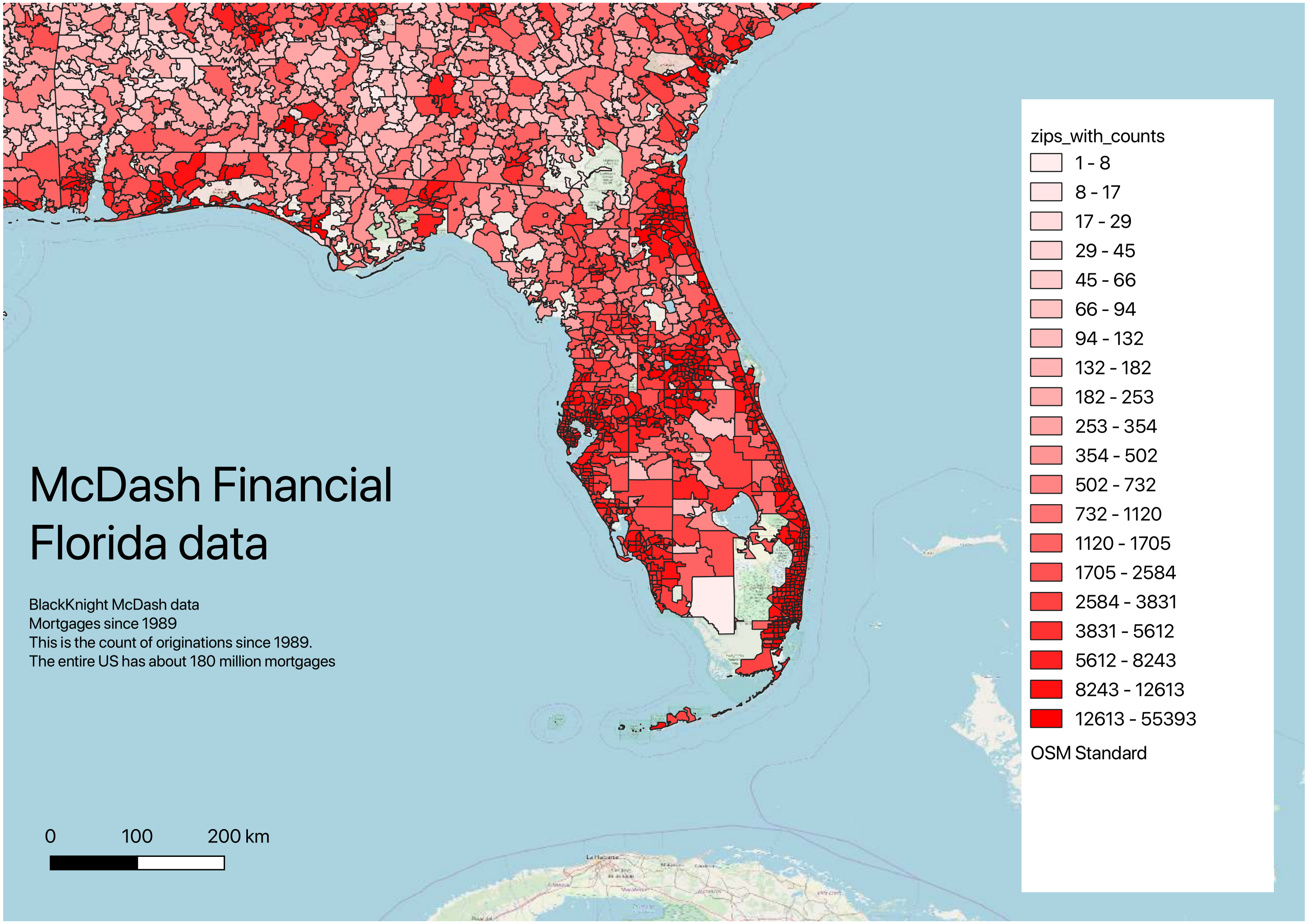
(b) Aggregate Statistics in Areas Hit by At Least One Wildfire

Securitized by Fannie or Freddie (k$)	Total Originated (k$)	Median Loan Amount (k$)	Approval Rate	Fannie and Freddie Securitization Rate
27,295,340	54,025,460	352	84.85%	50.52%

Source: National Interagency Fire Center. Home Mortgage Disclosure Act 2018.

Appendix Figure I: Data Appendix - Counts by 5 digit zip code

This map zooms in on Florida to show the distribution of counts of mortgages across 5-digit zip codes. Typical McDash data includes only the 3-digit zip code. The data used in this paper has the granularity required to assess the local impact of hurricanes on mortgage originations.



Appendix Table A: Baseline Sorting Regressions – Observable Mortgage Characteristics

These regressions estimate the sorting of mortgage characteristics around the conforming loan limit, for windows of decreasing sizes around the limit. All regressions include 5-digit ZIP code and year fixed effects.

	Window around conforming loan limit					
Variable	±10.0 pct	±4.0 pct	±3.0 pct	±2.0 pct	±1.0 pct	±0.5 pct
Jumbo Loan	0.871***	0.865***	0.833***	0.782***	0.680***	0.567***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.005)	(0.006)
Original Credit Score	4.723***	4.450***	4.464***	3.946***	3.727***	3.710***
	(0.374)	(0.391)	(0.449)	(0.544)	(0.755)	(0.946)
Interest Rate Differential (ppt)	0.000***	0.000***	0.000**	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Loan-to-Value Ratio	0.007***	0.010***	0.012***	0.014***	0.003*	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Combined Loan-to-Value Ratio	1.448***	1.486***	1.437***	1.007***	0.376	-0.088
	(0.169)	(0.176)	(0.206)	(0.251)	(0.353)	(0.446)
Second Mortgage	0.018***	0.018***	0.017***	0.012***	0.007	0.003
	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)	(0.006)
Full Documentation	-0.021***	-0.021***	-0.021***	-0.023***	-0.030***	-0.033***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.007)	(0.009)
Debt to Income Ratio	0.070	0.093	0.060	0.248	0.434*	0.312
	(0.133)	(0.139)	(0.157)	(0.189)	(0.262)	(0.340)
log(Property Value)	0.076***	0.065***	0.040***	0.015***	0.010***	0.007*
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.004)
Mortgage Term	4.311***	4.520***	4.612***	4.581***	3.711***	3.291***
	(0.308)	(0.321)	(0.369)	(0.462)	(0.651)	(0.878)
Fixed Rate Mortgage	-0.023***	-0.024***	-0.025***	-0.032***	-0.038***	-0.040***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.006)	(0.008)
Private Mortgage Insurance	-0.030***	-0.029***	-0.030***	-0.032***	-0.043***	-0.048***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)	(0.005)

*p<0.1; **p<0.05; ***p<0.01. Standard errors clustered at the ZIP-year level.

Appendix Table B: Baseline Sorting Regressions – Defaults

These regressions estimate the impact of the conforming loan limit on the mortgage's payment history for windows of decreasing sizes around the limit. All regressions include ZCTA and year fixed effects.

	Window around conforming loan limit					
Variable	±10.0 pct	±4.0 pct	±3.0 pct	±2.0 pct	±1.0 pct	±0.5 pct
Foreclosure at any point	-0.020***	-0.019***	-0.018***	-0.016***	-0.017***	-0.014***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)
30 days delinquent at any point	-0.009***	-0.008***	-0.007**	-0.004	-0.005	-0.004
	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)	(0.005)
60 days delinquent at any point	-0.016***	-0.015***	-0.013***	-0.009***	-0.012***	-0.010**
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)
90 days delinquent at any point	-0.014***	-0.013***	-0.012***	-0.008***	-0.010***	-0.007*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)
120 days delinquent at any point	-0.004**	-0.003**	-0.003*	-0.001	-0.000	-0.004
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)
Voluntary Payoff	0.053***	0.052***	0.043***	0.034***	0.026***	0.011
	(0.003)	(0.003)	(0.003)	(0.004)	(0.006)	(0.007)

*p<0.1; **p<0.05; ***p<0.01. Standard errors clustered at the ZIP-year level.

Appendix Table C: Changes in Interest Rates and Mortgage Structure at the Conforming Loan Limit

This table presents the estimation of the paper's main specification (1), with a different set of dependent variables: measures of interest rate (original rate, 1st observed rate), and of additional mortgage structure (LTV, combined LTV, whether a 2nd mortgage was originated as a second lien on the same property).

	Orig. Rate	1^{st} Obs. Rate	Orig. LTV	CLTV	2^{nd} Mortgage
Below $\text{Limit}_{it} \times \text{Treated}_{jt=-4}$	-0.12	-0.10	0.00	0.01	0.01
	(0.14)	(0.13)	(0.02)	(0.02)	(0.01)
Below $\text{Limit}_{it} \times \text{Treated}_{jt=-3}$	-0.04	-0.05	-0.02^{*}	-0.02^{*}	0.01
	(0.13)	(0.13)	(0.01)	(0.01)	(0.01)
Below $\text{Limit}_{it} \times \text{Treated}_{jt=-2}$	-0.10	-0.10	-0.01	-0.01	0.00
	(0.11)	(0.11)	(0.00)	(0.00)	(0.00)
Below $\text{Limit}_{it} \times \text{Treated}_{jt=0}$	0.06	0.06	-0.00	-0.00	-0.01^{**}
	(0.12)	(0.12)	(0.00)	(0.00)	(0.00)
Below $\text{Limit}_{it} \times \text{Treated}_{jt=+1}$	0.04	0.03	-0.00	-0.01	-0.01^{**}
	(0.13)	(0.13)	(0.00)	(0.00)	(0.00)
Below $\text{Limit}_{it} \times \text{Treated}_{jt=+2}$	-0.03	-0.03	-0.00	-0.00	-0.01
	(0.13)	(0.13)	(0.00)	(0.00)	(0.01)
Below $\text{Limit}_{it} \times \text{Treated}_{jt=+3}$	-0.10	-0.11	0.00	0.00	-0.00
	(0.13)	(0.13)	(0.01)	(0.00)	(0.01)
Below $\text{Limit}_{it} \times \text{Treated}_{jt=+4}$	0.04	0.04	0.05^{**}	0.05^{**}	-0.02
	(0.18)	(0.18)	(0.02)	(0.01)	(0.01)
Other controls	Treated_t for $t = -4, \dots, +4$, Year f.e., Disaster f.e., ZIP f.e., Below $\text{Limit}_{iy} \times \text{Year}_y$. See the paper's specification (1)				
Observations	1,697,338	1,697,338	1,623,373	1,624,144	1,623,373
R^2	0.60	0.59	0.19	0.19	0.07
Adjusted R^2	0.59	0.59	0.19	0.19	0.07

$^{**}p < 0.01$; $^{*}p < 0.05$

Orig. : Original. Obs.: Observed. CLTV: Combined LTV, accounting for 2nd mortgages.

Appendix Table D: Controlling for Price Changes in the Main Lending Standards Regression

This table presents the estimation of the paper's main specification (1) when controlling for 5-digit ZIP code annual price changes.

	Dependent variable:								
	Approved			Originated			Securitized		
	±10%	±5%	±2.5%	±10%	±5%	±2.5%	±10%	±5%	±2.5%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Below Limit$_{it}$ × Treated $_{t=-4}$	0.002	0.0003	0.007	0.022	0.019	0.027	0.042**	0.040**	0.071***
	(0.014)	(0.013)	(0.017)	(0.025)	(0.025)	(0.032)	(0.019)	(0.018)	(0.023)
Below Limit$_{it}$ × Treated $_{t=-3}$	0.014	0.013	0.014	0.025	0.025	0.044	−0.003	−0.006	−0.017
	(0.009)	(0.009)	(0.019)	(0.018)	(0.018)	(0.034)	(0.025)	(0.024)	(0.025)
Below Limit$_{it}$ × Treated $_{t=-2}$	−0.002	−0.002	0.003	−0.011	−0.010	0.001	−0.017	−0.018	−0.027
	(0.005)	(0.005)	(0.010)	(0.010)	(0.010)	(0.015)	(0.024)	(0.026)	(0.024)
Below Limit$_{it}$ × Treated$_{t=+0}$	0.003	0.001	0.005	0.007	0.005	0.017	0.005	0.005	0.013
	(0.014)	(0.013)	(0.013)	(0.018)	(0.017)	(0.020)	(0.021)	(0.021)	(0.029)
Below Limit$_{it}$ × Treated$_{t=+1}$	0.024***	0.024***	0.029**	0.024**	0.024**	0.043**	0.018	0.016	0.041*
	(0.008)	(0.008)	(0.011)	(0.011)	(0.011)	(0.017)	(0.019)	(0.019)	(0.021)
Below Limit$_{it}$ × Treated$_{t=+2}$	0.039***	0.039***	0.062***	0.036**	0.037**	0.075***	0.044*	0.046*	0.085***
	(0.011)	(0.011)	(0.014)	(0.017)	(0.017)	(0.019)	(0.024)	(0.024)	(0.027)
Below Limit$_{it}$ × Treated$_{t=+3}$	0.060***	0.061***	0.072**	0.056**	0.058**	0.079**	0.094***	0.096***	0.120**
	(0.016)	(0.016)	(0.029)	(0.021)	(0.021)	(0.037)	(0.029)	(0.029)	(0.043)
Below Limit$_{it}$ × Treated$_{t=+4}$	0.019	0.017	0.006	0.005	0.005	0.0003	0.153**	0.154**	0.191***
	(0.024)	(0.025)	(0.029)	(0.022)	(0.023)	(0.037)	(0.068)	(0.067)	(0.066)
Other Controls	Δ log Price, ZIP-level Treated$_t$ for $t = -4, \ldots, +4$, Year f.e., Disaster f.e., ZIP f.e., Below Limit$_{iy}$ × $Year_y$,								
Observations	1,345,012	1,310,397	803,424	1,345,012	1,310,397	803,424	1,500,360	1,461,539	900,765
R^2	0.066	0.066	0.070	0.069	0.070	0.072	0.249	0.250	0.229
Adjusted R^2	0.061	0.061	0.061	0.064	0.064	0.064	0.246	0.246	0.223
Note:	*p<0.1; **p<0.05; ***p<0.01								

Appendix Table E: Comparing Treatment Groups with the Paper's Original Definition (Damage Classifier) and NOAA's Storm-Surge-Based Definition

	ZIPs Treated		In Common	
Billion Dollar Event	NOAA Def.	Damage Classifier Def.	Number	Fraction (%)
Charley 2004	33	138	30	90.90
Dennis 2005	17	26	14	82.40
Dolly 2008	8	31	8	100.00
Frances 2004	96	251	92	95.80
Gustav 2008	110	136	77	70.00
Ike 2008	87	309	74	85.10
Irene 2011	204	310	134	65.70
Isaac 2012	58	47	39	67.20
Ivan 2004	84	134	69	82.10
Jeanne 2004	97	278	87	89.70
Katrina 2005	152	155	127	83.60
Ophelia 2005	43	42	37	86.00
Rita 2005	66	84	47	71.20
Sandy 2012	294	1,206	276	93.90
Wilma 2005	235	220	137	58.30
All	1,584	3,367	1,248	78.80

Appendix Table F: Alternative Treatment Group Definition - NOAA Storm Surge Model

This table presents the results of the estimation of the paper's main specifications (1) and (2) with the treatment group based on NOAA's "Sea, Lake, and Overland Surges from Hurricanes (SLOSH)" storm surge model. Columns (1)–(3) are for the lending standards regression, specification (1) of the main paper, and columns (4)–(7) for the bunching regression, specification (2) of the main paper. The methodology for this treatment group definition is described in Figure F of this appendix.

	Lending Standards Regressions:			*Bunching Regressions:*			
	Dependent variable:			*Dependent variable:*			
	Approved ±5% (1)	Originated ±5% (2)	Securitized ±5% (3)	Applications ±5% (4)	Approvals ±5% (5)	Originations ±5% (6)	Securitizations ±5% (7)
Below Limit × Treated$_{t=-4}$	0.009	0.025	0.044***	−0.037	−0.039	−0.026	−0.076
	(0.017)	(0.025)	(0.015)	(0.036)	(0.036)	(0.030)	(0.062)
Below Limit × Treated$_{t=-3}$	0.019	0.037	−0.011	0.036	0.031	0.042	0.044
	(0.020)	(0.028)	(0.013)	(0.032)	(0.032)	(0.035)	(0.053)
Below Limit × Treated$_{t=-2}$	0.001	0.011	−0.009	0.039	0.027	0.036	−0.001
	(0.005)	(0.008)	(0.026)	(0.024)	(0.033)	(0.037)	(0.051)
Below Limit × Treated$_{t=0}$	−0.0004	0.007	0.035	0.002	0.007	0.010	0.014
	(0.007)	(0.011)	(0.021)	(0.041)	(0.045)	(0.043)	(0.060)
Below Limit × Treated$_{t=+1}$	0.019**	0.029***	0.050***	0.013	0.023	0.032	0.049
	(0.008)	(0.009)	(0.017)	(0.043)	(0.037)	(0.036)	(0.057)
Below Limit × Treated$_{t=+2}$	0.044**	0.054***	0.111***	0.035	0.044	0.050*	0.051
	(0.017)	(0.016)	(0.023)	(0.031)	(0.027)	(0.029)	(0.039)
Below Limit × Treated$_{t=+3}$	0.035	0.026	0.159***	0.063**	0.081***	0.095***	0.112***
	(0.031)	(0.036)	(0.052)	(0.026)	(0.022)	(0.022)	(0.035)
Below Limit × Treated$_{t=+4}$	−0.021	−0.034*	0.160**	0.107***	0.112***	0.125***	0.118***
	(0.014)	(0.017)	(0.075)	(0.030)	(0.027)	(0.031)	(0.038)
Observations	2,030,401	2,030,401	2,254,816	188,571	188,553	188,503	188,005
R^2	0.062	0.071	0.234	0.771	0.768	0.765	0.761
Adjusted R^2	0.054	0.063	0.228	0.770	0.767	0.765	0.760

Appendix Table G: Descriptive Statistics for the HMDA and McDash Samples

This table describes the two main samples used in this paper: (i) the dataset of mortgage applications collected according to the Home Mortgage Disclosure Act (12 USC Banks and Banking, ch29, §§ 2801-2811, and § 461), and provided by the Federal Financial Institutions and Examination Council, merged with the Federal Reserve of Chicago's Report of Condition and Income using the reporter panel; and (ii) Black Knight Financial's McDash mortgage dataset, covering about 65% of the mortgage market, with 5-digit zip code identifiers. Each of these two datasets are merged with the treatment area geography described in Section 2.1. Both samples consider mortgages between 80% and 120% of the year- and county-specific conforming loan limits. The window is tightened to 95-105% in some specifications.

Variable	Mean	P10	P25	P50	P75	P90	Observations
Home Mortgage Disclosure Act							
Application Denied	0.152	0.000	0.000	0.000	0.000	1.000	10,835,083
Loan Originated	0.512	0.000	0.000	1.000	1.000	1.000	13,446,510
log(Applicant Income)	11.767	7.032	9.061	13.181	14.532	14.532	990,712
Loan to Income	2.654	1.508	1.976	2.606	3.308	3.889	9,892,849
Asian Applicant	0.099	0.000	0.000	0.000	0.000	0.000	9,084,807
Black Applicant	0.040	0.000	0.000	0.000	0.000	0.000	9,084,807
Hispanic Applicant	0.070	0.000	0.000	0.000	0.000	0.000	9,084,807
White Applicant	0.781	0.000	1.000	1.000	1.000	1.000	9,084,807
Lender's Liquidity Ratio	0.044	0.001	0.008	0.032	0.032	0.129	1,139,292
Lender's Securitizability	0.710	0.601	0.638	0.638	0.795	0.883	1,133,724
Credit Union	0.017	0.000	0.000	0.000	0.000	0.000	13,446,510
Reg. by Federal Reserve	0.110	0.000	0.000	0.000	0.000	1.000	13,446,510
McDash							
Below Conforming Limit	0.620	0.000	0.000	1.000	1.000	1.000	1,746,112
Credit Score	712.481	625.000	671.000	721.000	767.000	790.000	1,086,311
Term	345.996	300.000	360.000	360.000	360.000	360.000	1,744,975