White paper

Climate risk is already reshaping the U.S. housing market

ICE Climate

The U.S. housing market, valued at over $55 trillion,[1] is a cornerstone of the American economy. For decades, access to affordable mortgages and the path to homeownership has driven wealth creation and upward mobility for millions of low- and middle-income American households. Today, however, this critical sector of the economy faces growing pressure from climate-related risks and costs.

Recent ICE Climate research has demonstrated that the total cost of housing [2] has increased significantly over the last decade, due not only to rising insurance costs [3] but also property taxes and utility bills – all of which are influenced by climate-related factors.

This report goes further, presenting evidence of the direct impacts of climate-related hazards (tropical storms/hurricanes, wildfires and floods) and long-term physical climate risks on mortgage performance and home values. Mortgage performance can often signal early stress in local housing markets,[4] while home price trends tend to reflect longer-term structural and socioeconomic shifts.[5] Together, these two indicators provide distinct perspectives on how climate risk is impacting the U.S. housing and mortgage markets across different timescales and regions.

Key points include:

Short-term mortgage delinquency probabilities in tropical storm and hurricane-, flood- and wildfire- exposed areas increase by an **average of about 21%, 18% and 250%** respectively (relative to the baseline delinquency probability) for loans current before the event, after accounting for key borrower and loan-level characteristics.

Longer-term flood and hurricane risk is also associated with increased delinquency rates (30%+ relative to delinquency rates in areas with negligible risk) over periods greater than five years. Flood insurance coverage may have a protective effect.

Flood risk may be exerting a drag on home price appreciation in the highest risk areas; **on average, the compound annual growth rate of ICE's Home Price Index is ~0.2% to 0.4% slower in high flood risk zip codes**, after accounting for a suite of different socioeconomic factors. We estimate that from 2013 to 2024, ~$31B of total residential real estate value in the U.S. may have been lost due to this flood risk, compared to a counterfactual "zero flood risk" world.

Introduction

Over the past decade, awareness of the implications of climate risks for U.S. housing and mortgage markets has grown significantly. Much of this awareness has been driven by specific events that have captured the attention of the public and the media.

About 40,000 homeowners in areas affected by Hurricanes Helene and Milton became delinquent on their loans in the months following the hurricanes.[6] Wildfires often have similar impacts: more than one-fifth of borrowers within the perimeter of the 2025 Eaton and Palisades wildfires in California fell behind on their mortgage payments the month following the fires.[7] The Camp Fire in California, which killed 85 people and destroyed about 85% of the structures in the town of Paradise (about 18,800 in total),[8,9] had still longer-term effects on local housing. In Paradise's zip code (95969), the ICE Home Price Index fell by about 10%, from November 2018 (when the fire occurred) to January 2020, before starting to rise again.

[1] Treh Manhertz, "U.S. Housing Market Value Hits $55.1 Trillion," Zillow, September 8, 2025, zillow.com/research/housing-market-value-1-trillion-35518/.
[2] "The Full Cost of Homeownership," ICE Insights, April 30, 2025, ice.com/insights/sustainable-finance/the-full-cost-of-homeownership.
[3] "How Are Home Insurance Costs Changing across the United States?" ICE Research, November 2025, ice.com/article/how-are-home-insurance-costs-changing-across-the-united-states.
[4] "Mortgages 30-89 Days Delinquent," Consumer Financial Protection Bureau, 2021, consumerfinance.gov/data-research/mortgage-performance-trends/mortgages-30-89-days-delinquent/.
[5] James A. Kahn, "What Drives Housing Prices?" SSRN Electronic Journal, 2008, doi.org/10.2139/ssrn.1264048.
[6] ICE, ICE Mortgage Monitor Report (December 2024), mortgagetech.ice.com/publicdocs/mortgage/ICE_Mortgage-Monitor-Report-December-2024.pdf.
[7] ICE, ICE Mortgage Monitor Report (April 2025), mortgagetech.ice.com/publicdocs/mortgage/imt-april-2025-mortgage-monitor-report.pdf.
[8] P. Boghani, "Camp Fire: By the Numbers," PBS Frontline, October 29, 2019, pbs.org/wgbh/frontline/article/camp-fire-by-the-numbers/.
[9] J. Matt, "Paradise Redux," Places, March 2025, placesjournal.org/article/paradise-redux-five-years-after-camp-fire/.

Climate-related impacts on the U.S. housing market are likely to become ever more significant. According to the National Oceanic and Atmospheric Administration (NOAA), since 2018, the five-year running average cost associated with billion-dollar extreme weather events has exceeded $120 billion in the U.S.[10] These kinds of events are projected to become more frequent and more severe due to climate change.[11]

The U.S. housing market is a pillar of the U.S. economy, influencing everything from individual household wealth to financial market stability. Mortgage debt underpins this market and represents the largest share of liabilities for many households. The outsized role of these markets in the global economy means that any disruption to them may have long-term and widespread effects on economic growth, as seen in the aftermath of the 2008 financial crisis.[12] Understanding and mitigating the impacts of climate risk within the U.S. mortgage market is therefore not solely a domestic concern; it warrants attention within the wider macroeconomic context.

This report is focused on the direct impacts of climate hazards on mortgage performance and home values. It is divided into three chapters that each focus on a different timescale at which climate risks are influencing the market.

Chapter 1 focuses on ICE Climate's research into the immediate (<1 year) effects of extreme weather events on mortgage delinquency patterns. By analyzing millions of mortgages exposed to extreme weather events since 2011, we find that payment delinquency probabilities for loans that were current before the event increase significantly between one and three months afterwards: 250% ± 33% (95% confidence interval)[13] after wildfire exposure, 18% ± 0.6% after tropical storm and hurricane wind exposure and 21% ± 0.6% after flood exposure relative to baseline probabilities. Going forward, ICE Climate can forecast delinquency increases in the immediate aftermath of storms and wildfires, along with the ripple effects into mortgage-backed securities.

Chapter 2 examines longer-term (5+ year) trends in delinquency patterns in the context of climate risk exposure. Long-term climate risk is strongly correlated with severe delinquency risk, with properties in high hurricane and flood risk zones showing more than a 30% higher rate of prolonged (3+ month) nonpayment after accounting for key borrower characteristics.

Chapter 3 looks at home value changes between 2013 and 2024. While mortgage delinquency rates are an indicator of immediate financial stress, housing price changes can provide insight into slower moving structural trends. We find that home price appreciation is on average about 0.2–0.4% slower per year in areas with high flood risk after accounting for key socioeconomic measures. Put another way, flood risk may be exerting a "drag" on home price appreciation in the highest risk areas. Similar relationships are not observed for wildfire or hurricane risks.

Taken together, these findings highlight emerging hotspots of mortgage credit stress and the need for lenders, insurers and policymakers to integrate climate risk into housing finance strategies.

Chapter 1. The impact of extreme weather events on mortgage delinquency

Between 2016 and 2025, large climate-related events are estimated to have caused more than $1.5 trillion in total damage across the United States.[14] These events often have immediate follow-on impacts for homeowners: three months after Hurricane Ian made landfall in 2022, 90-day delinquencies in Florida increased by 21% month over month.[15] In the aftermath of Hurricane Beryl in 2024, an estimated 10,000 homeowners fell behind on payments in affected areas around Houston.[16]

Wildfires have similar impacts. The 2018 Camp Fire in Paradise, California led to significant out-migration[17] and ultimately the Paradise Redevelopment Agency's municipal default in 2023.[18]

[10] National Centers for Environmental Information, National Oceanic and Atmospheric Administration, "Billion-Dollar Weather and Climate Disasters," ncei.noaa.gov/access/billions/time-series/US/cost.
[11] Intergovernmental Panel on Climate Change, Climate Change 2021: The Physical Science Basis (Cambridge: Cambridge University Press, 2021), chap. 11, "Weather and Climate Extreme Events," ipcc.ch/report/ar6/wg1/chapter/chapter-11/.
[12] Steven B. Kamin and Laurie Pounder, "How Did a Domestic Housing Slump Turn into a Global Financial Crisis?" SSRN Electronic Journal, 2010, doi.org/10.2139/ssrn.1585195.
[13] Throughout this paper, values in parentheses following estimates represent 95% confidence intervals.
[14] Climate Central, "U.S. Billion-Dollar Weather and Climate Disasters," accessed October 23, 2025, climatecentral.org/climate-services/billion-dollar-disasters?types=tropical-cyclone&metric=count.
[15] Black Knight, Black Knight Mortgage Monitor Report (December 2022), mortgagetech.ice.com/publicdocs/mortgage/BKI_MM_Dec2022_Report.pdf.
[16] ICE, "ICE First Look at Mortgage Performance: Delinquencies Improved in July despite Hurricane Beryl's Impact on Houston Homeowners," August 22, 2024, ir.theice.com/press/news-details/2024/ICE-First-Look-at-Mortgage-Performance-Delinquencies-improved-in-July-despite-Hurricane-Beryls-impact-on-Houston-homeowners/default.aspx.
[17] Xudong An, Stuart A. Gabriel and Nitzan Tzur-Ilan, "The Effects of Extreme Wildfire and Smoke Events on Household Financial Outcomes" (Working Paper no. 4353113, SSRN, 2023), ssrn.com/abstract=4353113.
[18] Moody's Investors Service, US Municipal Bond Defaults and Recoveries, 1970–2022 (New York: Moody's Investors Service, 2023), hosted at Fidelity Investments, fidelity.com/bin-public/060_www_fidelity_com/documents/fixed-income/moodys-investors-service-data-report-us-municipal-bond.pdf.

Using ICE Climate's Hazard Watch capabilities to link historical extreme weather event data (tropical storm and hurricane wind paths, flood-exposed areas and wildfire burn perimeters across the U.S. between 2011–2024) with loan performance data for tens of millions of loans in ICE's datasets, ICE Climate found:

- The average probability of delinquency increases by more than 15% in the three months after exposure to tropical storm- and hurricane- force winds (50+ knots) for loans current before exposure.
- Similar short-term increases in average delinquency probability are observed in flood-exposed areas.
- Much larger increases in short-term delinquency probability (+250% relative to baseline delinquency probability) are observed in areas within wildfire burn perimeters.
- On average, these impacts appear to be significant but temporary, with delinquency rates falling back within the range of baseline (pre-event) rates within 12 months after the event.

These results are broadly consistent with existing literature. Research has found that loans exposed to a major hurricane (Category 3 or higher) were 13–18% more likely to fall into delinquency over their lifetime compared to other loans in exposed counties that were not active at the time of the storm. In November 2017, three months after Hurricane Harvey, the percentage of affected homeowners entering 90-day delinquency increased to more than 50 times the typical monthly rate, an initial spike that subsided over the following three.[19] Other studies have reported increase[20] in commercial mortgage delinquency associated with Hurricanes Harvey and Sandy.

However, unlike many previous studies that focus on single events or localized regions, ICE Climate's approach in the analysis below spans 48 tropical storms and hurricanes, as well as hundreds of flood and wildfire events across different regions of the U.S. This scope exposes more than 10 million loans to extreme weather events over a period of more than a decade. The breadth of this analysis in Chapter 1 allows us to identify patterns across hazards and regions, providing a comprehensive understanding of extreme weather-related delinquency risk across the country.

1.1 The data

Loan data. The ICE McDash dataset contains servicer records for over 35 million active mortgages (roughly two-thirds of U.S. residential loans)[21] and over 35 years of mortgage performance history, including loan-level data on unpaid principal balance, escrow costs, closing dates, original loan amounts, borrower credit scores and loan delinquency status through time.[22,23]

Every month, active loans that are not in foreclosure or bankruptcy are assigned payment statuses in McDash, including "current," "30+ days delinquent," "60+ days delinquent", "90+ days delinquent" and "12+ months delinquent." For this analysis, a loan is considered delinquent if it is 30+ days delinquent. (Loans that foreclose during a given month are also counted as delinquent.) All reported loan counts in the following analysis correspond to loans that were exposed and had the necessary data fields (explained in Section 1.2, The Model') in McDash for use in the analysis.

To identify and understand the effects of extreme weather events on loan delinquency, it is particularly important to know the locations associated with the homes collateralizing these loans. The McDash dataset includes zip codes for each loan, but ICE refines these locations using a privacy-preserving methodology that allows us to link loans to information about the underlying properties,[24] while always preserving borrower anonymity.

Historical storm tracks. ICE Climate sources tropical storm and hurricane tracks from the Global Disaster Alert and Coordinate System (GDACS). GDACS provides near-real-time access to forecasted and historical storm paths from 2002 to present, for areas affected by 34-, 50- and 64-knot wind speeds or greater (wind speeds above 64 knots are considered 'hurricane-force' winds, while wind speeds between 50–64 knots are often called 'tropical storm-force').

For this analysis, ICE Climate focuses on areas exposed to 50- and 64-knot wind speeds or greater since 2011 (an example of these two 'windspeed paths' are shown in Figure 1, left, for Hurricane Sandy). In total, there are 48 tropical storm wind speed paths (50+ knot wind speeds) between 2011 and 2024 included in our analysis. Of these, 31 storms were hurricanes with 64+ knot windspeed paths (Figure 1, right).

[19] Carolyn Kousky, Mark Palim and Ying Pan, "Flood Damage and Mortgage Credit Risk: A Case Study of Hurricane Harvey," Journal of Housing Research 29, no. sup1 (2020): S86–S120, doi.org/10.1080/10527001.2020.1840131.
[20] Roef Holtermans, Matthew E. Kahn and Nils Kok, "Climate Risk and Commercial Mortgage Delinquency," Journal of Regional Science 64, no. 4 (2024): 994–1037.
[21] ICE, "Housing Affordability Analytics," Ice.com, 2026, ice.com/fixed-income-data-services/mortgage-data-solutions/housing-affordability-analytics.
[22] ICE, "McDash: Comprehensive Loan-Level Data," Ice.com, 2026, ice.com/fixed-income-data-services/mortgage-data-solutions/mcdash.
[23] Loan-level analyses in this paper assume that loans in ICE McDash with the metadata necessary for the analyses are a representative of the U.S. mortgage market as whole.
[24] ICE Mortgage Map hashes borrower-specific information so that it is impossible for anyone (including ICE) to link borrower information to homes.

Hurricane Sandy (2012) windspeed paths

64+ knot windspeed paths for **Atlantic storms** (2012–2024)

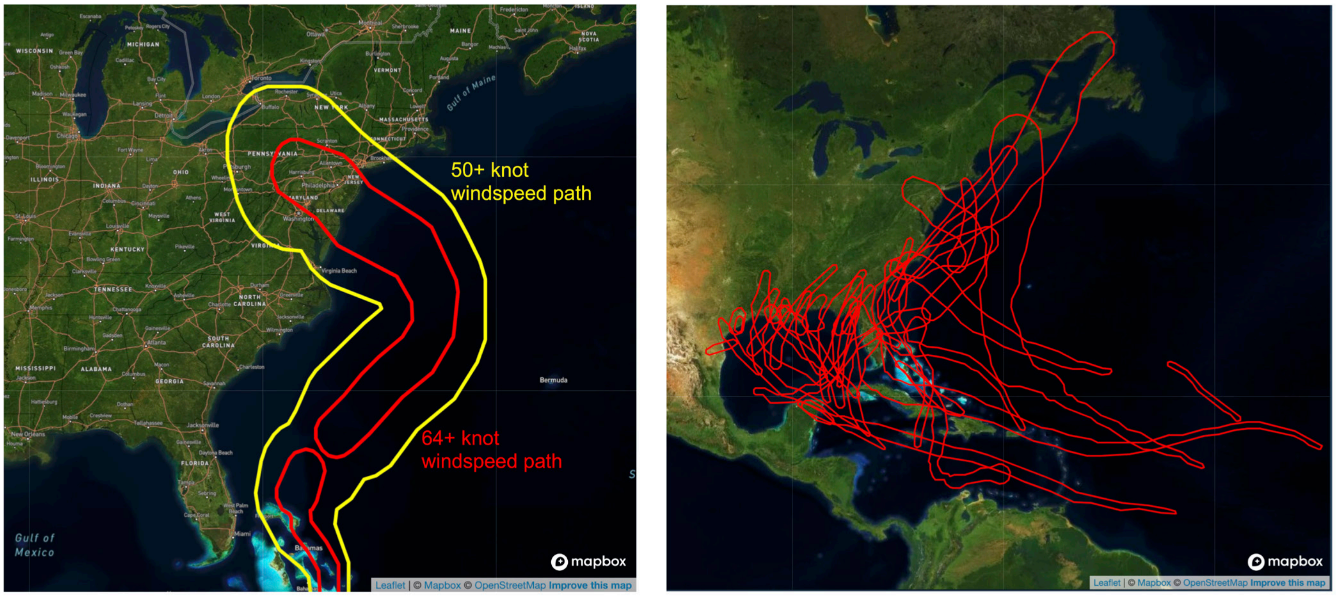


Figure 1. Storm tracks for 50+ knot and 64+ knot wind speeds associated with Hurricane Sandy (left) and Hurricane tracks for 64+ knot windspeed paths associated with the Atlantic storms (right) considered in this analysis.
Source: Global Disaster Alert and Coordinate System as of 9/1/2025.

Historical wildfire perimeters. To create a dataset of wildfire perimeters through time, ICE Climate performed burned area analysis on satellite imagery. More specifically, ICE Climate calculates a burned area measure called the normalized difference burned area index[25,26] post-fire directly on Landsat-8[27]/Landsat-9[28]/Sentinel 2 multispectral imagery gathered every 8–16 days. This relatively low temporal resolution of the imagery is counterbalanced by the satellites' extremely high spatial resolution (30 m). The final historical wildfire perimeter dataset used in this analysis consists of 481 wildfire perimeters across the U.S. from January 2012 through October 2024.

Tubbs fire (2017)

Camp fire (2018)

Woolsey fire (2018)

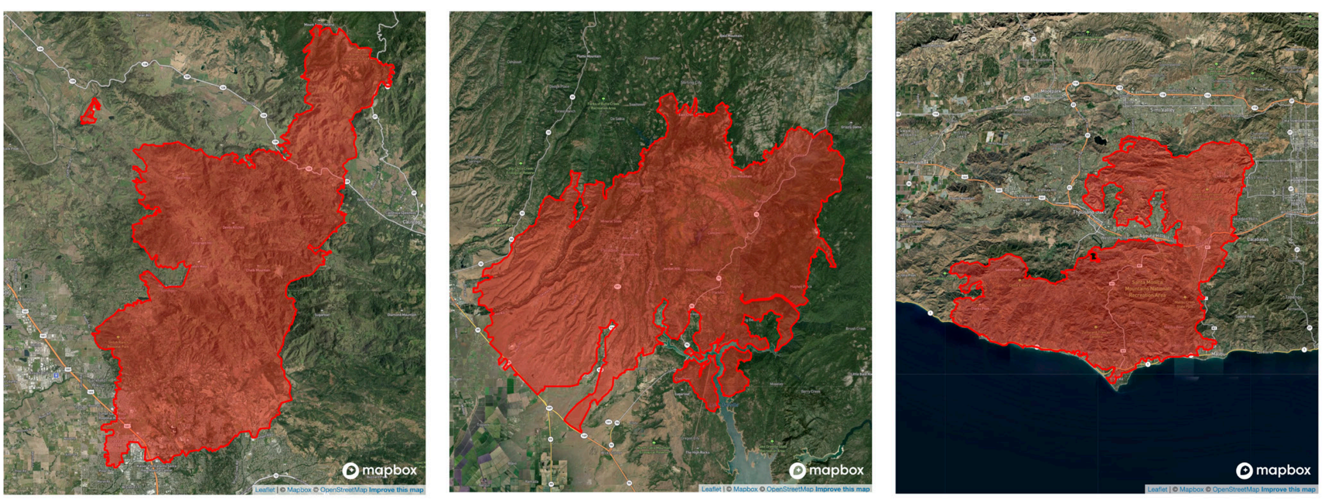


Figure 2. Fire perimeters derived from satellite data used in this analysis for (left) the Tubbs Fire in 2017, (center) the Camp Fire in 2018 and (right) the Woolsey Figure in 2018.
Source: ICE Climate as of 10/23/2025.

[25] Carl H. Key and Nathan C. Benson, "Landscape Assessment (LA)," in FIREMON: Fire Effects Monitoring and Inventory System, ed. Duncan C. Lutes, Robert E. Keane, John F. Caratti, Carl H. Key, Nathan C. Benson, Steve Sutherland and Larry J. Gangi, Gen. Tech. Rep. RMRS-GTR-164-CD (Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station, 2006), LA-1–55.

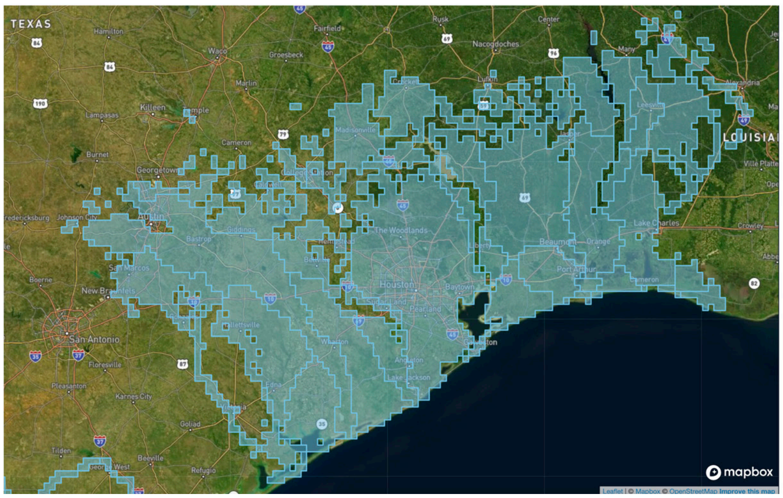
[26] Jon Keeley, "Fire Intensity, Fire Severity and Burn Severity: A Brief Review and Suggested Usage," International Journal of Wildland Fire 18, no. 1 (2009): 116–126, doi.org/10.1071/WF07049.

[27] U.S. Geological Survey, "Landsat 8," USGS, 2023, usgs.gov/landsat-missions/landsat-8.

[28] U.S. Geological Survey, "Landsat 9," USGS, 2023, usgs.gov/landsat-missions/landsat-9.

Historical flood exposure. ICE Climate sources global flood data from the Copernicus Emergency Management Service, a European Commission program that includes the Global Flood Awareness System (GloFAS)[29] for forecasting and monitoring flood events. GloFAS's estimates and forecasts of river discharge are based on Sentinel-1[30] satellite imagery as well as measurements of river flow rates from river gauges and hydrological models. For each 0.5° x 0.5° latitude-longitude grid cell globally, ICE Climate computes an average 10-year return period threshold of river discharge in cubic meters per second (the average rate of river discharge that would be expected once every 10 years on average) based on 40 years of historical GloFAS data. Daily GloFAS forecasts are compared against these thresholds. Cells with average river discharge rates exceeding their threshold are aggregated by hydrological basin to map flood-exposed areas. The resulting boundaries should be considered flood-exposed areas rather than areas of actual flooding (Figure 3). This analysis includes 4,458 flood-exposed areas identified between January 2012 and December 2024.

Flood exposed areas along Texas coast: **Hurricane Harvey** (2017)



Greater Asheville, NC: **Hurricane Helene** (2024)

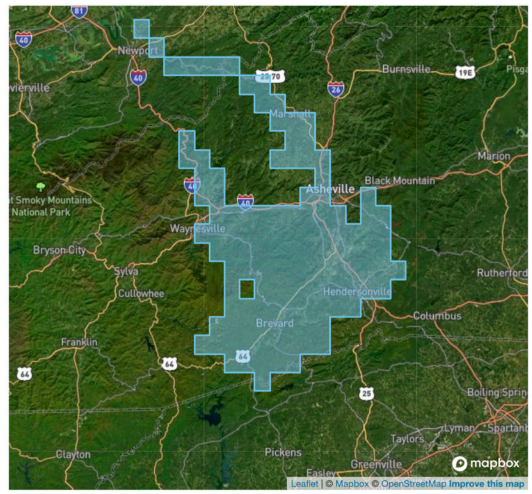


Figure 3. Examples of flood-exposed areas during Hurricane Harvey (left) and Hurricane Helene (right) used in this analysis. These flood-exposed areas are derived from data from the Copernicus Emergency Management Service, a European Commission program that includes the Global Flood Awareness System (GloFAS) for forecasting and monitoring flood events. **Source:** ICE Climate as of 10/23/2025.

Combining loan and hazard data. ICE Climate's Hazard Watch capabilities allow users to identify financial assets exposed to historical, active and forecasted extreme weather events, including hurricanes and tropical cyclones, tornadoes, floods and wildfires. This research is focused on loan exposure, but ICE Climate's capabilities span asset classes – providing insight into extreme weather event exposure for municipal bond securities, corporations, commercial mortgage-backed securities and 99.9% of U.S. properties.[31]

For this research, ICE Climate links hazard data – including tropical storm and hurricane wind tracks, flood-exposed areas and wildfire perimeters – to location information for over 110 million loans using an anonymized loan-property linkage methodology. This allows us to identify which loans in the ICE McDash dataset were active and exposed during each event. Using this approach, ICE Climate can distinguish loans in the ICE McDash dataset that were active and exposed to extreme weather events (i.e., within a high windspeed path, flood exposed area or wildfire perimeter) from those that were active and unexposed. We can then compare subsequent loan performance over the following months based on the relevant loans' delinquency status through time.

An example of loan exposure during Hurricane Milton is shown below (Figure 4). The red line represents the area exposed to hurricane-force winds (64+ knots) when Hurricane Milton made landfall along the western Florida coastline on the evening of October 9, 2024. The yellow lines delineate the area exposed to tropical storm-force winds (50+ knots). Within this exposed area, pre-storm (baseline') delinquency rates in September are shown by zip code. Across the 490,000 active loans in the ICE McDash dataset exposed to 50+ knot winds during this storm (within the yellow lines), the overall delinquency rate increased from about 2.4% pre-storm to 3.4% the month after the storm. For the roughly 201,000 active loans exposed to 64+ knots wind speeds (within the red lines), the delinquency rate increased slightly more, from about 2.5% to 3.7%.

[29] Copernicus Emergency Management Service, "Global Flood Awareness System: Global Ensemble Streamflow Forecasting and Flood Forecasting," accessed October 23, 2025, global-flood.emergency.copernicus.eu/.
[30] European Space Agency, "Sentinel-1," European Space Agency, accessed October 23, 2025, esa.int/Applications/Observing_the_Earth/Copernicus/Sentinel-1.
[31] Hazard Watch identifies this exposure by combining information about the spatial extent of extreme weather events (described above) with large-scale datasets of over 150 million properties across the U.S., three million global corporate asset locations and locations associated with over 50,000 U.S. municipal bond issuers.

Delinquency rates **before** Hurricane Milton (September 2024)   Delinquency rates **after** Hurricane Milton (November 2024)

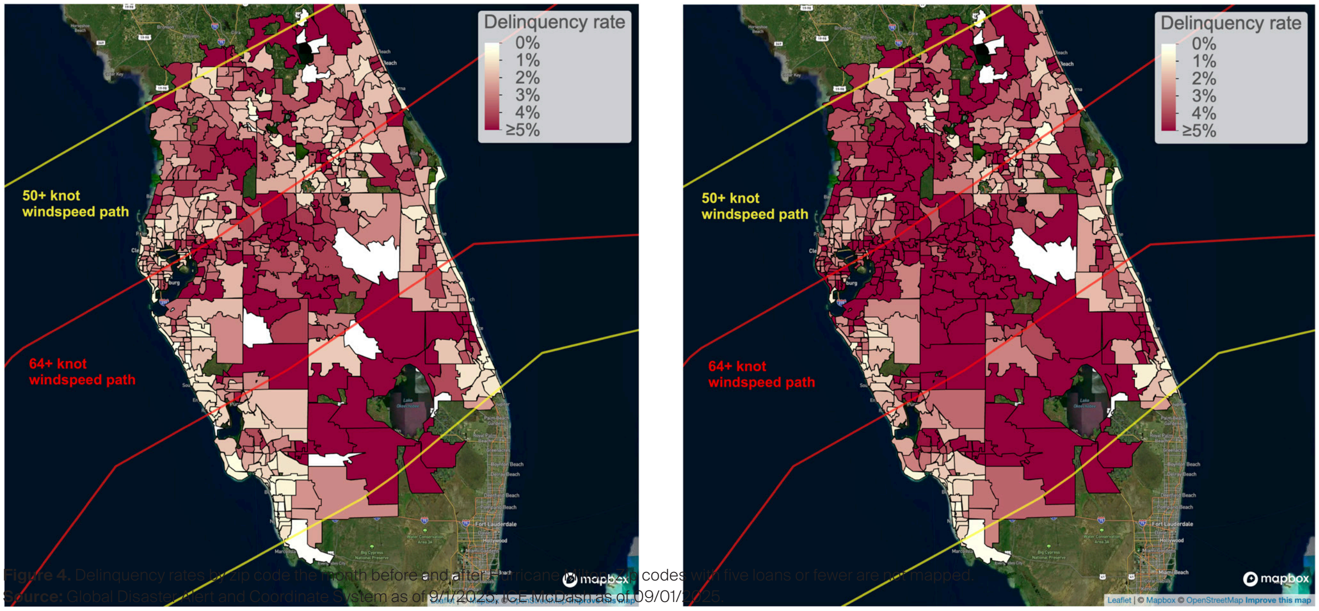


Figure 4. Delinquency rates by zip code the month before and after Hurricane Milton. Zip codes with five loans or fewer are not mapped.
Source: Global Disaster Alert and Coordinate System as of 9/1/2025; ICE McDash as of 09/01/2025.

In total, the 48 storms (both tropical storms and hurricanes) considered in this analysis exposed roughly 10.7 million active loans in the ICE McDash dataset (loans active at the time of each event) to wind speeds of 50 knots or greater (Figure 5). About 2.2 million of these loans were exposed in multiple storms. The scale of this exposure is impressive: the total unpaid balance exposed during these storms amounts to about $2.1 trillion (nominal dollars).

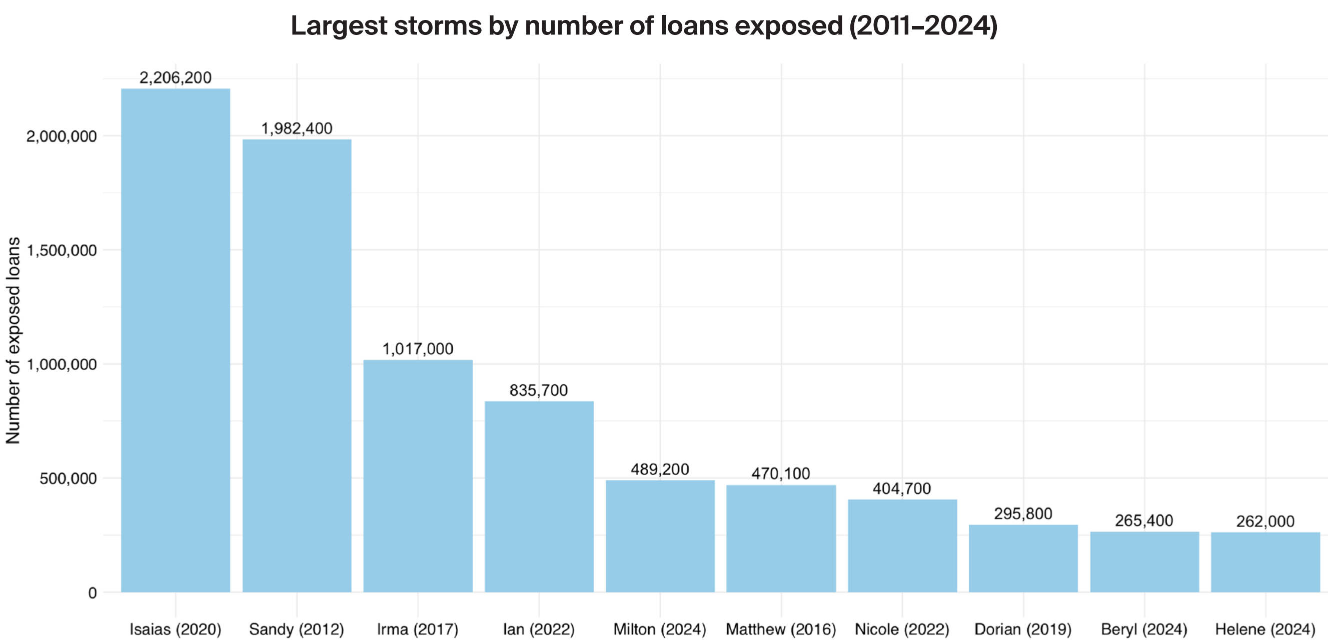


Figure 5: Number of loans exposed to 50+ knot winds during the 10 largest storms (in terms of loan exposure, not storm severity) in our dataset.
Source: Global Disaster Alert and Coordinate System as of 9/1/2025; ICE McDash as of 09/01/2025.

The scale of flood exposure is similarly large. In total, the 4,458 flood-exposed areas in this analysis exposed about 15.9 million loans and about 4 million of these loans were exposed more than once (as in the case of tropical storm- and hurricane- exposed loans, loans with insufficient information – including credit score, interest rate, unpaid principal balance – are excluded from the analysis).

Compared to flood and tropical storm/hurricane exposure, the scale of wildfire exposure is much smaller. In total, the wildfires in our dataset exposed 16,020 loans with the necessary information between January 2012 and October 2024.

Hazard	Number of events	Loan-event exposures	Unique loans	UPB exposed	Date range
Tropical storm (50+ knots)	48	10.7M	6.8M	$2.1T	Sep 2011 – Oct 2024
Hurricane (64+kt)	31	2.8M	2.4M	$507B	Aug 2012 – Oct 2024
Wildfire	481	16K	16K	$5.7B	Jan 2012 – Oct 2024
Flood	4,458	16M	10.8M	$3.2T	Feb 2015 – Dec 2024

Table 1. Summary of the linkage of ICE McDash to hazards. Each hazard is listed with the number of events, the number of loan-event exposures, the number of unique loans exposed over all loan-event exposures, the nominal UPB exposed and the observed date range. Loans exposed to 64+ knot windspeeds are by definition a subset of the loans exposed to 50+ windspeeds.
Source: ICE McDash and ICE Climate as of 09/01/2025.

1.2 The model

The probability of a delinquency can be affected by many factors, including the unpaid principal balance of a loan, the credit score of the borrower and the interest rate of the loan. To try to isolate the impact of extreme weather event exposure, ICE Climate models loan-level delinquency every month for 12 months following exposure to a tropical storm/hurricane, flood or wildfire.

Specifically, the models are loan-level logistic regressions,[32] designed to estimate the probability of delinquency given exposure to an extreme weather event, while controlling for important loan characteristics at both origination (property value, credit score and debt to income ratio) and at the time of the event (unpaid balance, interest rate and loan age). We also include a binary delinquency indicator in the model, allowing us to control for whether a loan was current or delinquent the month prior to the extreme weather event.

A separate model is fit for each month from the time of the event, resulting in 12 models for each hazard (flood, wildfire and tropical storm/hurricane) to predict delinquency probabilities each month after the events, all controlling for loan characteristics at origination and the time of the event, as well as delinquency status the month prior. Compared to other more complex modeling frameworks, this approach allowed the model results and output to be easily interpretable.

Loan-level controls

Original property value	Original credit score	Original debt to income ratio
Unpaid loan balance*	Interest rate*	Loan age*
Delinquency rate on single-family residential mortgages*	Delinquency status*	

*The month prior to the event

Table 2. List of loan-level, market-level and borrower characteristics included as controls in the analysis of extreme weather event exposure and delinquency. Three controls (no asterisks) are at time of origination; the others (with asterisks) are from the month prior to the event.
Source: ICE McDash, ICE Climate and the Board of Governors of the Federal Reserve System (U.S.) via FRED.[33]

For each hazard (wildfire, tropical storm/hurricane and flood), ICE Climate generated a control sample of loans that were active at the time of the event but not exposed. For the hurricane analysis, the control group consists of loans active during each storm's landfall that had no exposure to the hazard events (wildfires, tropical storms/hurricanes or floods) in our datasets. For each model, the control sample is selected to be roughly the same size as the exposed sample. In practice, this means that areas of Florida, Louisiana, the Texas Gulf Coast and California are underrepresented in the controls, since many properties in these areas are exposed repeatedly. While this geographic differentiation could introduce some economic and demographic confounding into the modeling, our analysis minimizes these potential biases by tracking the same loans over time, comparing their performance before and after exposure. The within-loan temporal design acts as a form of implicit control, since each loan effectively serves as its own baseline. Flood exposed loans are less concentrated geographically and would be expected to have less of this kind of confounding. As shown in the results below, flood-exposed loans behave similarly to other hazards suggesting that if present, this confounding would not substantively change the results.

[32] Logistic regression is a statistical method well-suited to binary outcomes – in this case, whether a loan becomes delinquent or not – and allows us to isolate the contribution of individual factors, such as extreme weather exposure, while holding other characteristics constant.
[33] The Delinquency Rate on Single-Family Residential Mortgages is used as a market-level control in the model, serving as a proxy for overall delinquency rate in the market at the time of an event. It is produced on a quarterly basis and available here: fred.stlouisfed.org/series/DRSFRMACBS.

Importantly, each regression model includes an indicator for whether the loan was exposed to an event. This structure allows ICE Climate to estimate the additional (marginal) probability of delinquency associated with exposure to an extreme weather event, by comparing predicted outcomes with and without the event indicator. The model does not explicitly consider whether a loan was exposed multiple times to an event, indeed, since the analysis is based on a limited time window of events it is possible that loans were exposed prior to the first observed event. However, the majority of loan-event combinations correspond to unique loans across all hazards and the model provides average responses over a large number of events, suggesting that differences in responses based on multiple exposure could be averaged out.

1.3 Results

Across loans that were current before the events, ICE Climate estimates a ~21% ± 0.6% increase in the probability of loan delinquency one to three months after exposure to 50+ knot wind speeds during tropical storms and hurricanes (Figure 6). This increase in delinquency probability is larger – over 40% – for the three months after landfall for loans exposed to 64-knot wind speeds or greater.

In the aftermath of flood exposure, ICE Climate estimates an ~18% ± 0.6% increase in the average probability of loan delinquency in the three months following exposure. These percentage increases are measured relative to the delinquency rate observed in unexposed loans. The increase in delinquency probability for flood- and tropical storm/hurricane-exposed appears to be mostly temporary, fading to zero by nine months after landfall.

ICE Climate estimates a significantly larger increase in delinquency probability (~250% ± 33%) in the three months after the event for wildfire-exposed loans that were current before the events. The larger increase in delinquency probability following wildfire exposure – relative to flood and tropical storm/hurricane exposure – likely reflects differences in how hazard exposure is identified across ICE Climate's datasets. Wildfire perimeters are derived from satellite-based burned area analyses, implying that loans within these boundaries are likely to be associated with homes that experienced either direct damage or significant disruption. In contrast, within windspeed paths and flood exposure areas, not all homes are necessarily going to be impacted. (Note that the increase in delinquency probability is already elevated during the month the wildfires occur – Month 0 in Figure 6. Much of this effect is likely due to wildfires that took place towards the beginning or middle of Month 0 and therefore may have affected borrowers' payments later that same month.)

Average percentage increase in delinquency probability after extreme weather events
(for loans current before the events)

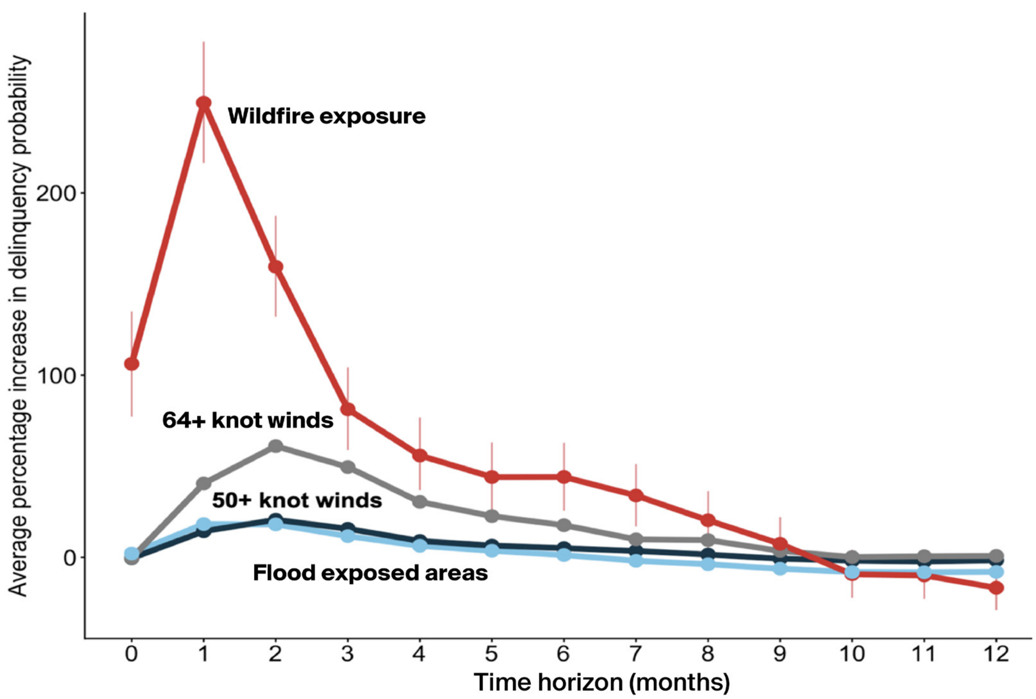


Figure 6: Average percent increase in delinquency probability relative to baseline in tropical storm- and hurricane-exposed (50+ and 64+ knot winds), flood-exposed and wildfire-exposed areas for loans current before the events.
Source: ICE Climate as of 10/10/2025.

Increases in delinquency rates after extreme weather events reflect immediate financial stress on homeowners due to factors such as property damage, displacement and disruptions in income (e.g., service workers). Previous studies have documented a spike in the rate of loans entering 90-day delinquency between three to four months after Hurricane Harvey, an effect that decreases rapidly over the following six to eight months.[34]

Delinquency rate increases may often be short-lived because of several mitigating factors. Federal disaster relief programs and mortgage servicer forbearance policies allow borrowers to pause or defer payments, enabling homeowners to resume paying a few months later without penalty. Insurance payouts also play a significant role: homeowners affected by Hurricane Harvey who had flood insurance were less likely to be delinquent or in default two years after the storm.[35] Additionally, post-disaster economic activity – reconstruction jobs, federal aid, etc. may often help to stabilize household finances over longer time scales.

Beyond approximately nine months after exposure to a wildfire, tropical storm/hurricane or flood, delinquency probabilities become slightly negative relative to the month preceding the event (Figure 6). This pattern likely reflects a sample composition and survivorship effect. Our analysis follows the cohort of loans that were outstanding prior to the hazard events and remain active in each subsequent month. Loans that default, are foreclosed or are voluntarily prepaid in the months following the event exit both the control and the exposed samples in the month after the loans are listed as foreclosed or prepaid.[36] Essentially, the predicted probabilities of delinquency for exposed loans fall slightly below their baseline level after eight to 10 months because the model learns that exposed loans that survive that long tend to be less risky than they appear based on their loan and borrower characteristics alone.

As with any large-scale empirical study, the analysis in this chapter has some limitations. The methods used to identify hazard exposure vary across event types, so the delinquency probability uplifts should not be directly compared across hazards. (As noted above, wildfire perimeters are derived from satellite-based burned area analysis, meaning loans within these boundaries likely experienced either significant disruption or property damage. Wind speed paths and flood-exposed areas represent broader geographic zones where not all properties necessarily sustain damage). ICE Climate's models control for key borrower and loan characteristics, but factors such as insurance coverage amounts, hazard deductibles, forbearance programs, local policy responses, federal relief dollars, community resilience and disaster preparedness may influence delinquency patterns and these are not captured in the analysis. As noted above, survivorship and geographic effects may impact longer-term estimates. Delinquency forecasts are based on average effects observed across historical events and therefore may not accurately predict impacts for any individual future event. Finally, we examine loans with the necessary metadata to run these models in the ICE McDash dataset, a dataset which tracks about two-thirds of U.S. mortgage loans at any given time. Loan-level analyses and conclusions in this chapter implicitly assume that loans in ICE McDash with the metadata necessary for the analyses are a representative of the U.S. mortgage market as whole.

Despite these limitations, taken together, the findings in this chapter establish a clear pattern: extreme weather events are associated with measurable and significant increases in mortgage delinquency within the first three months after exposure, with effects that are temporary for most loans but may be a signal of financial stress for others that exit the market through foreclosure or prepayment. Understanding these patterns has important implications for a range of market participants.

1.4 Discussion

The U.S. housing market is a critical component of the U.S. economy; investors all over the world often look to the performance of the U.S. housing and mortgage markets as an indicator of the global economic landscape.[37] Within these markets, delinquency rates play an important role as a measure of homeowner financial stress, local employment conditions and general market stability. ICE Climate's analysis of mortgage delinquency has direct implications for homeowners as well as local banks and credit unions which might experience strain due to short-term spikes in delinquency.

[34] Carolyn Kousky, Mark Palim and Ying Pan, "Flood Damage and Mortgage Credit Risk: A Case Study of Hurricane Harvey," Journal of Housing Research 29, no. sup1 (2020): S86–S120, doi.org/10.1080/10527001.2020.1840131.

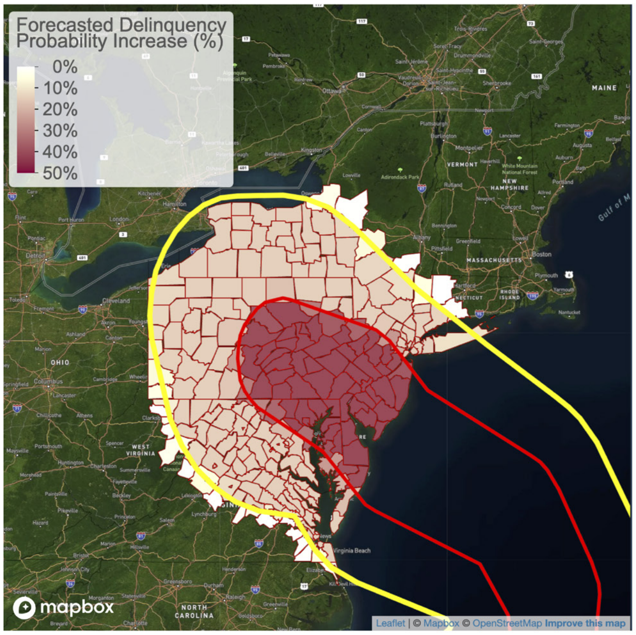
[35] Carolyn Kousky, Mark Palim and Ying Pan, "Flood Damage and Mortgage Credit Risk: A Case Study of Hurricane Harvey," Journal of Housing Research 29, no. sup1 (2020): S86–S120, doi.org/10.1080/10527001.2020.1840131.

[36] This reflects how loan payment status is recorded in the ICE McDash dataset. If in one month a loan is prepaid, the next month the payment status is empty. All loans with empty payment statuses are removed from each analysis.

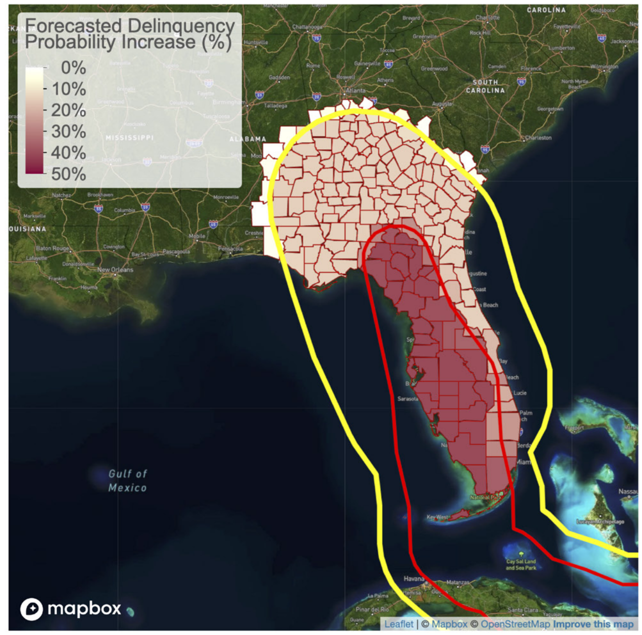
[37] K. Montevirgen, "What Housing Market Data Can Indicate about the Broader Economy," Britannica Money, britannica.com/money/housing-market-data.

An interesting implication of this modeling is that it allows ICE Climate to "forecast" the increase in delinquency after three months due to an extreme weather event. Figure 7 shows four example delinquency forecasts three months after tropical storms and hurricanes due to exposure to high wind speeds (50+ knots) at a county level, using the paths of the four largest storms by number of loans exposed. (Importantly, these model forecasts are based on the average delinquency uplift signal across 48 tropical storms and hurricanes and are therefore not necessarily going to be representative of true impacts for any one storm.)

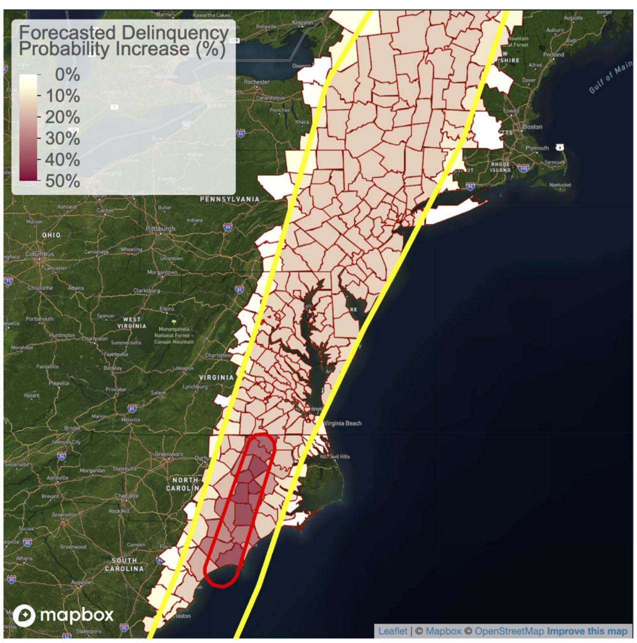
Sandy (2012)



Irma (2017)



Isaias (2020)



Ian (2022)

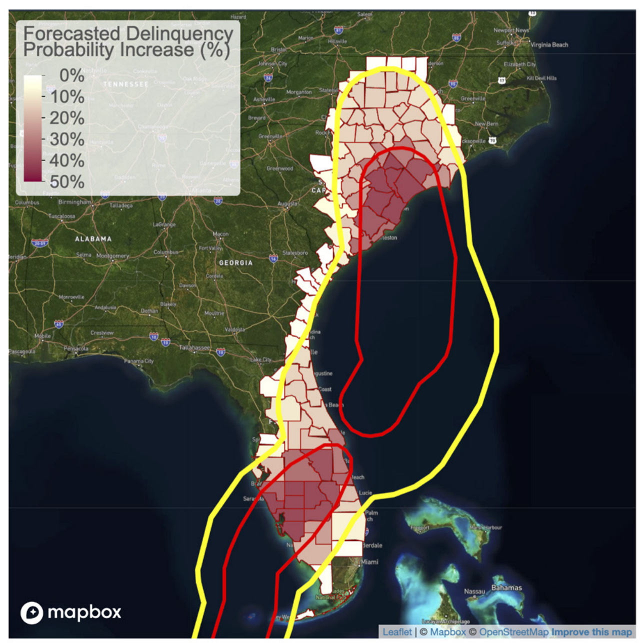


Figure 7: Examples of how ICE Climate can use these models to 'forecast' patterns of increases in delinquency probability relative to baseline going forward.
Source: Global Disaster Alert and Coordinate System as of 9/1/2025; ICE Climate as of 10/10/2025

There is additional potential for disruptions to investments that rely on regular mortgage payments. Investors in non-agency residential mortgage-backed securities (RMBS) and agency credit risk transfer (CRT) pools may experience losses, especially in riskier tranches. Agency RMBS investors may also feel the effects of short-term delinquency increases indirectly, because more delinquencies will disrupt cash flows, cause payment delays and often increase servicing costs. The uptick in delinquencies in the aftermath of extreme weather events may also have implications for municipal bond investors. Especially in cities and towns that are struggling financially, an increase in delinquency rate in the aftermath of a storm or wildfire could further exacerbate affordability challenges.

Going forward, ICE Climate's ability to forecast delinquency increases in the aftermath of extreme weather events could enable a series of important and novel applications, including:

- Large financial institutions, small banks and local municipalities alike can perform stress tests based on hypothetical events as well as fast-response assessments of their exposure as tropical storms and hurricanes approach.
- CRT investors and RMBS investors that are most likely to be impacted by delinquency could change their investment strategies in the face of an incoming hurricane or active wildfire.
- Agency RMBS investors could adjust prepayment models using these kinds of insights – both during active wildfires and before hurricanes make landfall.

Beyond these specifics, the link between extreme weather events and delinquency rate increases makes one thing clear: investors should consider integrating event-based delinquency modeling into their risk assessment frameworks.

Chapter 2. Long-term climate risk and mortgage delinquency

The previous chapter focused on the loan delinquency patterns in the immediate (≤1 year) aftermath of extreme weather events. In this section, we take a longer-term perspective, examining how climate-related pressures may influence delinquency patterns over 5+ years – even in the absence of a specific event.

By linking loan performance data for millions of loans originated between 2016 and 2019 to climate risk estimates for the underlying properties, ICE Climate has found:

- After accounting for key loan characteristics, loans associated with properties with high flood and hurricane risk have higher probabilities – 43% ± 3% and 79% ± 2% higher respectively – of experiencing severe delinquency compared to loans for properties with negligible risk.
- Loans with high wildfire risk, on the other hand, tend to have slightly lower probabilities of delinquency compared to loans with negligible risk.

Climate risk can impact the long-term probability of delinquency in multiple ways. Significant property damage during an extreme weather event may lead homeowners to prioritize repairs over mortgage payments, while forbearance programs can temporarily reduce the consequences of falling behind. As we saw in the previous chapter, these effects often translate into significant increases in short-term delinquency after extreme weather events, even after controlling for key loan and borrower characteristics.

However, the influence of climate risk extends beyond direct exposure. Even in the absence of an extreme weather event, the costs associated with living in a high-risk area can create financial pressure on homeowners. One recent study found that homeowners with increasing insurance premiums have a higher probability of loan delinquency, an effect that is most pronounced among borrowers with high debt-to-income ratios.[38]

The cost pressure of home insurance is often particularly acute for homeowners in the U.S. Federal Emergency Management Agency's Special Flood Hazard Areas (FEMA SFHAs), where homeowners are required to purchase flood insurance to obtain a mortgage. Since the implementation of FEMA's new Risk Rating 2.0 Program in 2021, many homeowners continue to face premium increases (according to the Government Accountability Office, as many as 9% of homeowners covered by the National Flood Insurance Program could see their premiums eventually increase by 300%).[39]

[38] S. Ge, S. Johnson and N. Tsur-Ilan, "Climate Rise, Insurance Premiums and the Effects on Mortgage and Credit Outcomes" (Working Paper no. 2505, Federal Reserve Bank of Dallas, 2025), dallasfed.org/~/media/documents/research/papers/2025/wp2505.pdf.
[39] Government Accountability Office, Flood Insurance: FEMA's New Rate-Setting Methodology Improves Actuarial Soundness but Highlights Need for Broader Program Reform, GAO-23-105977 (Washington, DC: Government Accountability Office, July 2023), gao.gov/assets/gao-23-105977.pdf.

Property taxes represent another pressure point. Municipalities such as Virginia Beach have raised property taxes over the past decade to fund large-scale flood mitigation and resilience projects. Over the long term, the protective benefits of these investments often far outweigh their costs, even though they can increase financial strain for individual homeowners in the near term. Taken together, climate-related expenses – including insurance premiums, property taxes, repair and recovery costs and utility bills – may start to compound for many homeowners, further increasing affordability pressures across the mortgage market. These cost pressures suggest that climate risk may influence mortgage performance through multiple channels simultaneously – a dynamic that this chapter attempts to examines at scale by linking long-term delinquency outcomes for 6.9 million loans to loan-level climate risk scores.

2.1 The data

Loan data. This analysis draws on the same ICE McDash dataset described in Section 1.1, which contains servicer records for over 35 million active mortgages and decades of mortgage performance history. For a large subset of these loans, the ICE McDash dataset also has insurance coverage and premium information.

To assess the climate risk of properties underlying these loans, it is important to know their underlying locations. The ICE McDash dataset includes zip codes for each loan, but ICE Climate refines these locations using a privacy-preserving methodology that allows us to link loans to information about the underlying properties,[40] including climate risk estimates, while always preserving borrower anonymity. The following analysis is based on the subset of loans in the ICE McDash dataset with the necessary metadata (including insurance data) and a closing date between 2016 and 2019, a selection criterion that allows us to examine a large sample of loans (6.9 million) over a 5+ year time window far removed from the housing market crisis of 2008. The payment status of these loans was tracked through November 2025.

The previous chapter considered the impact of extreme weather events on all mortgage delinquencies (all loans 30+ days delinquent) to understand the immediate effects of these events on homeowners' ability to pay their mortgages. Here, we focus on severe delinquency (90+ days delinquent) to understand the relationship between climate risk and longer-term systemic risks to housing market stability and home affordability in high-risk areas.

Climate risk. ICE Climate's Flood, Hurricane and Wildfire Risk Scores quantify the level of risk associated with U.S. properties and ICE McDash loans on a 0 to 5 scale (5 is the highest risk). These scores are developed on top of flood, wildfire and hurricane hazard models that yield expected insurance-equivalent annual losses due to wildfires, hurricane winds and riverine, rainfall-driven and coastal flooding. Expected losses are estimated by combining model outputs (flood probabilities and depths, wind speeds and their probabilities, etc.) with information about the locations and characteristics of more than 150 million buildings across the U.S. sourced from ICE property assessor records. Scores are relative (a flood score of 5 corresponds to the 2% of the most flood-exposed properties in the U.S.; a score of 4 represents 80% of the level of the risk of a score of 5; a score of 3, 60% the risk of a score of 5, etc.) and capture the statistical risk associated with each peril. Scores do not vary significantly year to year because they effectively reflect average climate risk over a ~20–30-year period; they gradually change on decadal timescales based on a range of different climate scenarios. We focus on contemporary risk here. A high score does not necessarily mean that an area has been impacted by an extreme weather event in recent history.

2.2 The model

Many factors can affect the probability that a loan falls into severe delinquency, including borrower credit scores, loan balance and interest rate. To isolate the relationship between climate risk exposure and the probability of severe delinquency, ICE Climate built a logistic regression model to account for key loan-level characteristics at origination: original property value, loan amount, credit score, debt-to-income ratio, interest rate and loan age.

Loan-level controls

Original property value	Borrower credit score	Borrower debt to income ratio
Original loan amount	Interest rate	Loan age

Table 3. List of loan-level and borrower characteristics included as controls in the analysis of climate risk and delinquency.
Source: ICE McDash, ICE Climate

[40] ICE Mortgage Map hashes borrower-specific information, so that it is impossible for anyone (including ICE) to link borrower information to homes.

For each loan in the analysis, we track its performance from origination through November 2025 and create an indicator: "1" if the loan was ever severely delinquent over this time period, "0" if not.

The three final logistic regression models (one for wildfire risk, one for flood risk and one for hurricane risk) are designed to predict the probability of a loan ever being delinquent based on the relevant risk score, after controlling for the loan-level characteristics in Table 3. As an additional component of the analysis, to understand the impact of flood insurance on delinquency, we also ran a version of the flood risk model for only loans with flood insurance policies that were active at some point during the observation window.

2.3 Results

The results of the logistic regression models suggest high flood and hurricane risks are associated with an increase in severe delinquency probability. On average, loans in our sample with an ICE Hurricane Score of 5 have a severe delinquency probability that is roughly 80% higher than that of an average loan with negligible hurricane risk, after accounting for key loan-level characteristics (Table 3). Similarly, loans associated with homes with high flood risk have a ~40% higher probability of severe delinquency, compared to loans with lower flood risk.

The probability of severe delinquency increases with flood and hurricane risk

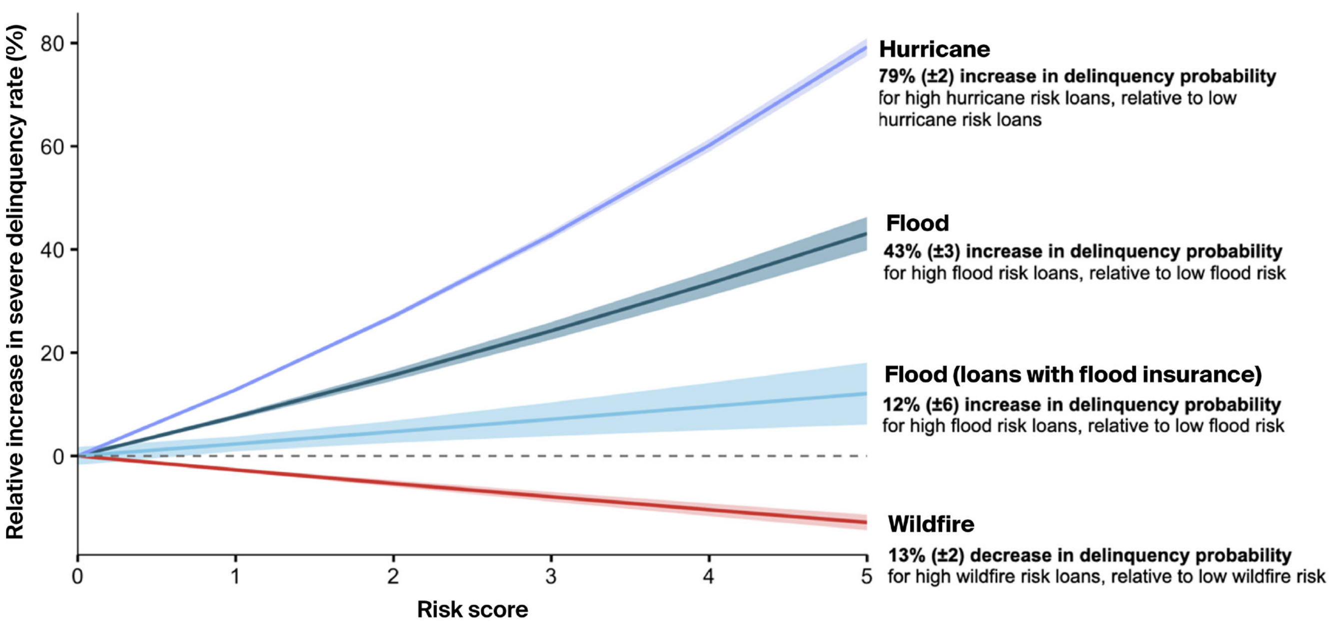


Figure 8. The relationship between the relative increase in delinquency rate (relative to baseline delinquency rate for properties with an ICE Risk Score of 0 for the respective hazard) and ICE Risk Score for hurricanes, flood (all loans and only loans with flood insurance) and wildfire.
Source: ICE Climate as of 01/16/2026.

Interestingly, the trend is less steep when the model is run across the subset of our loan sample with flood insurance coverage (about 175,000 loans in total). At the outset, the direction of this effect was not obvious. A reasonable assumption might have been that flood insurance could increase delinquency rates because of the added financial burden of premium payments. Instead, our analysis suggests the opposite: on average, the protective benefits of flood insurance may outweigh its affordability burden. This result not only points to the role of flood insurance in reducing financial vulnerability, it also suggests that flood risk may primarily affect loan performance through direct exposure to extreme weather events, rather than the flood insurance costs.

The relationship between wildfire risk and severe delinquency probability is distinct from that of hurricane and flood risks. After accounting for borrower characteristics at origination, we see a relatively small (~13% ± 2%) decrease in the probability of severe delinquency for loans with the highest wildfire risk, compared to those with negligible exposure. Several potential reasons for this different relationship are discussed in detail below, including the relatively small percentage of loans with high wildfire risk that have been exposed to a wildfire since 2016, as well as the geographic concentration of wildfire risks in California.

The robustness of these relationships was tested by examining two other loan subsets from the McDash dataset: all active loans with continuous insurance information between 2019 and 2025 and all loans originated in 2022. For both subsets, loan performance was tracked through November 2025. Though the magnitudes of the relationships vary, similar trends hold.

2.4 Discussion

The mediating impact of flood insurance on delinquency risk shown in Figure 8 suggests that extreme weather event exposure – and the associated damage – may play an important role in the relationship between climate risk and delinquency rates.

Additional evidence of this link comes from examining the share of loans in each Risk Score category that have experienced at least one extreme weather event since 2012. (See Section 1.1) for details on how we source and identify location information for hurricanes, wildfires and flood events since 2012.)

As might be expected, a substantial proportion of loans (30%+) with high hurricane risks (ICE Hurricane Score ≥ 4) have been exposed to tropical storm force winds (50+ knots) since 2012. This likely contributes to the strong relationship observed between hurricane risk and severe delinquency. That said, 70% of high hurricane risk loans have not experienced 50+ windspeeds associated with the storms in our dataset, suggesting that other factors must also be at play.

For wildfires, the exposure rate is much lower: only about 0.2%+ of loans with high wildfire risk have been exposed to a wildfire in our dataset. This difference may help explain the different relationship between wildfire risk and delinquency compared to hurricanes. High wildfire risk loans are also disproportionately concentrated in California, where homeowners have historically faced relatively low insurance costs in part to due to state regulations that limited rate increases.[41]

This geographic concentration is reflected in original property values: high wildfire risk loans (Wildfire Score > 3) in our sample have significantly higher original property values (over $530,000 on average) compared to lower wildfire risk loans (Wildfire Score ≤ 1; under $370,000). Put another way, because wildfire risk is geographically concentrated and our models do not incorporate location-based fixed effects (e.g., county, Metropolitan Statistical Area (MSA), zip code or tract), the Wildfire Score may be effectively serving as a proxy for loans associated with larger equity cushions due to strong home price appreciation and higher borrower income levels. The same concerns about the geographic concentration of high-risk loans within one state do not apply to hurricane and flood risk.

This analysis has several other limitations as well. As noted above, these models do not incorporate geographic fixed effects (such as county, MSA or zip code controls), meaning we cannot fully separate the effect of climate risk from regional differences in economic conditions, housing market dynamics, employment opportunities or state and local policy environments that may independently affect delinquency rates. The sample is based on loans originated between 2016 and 2019 and tracked through 2025, though overall trends appear to be consistent across other samples as well. Finally, our binary delinquency measure (whether or not a loan was ever severely delinquent over the observation period) was designed to shed light on the overall relationship between delinquency risk and long-term climate risk. By design it does not capture information about the timing, duration and frequency of delinquency episodes; understanding these timing dynamics would require further modeling.

Taken together, these findings highlight the growing importance of climate risk as a long-term factor shaping mortgage performance. Elevated flood and hurricane risks are associated with materially higher probabilities of severe delinquency over time, suggesting that climate exposure can influence credit outcomes well beyond the immediate aftermath of extreme events. As insurers, municipalities and homeowners adjust to rising climate-related costs, these dynamics are likely to become an increasingly important component of long-term mortgage risk and housing affordability analyses.

[41] ICE Climate, "How Are Insurance Costs Changing across the United States? A Ten-Year Visual Perspective," November 2025, ice.com/article/how-are-home-insurance-costs-changing-across-the-united-states.

Chapter 3. Flood risk and home value appreciation

Earlier sections of this report examined short-term (<1–10 years) effects of extreme weather events and climate risk on mortgage delinquency rates. Over longer periods, climate-related pressures – particularly flood risk – may influence housing markets in a more structural way via home values.

Floods are one of the most frequent, deadly and expensive natural disasters in the United States. The risk is also not concentrated in any one part of the country: over the past 20 years, 99% of U.S. counties have experienced a flood.[42] One recent study suggested that U.S. residential real estate in high flood risk areas may be overvalued by as much as $121–$237 billion, depending on the discount rate that these homes may eventually face due to their risk. Many other studies[43,44] have also documented price discounts for homes located within FEMA SFHAs, though the degree of this estimated discount varies significantly. (Awareness of flood risks might be expected to play a larger role in home sales in SFHAs where homebuyers with federally backed mortgages are required to purchase flood insurance.) However, much of this evidence is limited to specific counties and metropolitan areas,[45,46] specific events,[47] or short time windows (e.g., 1–5 years)[48] and are also typically focused on home prices, rather than home price appreciation trends.

This analysis provides new evidence that flood risk may already be reflected in larger-scale home value trends across the country over the past decade. Using ICE's Home Price Index for over 25,000 zip codes, we find that – after controlling for socioeconomic variables and trends – homes in areas exposed to flood risk appreciated at a roughly 0.2–0.4% average annual percentage point discount compared to unexposed homes between 2013 and 2024. Combining this discount insight with national aggregate Zillow data,[49] we estimate that over that 11-year period, ~$31 billion of total residential real estate value in the U.S. may have been lost compared to a counterfactual "zero flood risk" world. The range of overvaluation of $121–$237 billion previously cited suggests that, while this ~$31 billion value attrition is significant, flood risk may still be far from being fully priced into U.S. residential real estate.

Put another way, this implies that if two homes both had a value of $250,000 in 2013, by 2024:

- **House A** (no flood risk) might be worth approximately $489,500, 6.3% compound annualized growth rate (CAGR)
- **House B** (high flood risk) might be worth approximately $474,500 (6.0% CAGR).

In a decade of strong housing appreciation, this kind of average discount has been masked by overall market growth and low mortgage rates. But signs of a softening housing market are emerging – especially in metropolitan areas and markets with high climate exposure. According to the ICE Mortgage Monitor, home prices in Cape Coral and North Port, Florida were down over 11% in July 2025 relative to their peak in June 2022.[50] If these trends continue, this apparent "flood risk penalty" could translate into higher mortgage default rates, potentially impacting mortgage-backed securities and broader financial markets.

3.1 The data

To understand how changes in home prices vary systematically with flood risk, ICE Climate combines several different datasets:

The ICE Home Price Index. The ICE Home Price Index (HPI) provides home price information for over 25,500 five-digit zip codes in the U.S. at a monthly resolution. In many zip codes, HPI estimates exist only for single-family homes; in others, it is broken out for three classes of residential property (single family, condos and mobile homes). We base this analysis on the average of the existing ICE HPI for all property types in each zip code, averaging monthly HPI across each year between 2013 and 2024.

[42] A flood is an excess of water on land that is normally dry. Source: Federal Emergency Management Agency, "What Is a Flood?" FloodSmart.gov, accessed October 20, 2025, floodsmart.gov/know-your-risk/what-is-a-flood.
[43] L. Zhang, "Flood Hazards Impact on Neighborhood House Prices: A Spatial Quantile Regression Analysis," Regional Science and Urban Economics 60 (2016): 12–19.
[44] D. Harrison, G. T. Smersh and A. Schwartz, "Environmental Determinants of Housing Prices: The Impact of Flood Zone Status," Journal of Real Estate Research 21, nos. 1–2 (2001): 3–20, doi.org/10.1080/10835547.2001.12091045.
[45] L. Zhang, "Flood Hazards Impact on Neighborhood House Prices: A Spatial Quantile Regression Analysis," Regional Science and Urban Economics 60 (2016): 12–19.
[46] D. Harrison, G. T. Smersh and A. Schwartz, "Environmental Determinants of Housing Prices: The Impact of Flood Zone Status," Journal of Real Estate Research 21, nos. 1–2 (2001): 3–20, doi.org/10.1080/10835547.2001.12091045.
[47] R. G. Miller and N. Pinter, "Flood Risk and Residential Real-Estate Prices: Evidence from Three US Counties," Journal of Flood Risk Management (2021).
[48] F. Ortega and S. Taspinar, "Rising Sea Levels and Sinking Property Values: Hurricane Sandy and New York's Housing Market," Journal of Urban Economics 106 (2018): 81–100.
[49] Treh Manhertz, "U.S. Housing Market Value Hits $55.1 Trillion," Zillow, September 8, 2025, zillow.com/research/housing-market-value-1-trillion-35518/.
[50] ICE, ICE Mortgage Monitor Report (July 2025), mortgagetech.ice.com/publicdocs/mortgage/imt-july-2025-mortgage-monitor-report-sMm33rhnRWDK.pdf.

Socioeconomic data: Many factors have the potential to influence home value appreciation, including changes in local housing stock, employment rates and income levels. To account for these other factors, we assembled a suite of different socioeconomic metrics for 2013, along with changes in these metrics over time between 2013 and 2021, from the U.S. Census Bureau's American Community Survey, also at the five-digit zip level (Table 4).

Socioeconomic controls

State	Median household income	Average household income
Population density	Unemployment (%)	Per capita income
Median household discretionary income	Percent of population under the poverty line (%)	Percent of working population that is under the poverty line (%)
Median year housing stock built	Stressed renters (%, all income brackets)	Percent of households receiving SNAP benefits (%)
Latitude	Longitude	

Table 4. List of socioeconomic and geographic controls included in our analysis. Metrics are collected at the zip code level in 2013. Using ICE Climate's downscaling and reaggregation methodology, we can infer changes in the socioeconomic and demographic metrics for the same zip code boundaries from 2013 through 2021; these changes are incorporated in the model as well.
Source: U.S. Census Bureau American Community Survey (2013 and 2021) and ICE Climate as of 10/23/2025.

Location: The state in which a zip code is located is used as a proxy for factors that likely have an influence on home demand and prices (e.g., state income taxes, property assessment caps, etc.). The latitude and longitude of the centroid of the zip code are included for similar reasons.

Flood Risk Scores: The ICE Flood Risk Score represents the level of flood risk for each zip code on a 0 to 5 scale (5 is the highest risk). The scores are developed on top of a global flood risk model that yields expected insurance-equivalent annual losses from riverine, rainfall-driven and coastal flooding. These losses are estimated by combining flood model outputs (flood probabilities and depths) with information about the locations and characteristics of more than 150 million buildings across the United States. Flood Scores are designed to be relative in nature (an ICE Flood Score of 5 would represent the 2% most-exposed municipalities in the U.S.) and capture the statistical risk across all three types of flooding. Scores do not vary significantly year to year because they effectively reflect average climate risk over a ~20–30-year period (they gradually change on decadal timescales based on a range of different climate scenarios, but we focus on contemporary risk here). Locations with high flood risk have not necessarily experienced a recent flood.

By combining these sources, we constructed a dataset of over 25,500 zip codes with data on HPI, socioeconomic indicators (Table 4) and Flood Risk Scores over time.

3.2 The model

At first glance, there seems to be a relationship between flood risk and HPI CAGR (Figure 9). The average CAGR between 2013 and 2024 is approximately 6.6% across the zip codes in this analysis, but the HPI trajectories for zip codes with high levels of flood risk (ICE Flood Scores ≥ 4) between 2013 and 2024 are less steep than zip codes with moderate (ICE Flood Scores between 1 and 4) and low (ICE Flood Scores < 1) flood risk.

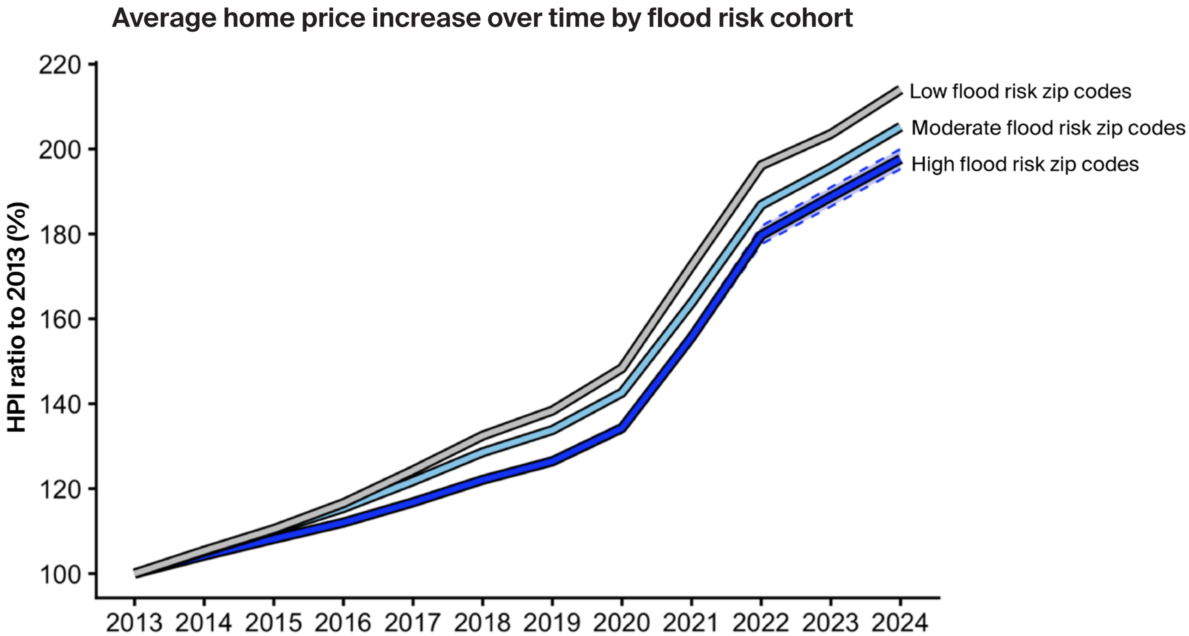


Figure 9: Average Home Price Index (HPI) increase weighted by population for zip codes in different flood risk cohorts in percentage terms relative to 2013. The vertical axis represents the weighted-average ratio of the HPI relative to 2013 for each group of zip codes. Error bars represent 95% confidence bounds based on the standard error of each zip codes sample.
Source: ICE Climate as of 11/24/2025.

Average HPI CAGR between 2013 and 2024 shows a similar pattern (Figure 10). Zip codes with higher flood risk tend to have slower housing price appreciation over this period than zip codes with no flood risk.

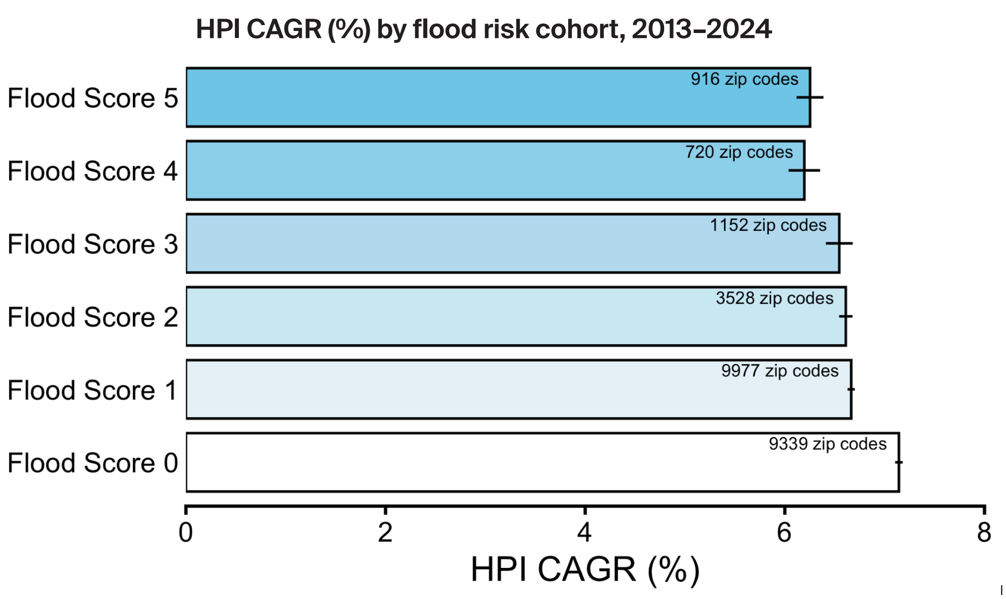


Figure 10: The horizontal axis represents the population-weighted average compound annualized growth rate (CAGR) in the Home Price Index (HPI) from 2013 to 2024. The vertical axis represents the ICE Flood Risk Score rounded to the nearest integer. The number on each bar represents the count of 5-digit zip codes associated with the given averaged CAGR value and Flood Risk Score. Error bars represent 95% confidence bounds based on the standard error of each zip codes sample.
Source: ICE Climate as of 11/24/2025.

However, we cannot directly associate differences in HPI trajectories to flood risk until we account for other factors that can influence home price changes over time. Put another way, our goal is to isolate the marginal relationship between flood risk and housing price growth, minimizing confounding effects.

To do this, we built a random forest model with the compound annual growth rate (CAGR) of ICE's zip code level HPI from 2013 to 2024 as the response variable. We chose a random forest model due to its ability to capture complex interactions and nonlinear relationships. The year 2013 was selected as the starting point to reduce residual effects from the 2008 financial crisis and maximize the time window to smooth out short-term volatility.

We first trained a random forest model to estimate zip code-level CAGR based on 14 socioeconomic, geographic, demographic and housing stock metrics (Table 4), as well as changes in these metrics between 2013 and 2021. This base model explains about 67% of the variance in CAGR.

Next, we computed the residuals:

Residual CAGR = actual CAGR – estimated CAGR

These residuals represent the portion of CAGR not explained by socioeconomic or state-level factors. We can then test whether Flood Risk Scores help explain this residual variation. Put another way, by looking at how the model residuals vary as a function of Flood Risk Score, we can assess whether flood exposure may contribute to housing price changes – after accounting for structural socioeconomic influences.

3.3 Results

After accounting for socioeconomic controls (the metrics in Table 4 in 2013 for each zip code, as well as the change in these metrics for each zip code between 2013 and 2021)[51] we see a clear relationship between flood risk and home price appreciation. Based on socioeconomic factors alone, our model significantly overpredicts HPI CAGR for high flood risk areas (Figure 11). Put another way, after accounting for socioeconomic factors, the average HPI CAGR for high flood risk zip codes is about 0.2–0.4% ±0.1% lower on average than it is in zip codes with little to no flood risk.

Highest flood risk zip codes have an appreciation discount

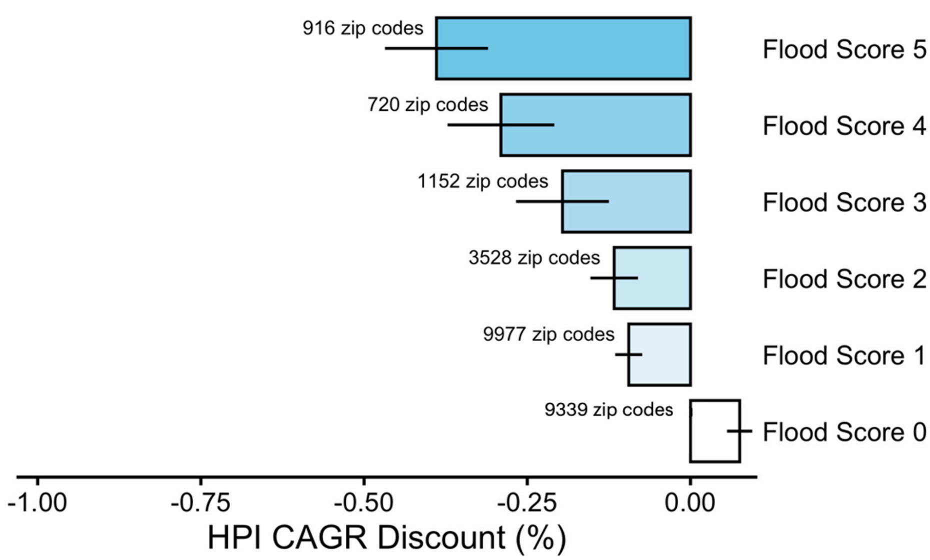


Figure 11: The horizontal axis represents the residual population-weighted average compound annualized growth rate (CAGR) of the ICE Home Price Index (HPI) from 2013 to 2024, after extracting the effects of relevant socioeconomic control variables (Table 4) via a random forest. The vertical axis represents the ICE Flood Score rounded to the nearest integer. The count of 5-digit zip codes associated with the given averaged residual CAGR value and Flood Risk Score are shown to the left of each bar. Error bars represent 95% confidence bounds based on the standard error of each zip codes sample.
Source: ICE Climate as of 11/24/2025.

[51] The U.S. Census Bureau's American Community Survey data beyond 2021 (inferred for 2010 zip codes using ICE's downscaling and reaggregation methodology) are not yet available in ICE's datasets.

The key insight here is that home values in high-risk areas appreciated in value between 2013 and 2024, but they appear to appreciate less than their less risky counterparts after accounting for socioeconomic factors. These results may, of course, be influenced by confounding factors that are not fully captured in the model, but they suggest that over the past decade, high flood risk may have exerted a measurable drag on long-term housing price growth. Discounts of comparable magnitudes for zip codes with flood scores of 4 or greater are consistently observed when we look over a shorter time window (2017–2023) and when we exclude zip codes in non-disclosure states (the analysis in Figures 9–11 includes zip codes from non-disclosure states).

However, we do not observe the same systematic relationships between housing price appreciation and wildfire or hurricane risk (Figure 12). In fact, in the highest hurricane risk areas, we see home values increasing faster than our socioeconomic model predicts. This pattern may be driven partially by the geographic concentration of risks in Florida, a state that saw particularly rapid home price growth over the past decade.

Analogous HPI appreciation discoounts are not seen in high hurricane and wildfire risk areas

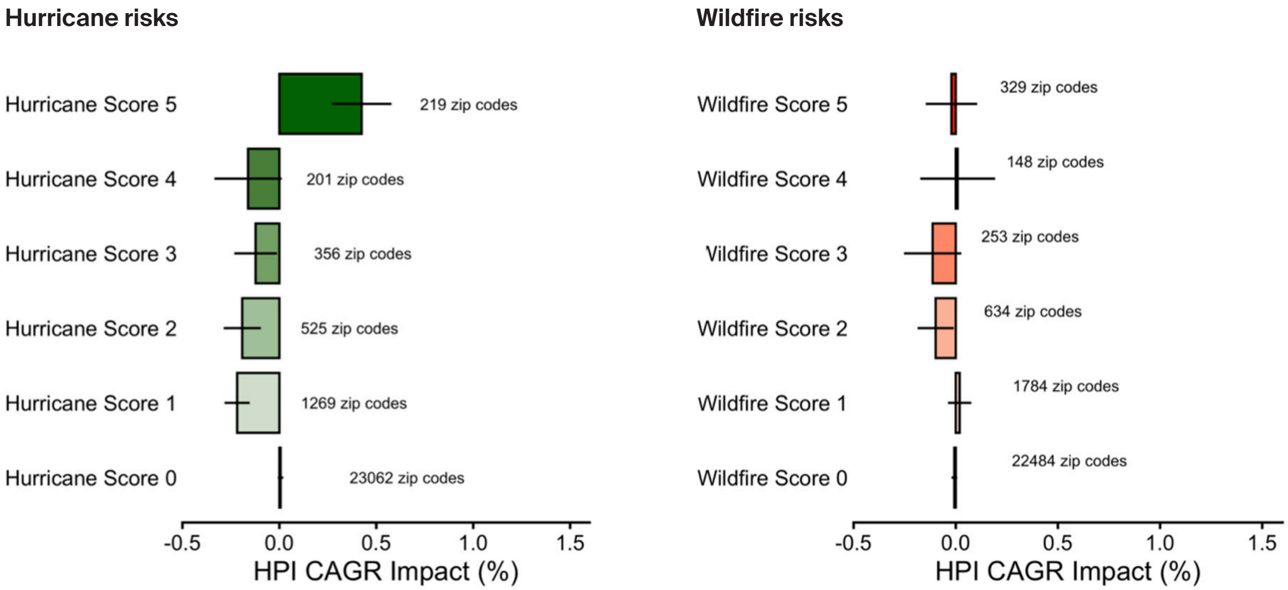


Figure 12: The horizontal axis represents the residual population-weighted average compound annualized growth rate (CAGR) in the ICE Home Price Index (HPI) from 2013 to 2024, after extracting the effects of relevant socioeconomic control variables (Table 4) via a random forest. The vertical axis represents the ICE Hurricane Score (left) and the ICE Wildfire Score (right) rounded to the nearest integer. The count of 5-digit zip codes associated with the given average residual CAGR value and score are shown to the right of each bar. Error bars represent 95% confidence bounds based on the standard error of each zip codes sample.
Source: ICE Climate as of 11/24/2025.

Compared to zip codes with high hurricane and wildfire risks, zip codes with high flood risk are less regionally concentrated. Over time, the discounts associated with high flood risk may become financially significant for many municipalities (Figure 11).

A large portion of municipal revenue is generated from property taxes, a revenue stream that could decrease as assessed home values decline. To understand where these impacts might be greatest, we posed a hypothetical question: what would home price growth look like across the country if flood risk did not exist?

To get at this question, we started with the observed zip code level HPI CAGRs between 2013 and 2024. ICE's Home Price Index covers over 25,500 zip codes nationwide; for zip codes not included in ICE HPI, we used the HPI CAGR for the state in which the zip code is located. For zip codes with high flood risk scores, we adjusted the observed CAGRs based on the discounts shown in Figure 11 – for example, adding 0.3% to the CAGR in a zip code with an ICE Flood Risk Score (rounded) of 4 and 0.4% for a score of 5. The purpose of this adjustment was to approximate the hypothetical CAGRs in these zip codes in the absence of flood risk.

Estimated CAGR loss associated with flood risk, 2013–2024

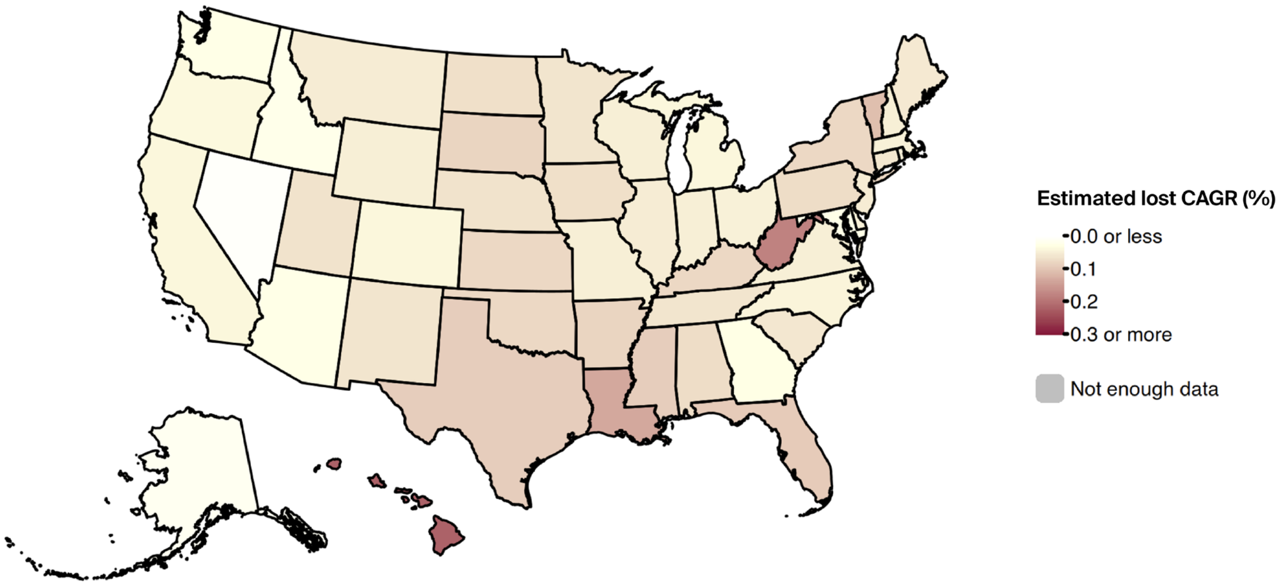


Figure 13: Estimated CAGR loss associated with flood risk exposure (state-aggregated based on population weighting at the zip code level) over the time window of 2013–2024. In a hypothetical world without flood risk, the average CAGR in West Virginia and Hawaii could have potentially been more than 0.15% larger than actual home price CAGR over this period.
Source: ICE Climate as of 11/24/2025.

When aggregated to the state level, the results suggest that average home price CAGR in West Virginia and Hawaii could have potentially been more than 0.15% higher in a hypothetical world with no flood risk; and in Louisiana and Vermont, more than 0.10% (Figure 13). While these numbers are gross approximations, they offer a sense of the scale and locations where flood risks may be quietly limiting homeowners' ability to build wealth and over time, potentially reducing municipal revenues as these lower value homes lead to decreases in property taxes.

3.4 Discussion

Home price appreciation plays an important role in shaping economic outcomes for local governments, homeowners and the broader U.S. economy. For individual homeowners, less appreciation could erode a key pathway to wealth accumulation. For local governments, it threatens the stability of property tax revenues that fund essential services. And for the broader U.S. economy, it introduces a new source of vulnerability in a sector that has historically underpinned financial growth and resilience.

Given the implications, it is important to note that this analysis of flood risk and home price appreciation has several limitations. First and foremost, the relationships we see are average trends across hundreds of zip codes. Unobserved factors – such as school quality changes, local infrastructure investments, proximity to employment centers, neighborhood amenities, coastal location premiums and changing preferences for urban versus suburban living – may be correlated with both flood risk and home price appreciation, potentially confounding these trends. Our socioeconomic control variables are measured in 2013 with changes tracked only through 2021, while our home price analysis extends through 2024, meaning we do not capture socioeconomic changes during the final three years of the study period. Socioeconomic characteristics are defined for zip code tabulated areas and used to approximate the characteristics of zip codes in the ICE HPI. The analysis uses zip code-level aggregation, which may mask considerable within-zip heterogeneity; not all properties within a high flood risk zip code face equal exposure and the ICE HPI represents a composite measure rather than individual property values. While we observe similar trends when excluding non-disclosure states and looking over shorter time windows, data quality and coverage vary across states, potentially introducing biases.

As this report is being written in early 2026, there are signs of housing market softening. Home prices are falling in some Florida markets; there is evidence that liquidity is particularly low in areas exposed to coastal flood risk. Liquidity is down more generally as well, as homeowners with record low interest rates from 2020–2021 have a strong incentive to stay put, especially after rate increases in 2022 and 2023. At the same time, awareness of flood risks among would-be homeowners is increasing. While Zillow removed flood risk estimates in late 2025,[52] similar information is still available on websites like Redfin and Realtor.com. Recent studies suggest that flood risk awareness translates into behavior changes on the part of homebuyers throughout the home buying process.[53] Another longitudinal study documented decreases in home prices and rents of 5.2% and 2.5% respectively over the decade after natural disasters between 1970 and 2010.[54]

HPI impacts are a logical extension of local home price changes. The key question now may not be not whether flood risk seems to be affecting home prices – it is how much more it may affect home prices in the future. Understanding and quantifying this relationship going forward will be essential for policymakers, investors and communities seeking to navigate a changing climate and a shifting housing landscape.

Conclusion

Climate risk and extreme weather events are already affecting mortgage performance and housing values in clear, measurable ways. This analysis shows that mortgage delinquencies rise in the aftermath of extreme weather events – by about 250% on average after wildfires, 21% after hurricanes and 18% after floods – potentially creating short-term financial strain on local banks, credit unions and mortgage servicers. ICE Climate's Hazard Watch capabilities can help estimate these delinquency increases as events unfold, giving servicers and credit holders time to prepare. By linking exposed loans to mortgage-backed security pools, ICE Climate can also inform prepayment modeling and help investors in Credit Risk Transfer pools and non-agency MBS understand their potential delinquency risk exposure in the aftermath of these events.

Longer-term impacts are just as significant. Properties in high hurricane and flood risk zones show more than 30% higher rates of prolonged (3+ month) nonpayment over five years or more, even after accounting for borrower and loan characteristics. This result highlights the implications of climate-related risks facing homeowners, investors, asset managers and mortgage insurers alike over the longer term.

Home price appreciation is also affected. In high flood risk areas, home appreciation appears to be about 0.2–0.4% slower per year than in low flood risk areas after adjusting for socioeconomic factors. This apparent "flood penalty" may reduce household wealth and limit collateral growth for lenders and investors.

Taken together, these trends suggest that climate risk is not just a local issue – it is a macroeconomic challenge with global implications. To maintain the stability of the U.S. housing market, banks, credit unions, investors, asset managers, insurers and homeowners should integrate climate risk into buying, lending, investment and risk management strategies.

The analyses described in this paper were conducted by ICE Climate. The report has not been subject to external peer review and should be considered informational in nature.

[52] E. Milson, "The Real Estate Industry Is Pressuring Zillow and Other Sites to Nix Extreme Weather Risk Data Buyers Have Come to Rely On," CNN, December 2, 2025, cnn.com/2025/12/02/climate/zillow-climate-data-extreme-weather-first-street-redfin.
[53] D. Fairweather, M. E. Kahn, R. D. Metcalfe and S. S. Olascoaga, "Expecting Climate Change: A Nationwide Field Experiment in the Housing Market" (Working Paper no. 33119, National Bureau of Economic Research, November 2024), https://www.nber.org/papers/w33119.
[54] L. P. Boustan, Matthew E. Kahn, P. W. Rhode and M. L. Yanguas, "The Effect of Natural Disasters on Economic Activity in US Counties: A Century of Data," Journal of Urban Economics 118 (2020): 103257.

Contact us

Wildfires, flooding and increased insurance costs are driving integration of climate physical risk and transition risk into the assessment of portfolios and assets. Climate risks such as extreme weather events can impact the value of portfolios, while also serving as an additional input into identifying investment opportunities. ICE provides data and analytics that can help investors to quantify the impacts their portfolios and investments face from transition risks as well as physical climate risks posed by extreme weather events.

Reflecting our core focus on Fixed Income, ICE offers an array of climate metrics across several fixed income asset classes, including corporates, munis, sovereigns, MBS and more.

For more information: ice.com/climate
Contact us today to schedule a demo: climaterisk@ice.com