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Climate risk in mortgage markets: Evidence from Hurricanes Harvey and Irma

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Abstract

Using the Credit Risk Transfers (CRTs) issued by Fannie Mae and Freddie Mac, we study how, absent government intervention, mortgage markets would price hurricane risk. Currently, such risk is priced equally across locations even if it is location-specific. We hand collect a novel and detailed database to exploit CRTs' heterogeneous exposure to Hurricanes Harvey and Irma. Using a diff-in-diff specification, we estimate the reaction of private investors to hurricane risk. We use the previous results to calibrate a model of mortgage lending. We simulate hurricane frequencies and mortgage default probabilities in each US county to derive the market price of mortgage credit risk, that is, the implied guarantee fees (g-fees). Market-implied g-fees in counties most exposed to hurricanes would be 70% higher than inland counties.

KEYWORDS
climate risk, credit risk, CRT, GSEs, hurricanes, mortgages

1 INTRODUCTION

This article studies how private investors would price mortgage credit risk in the United States absent the Government-Sponsored Enterprises (GSEs) that currently price such risks either directly or indirectly (Lucas & McDonald, 2010).[1] To do so, we hand collect and analyze a database on a new financial product, the Credit Risk Transfers (CRTs) issued by the GSEs. As we explain below, CRTs allow us to measure market pricing of credit risk. Our diff-in-diff approach allows us to estimate private markets' reaction to hurricane risk. We use these estimates to calibrate a model of mortgage lending. Then, we simulate hurricane frequencies and mortgage default probabilities in each US county to derive the market price of mortgage credit risk.

Studying market-based risk pricing is important because, in the absence of appropriately priced insurance, uniform mortgage rates could promote the US population to increasingly locate in disaster-prone areas (Schuetz, 2022). Inappropriately priced insurance, and subsidies to mortgage rates, may encourage households to live in areas exposed to climate risk. In this article, we quantify cross-subsidies in mortgage rates due to differential exposure of locations to climate risk. These cross-subsidies may not only affect borrowers, but also lenders, taxpayers, and overall financial stability.

A CRT is a structured security issued by Fannie Mae or Freddie Mac (the GSEs) and linked to a pool of mortgages that Fannie or Freddie insure. The investors pay the GSEs to buy CRTs, and will receive interest plus the invested principal as long as the mortgages do not default. If the mortgages default, the CRT investors suffer losses and receive smaller payments than planned. Hence, the GSEs are transferring the credit risk of such mortgages to the investors who hold the CRTs (Levitin & Wachter, 2020). The GSEs started to issue CRTs in 2013 and there is also a secondary market for CRTs.[2]

We create a unique database combining information from different data sources: data on all issuances of CRTs from Bloomberg, price data from the secondary CRT market from Refinitiv Eikon, and data on delinquencies in each CRT reference pool from the GSEs. To our knowledge, this is the most detailed database about CRTs. We also use loan characteristics and credit performance data from Freddie Mac that we merge with data of hurricane occurrences from the Federal Emergency Management Agency (FEMA).

We proceed in three steps. First, we exploit that CRTs had heterogeneous geographical exposure to a positive shock to default risk, caused by Hurricanes Harvey and Irma. The hurricanes were unforeseen events that suddenly generated large expectations of local mortgage defaults.[3] The identification satisfies all conditions for a difference-in-difference analysis. Thus we measure how the prices of CRTs react to an increase in the probability of mortgage default caused by the hurricanes. Second, we run logistic regressions to estimate how exposed US counties are to hurricane-induced mortgage default. Third, we combine the information from steps 1 and 2 into

[1] As of December 31, 2021, nearly half of the mortgage debt outstanding ($7.1 trillion) is owned or guaranteed by Fannie Mae and Freddie Mac, which have been in conservatorship since 2008. Moreover, Ginnie Mae, a federal government corporation, guarantees about $2.1 trillion mortgages (FHFA, 2022; Ginnie Mae, 2022).

[2] By "CRTs," we refer to the synthetic notes Fannie Mae's Connecticut Avenue Securities (CAS) and Freddie Mac's Structured Agency Credit Risk securities (STACR). Finkelstein et al. (2018), Golding and Lucas (2022), Echeverry (2022), and O'Neill (2022) study different aspects of the CRT market.

[3] Harvey hit mostly Houston in late August 2017, and Irma hit the southern part of Florida in early September 2017. They rank in the top five of the costliest storms on record up to that year, with damages of approximately $125 and $77 billions, respectively (National Hurricane Center, 2018).

a credit model. We solve for mortgage rates and run simulations like Campbell and Cocco (2015) to estimate the market-implied mortgage rates in areas with heterogeneous exposure to hurricane risk. The model allows for an alternative to "back-of-the-envelope calculations" that would extrapolate the price of credit risk based on the estimated changes in CRT prices.

CRTs have heterogeneous exposure to the hurricanes as they differ in the geographical composition of their reference pool. For example, even though all CRTs are backed by pools of mortgages from all US states, some CRTs have a higher share of mortgages in hurricane exposed areas. These areas are exposed to higher delinquency rates following a hurricane. Markets are able to price these higher risk exposures as investors have all the information about the characteristics of the mortgages underlying the CRTs. Moreover, different tranches of the same CRT deal have different exposure to the default risk of the underlying mortgage pool. This is the first article to show and exploit these heterogeneities.

News about the arrival of Hurricanes Harvey and Irma are shocks that alter investors' expectations about mortgage default in the counties that will be hit by these hurricanes. These counties were already exposed to different pricing since their hurricane risks were higher. Hurricanes Harvey and Irma suddenly accentuate such differences as markets expected large mortgage losses in exposed areas. The parallel trends identifying assumption for the diff-in-diff analysis holds. Yields of CRTs with different exposure to the hurricanes' default risk move in parallel until shortly before the hurricane landfall. Confirming our interpretation of heightened loss expectations, a month after Harvey and Irma landfall, the Association of Mortgage Investors asked the GSEs and the FHFA to remove natural catastrophe risk from the CRTs because they were afraid of large spikes in mortgage losses (Yoon, 2017).

Diff-in-diff regressions show significant increases in yield spreads to Libor, that is, decreases in prices, for those CRTs more exposed to the credit risk caused by Harvey and Irma.[4] For example, the spread of the junior tranche of the CRTs with the largest percentage of unpaid principal balance in hurricane-affected areas increases by 13% compared to the average spread before the landfall. This result is not driven by increased liquidity risk, nor increased prepayment risk. CRT investors are absorbing part of the risk of natural disasters and ask for higher compensation as the risks intensify. This result is not affected by the government intervention that prevented a surge in foreclosures once the hurricanes hit.

In the second part of the article, we estimate logistic regressions for the probability of mortgage defaults due to hurricanes. That is, we quantify the extent to which the occurrence of hurricanes in US counties affects mortgage default rates. This step helps to quantify what the default consequences are that investors associate to hurricanes. We use the timing and location of all Atlantic hurricanes reported in the United States between the years 1999 and 2019, and the annual performance of 260,000 mortgages across the United States. This detailed panel data allow us to control for a large array of mortgage characteristics, location, and time fixed effects. We find that counties that are most frequently hit by hurricanes, 0.8 times per year on average, have 0.5 percentage points (pp) higher probability of mortgage default than counties not affected by hurricanes. This is a substantial increase of 70% higher probability of default.

Finally, we integrate the previous results into a macrofinance model that prices mortgage credit risk for each probability of default. We compute the market-implied guarantee fee (g-fee), that is, what the GSEs would charge to insure credit losses, if the risk was priced by the market. We find that the market-implied g-fee in inland counties is 56.5 basis points, whereas in counties most exposed to Atlantic hurricanes is 95.8 basis points (70% higher). To put this result into perspective,

[4] The relevant spread is the bond yield to Libor, because CRTs pay the Libor plus a spread.

the increase in the market-based g-fees from the least risky to the most risky counties is 40% higher than the increase in the actual statutory g-fees for the lowest credit score band (< 660) to the highest credit score band (≥720) (FHFA, 2018). Another way to look at this result is that homeowners in Miami-Dade county in Florida would have paid an average mortgage rate of 4.24% for a 30-year fixed rate agency mortgage in 2017, whereas homeowners in Salt Lake county in Utah would have paid an average of 3.85% rate for the same mortgage if these were priced based on hurricane risk.

We also quantify the implicit subsidy to credit risk that the GSEs provide relative to market pricing of risk. We define this implicit subsidy as the difference between the market-priced cost of credit risk predicted by the model, based on CRT pricing, and the statutory g-fees that the GSEs charge. The average statutory g-fee for 30-year fixed rate mortgages was 59 basis points in 2017 (FHFA, 2018). Hence, our results suggest that counties with zero hurricane risk are paying 4% higher g-fees relative to the market-implied level. In contrast, counties with the highest hurricane risk are paying 38% lower g-fees relative to the market-implied level.

Our interpretation of the results assumes that CRT investors expected some degree of insurance and government aid following Hurricanes Harvey and Irma, although they were uncertain about the amount. Our results would become larger if the investors expected no support from the government or no insurance coverage as elevated delinquencies would translate into heightened defaults and foreclosures.

The rest of the article is organized as follows: Section 2 relates the article to the existing literature. Sections 3 and 4 describe the CRTs and our database. Section 5 presents the diff-in-diff analysis to estimate the impact of the hurricanes on the market pricing of credit risk. Section 6 estimates the default probability of mortgages due to hurricanes. Section 7 analyzes the model. Section 8 concludes.

2 | RELATED LITERATURE

This article builds on an expanding literature that exploits the occurrence of hurricanes or other natural disasters as an exogenous shock to study effects on mortgage markets (see, e.g., Berg & Schrader, 2012; Chavaz, 2016; Cortés & Strahan, 2017; Garbarino & Guin, 2021; Issler et al., 2021; Morse, 2011; and Ouazad & Kahn, 2022). Related literature has studied other financial and economic effects of hurricanes, like effects on commercial real estate (Addoum et al., 2023), housing prices (Ortega & Taspinar, 2018), Real Estate Investment Trusts (Rehse et al., 2019), retail businesses (Meltzer et al., 2021), bank stability (Schüwer et al., 2019), stock returns (Lanfear et al., 2019), managers' perception of disaster risk (Dessaint & Matray, 2017), fiscal costs (Deryugina, 2017), homeownership (Bleemer & van der Klaauw, 2019), local population turnover (Liao et al., 2023), and households' balance sheets (Billings et al., 2022; Deryugina et al., 2018). Ouazad and Kahn (2022) model distortions that the GSEs create for mortgage origination.[5] They focus on distortions operating through lending standards or quantities, while we show effects on prices.

Our article is novel in analyzing how hurricane-induced default risk translates into market-based mortgage pricing. Our results show that existing mortgage rates in the United States do not reflect the climate risks that markets would price. This result brings a different risk dimension to Hurst et al. (2016), who show that lack of risk-based pricing provides insurance across locations.

[5] See Lacour-Little et al. (2024) for contrary findings.

We show that lack of risk-based pricing encourages climate risk taking. Inland locations subsidize the mortgages of risky coastal locations.

Another contribution of this article is to accurately estimate the increase in mortgage default probabilities caused by hurricanes. We show additional evidence of the effects of natural disasters on loan defaults (see, e.g., Du & Zhao, 2020; Holtermans et al., 2022; Issler et al. 2021; Kousky, Palim et al., 2020; Kousky, Kunreuther et al., 2020; and Rossi, 2021).

This article also contributes to the housing finance literature. We contribute to this literature by estimating the differences between market-based pricing and GSE statutory g-fees. Papers like Bi et al. (2024), Lucas and McDonald (2010), Jeske et al. (2013), Frame et al. (2013), Elenev et al. (2016), Hurst et al. (2016), Gete and Zecchetto (2018), and Wachter (2018) have analyzed different topics related to the role and future of the GSEs. Pavlov et al. (2021) and Stanton and Wallace (2011) study how mortgage credit risk was not reflected in the prices of credit default swaps during the 2008 financial crisis, pointing out the failure of transferring credit risk to the market.

3 | OVERVIEW OF CRTS

Directed by the Federal Housing Administration, the GSEs started to issue CRTs in July 2013 to mitigate the credit risk from the guarantees that they give to mortgage-backed securities. Up to the second quarter of 2017, which is the period we are focusing on, CRT securities provided GSEs with loss protection on about $1.3 trillion of mortgage loans (FHFA, 2017).

3.1 | CRT structure

The CRTs are notes with final maturity of 10 or 12.5 years. CRTs offer investors the rights to cash flows from a reference pool of mortgages that underlie recently securitized agency mortgage-backed securities. The notes pay monthly a share of the mortgage principal to the investors plus interest. The GSEs disclose the characteristics and performance over time of the underlying mortgage pools as well as of the individual loans. Investors have complete information.

The mortgage reference pools contain mortgages from all US states. The highest number of mortgages is usually in the states of California, Texas, Florida, Illinois, Georgia, and Virginia. Reference pools are split into two groups: high or low loan-to-value (LTV). The high LTV pools contain mortgages with LTV ratios between 80.01% and 97%, and the low LTV between 60.01% and 80%.

Figure 1 shows a sample CRT deal. The outstanding principal balance at issuance is divided into tranches with different levels of seniority. The most senior tranche is entirely retained by the GSEs. Next in seniority, there are two or three mezzanine tranches, followed by a subordinated ("junior") tranche. These tranches are sold to investors. A second subordinated tranche ("first loss") was retained by the GSEs in the early CRT transactions, but it has been sold to investors since 2016. A typical allocation of the outstanding principal balance is 94.5–96% to the most senior tranche retained by the GSEs, 3.5–4% to the mezzanine tranches, and 0.5–1.5% to the junior tranches. The GSEs also retain a vertical slice of each of the tranches to reduce the GSEs' moral hazard in the selection of mortgages.

The CRT performance is directly linked to the risk of default of the underlying mortgages. The cash flows from the mortgages in the reference pool repay the tranches according to the seniority pecking order. That is, once the outstanding principal balance of the most senior tranche is paid,

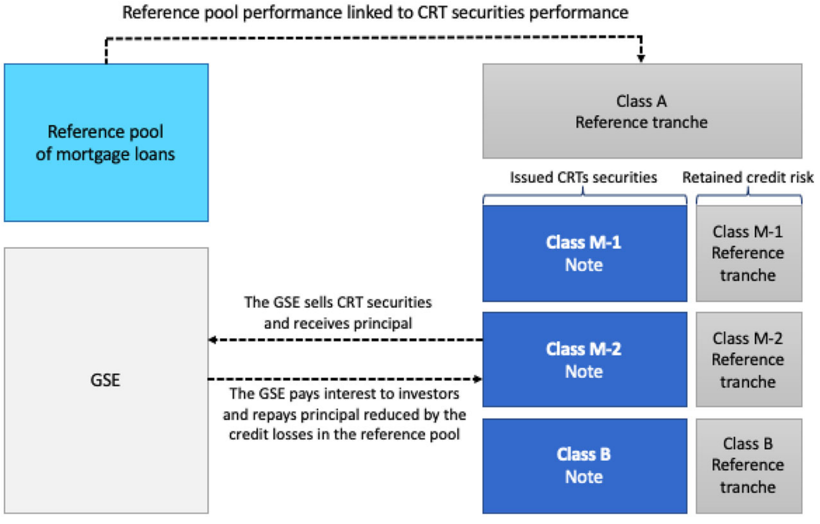

FIGURE 1 Example of Credit Risk Transfer (CRT) transaction. The figure shows an example of CRT linked to a reference pool of loans. Credit losses on the reference pool reduce the interest and principal repayment received by the CRT buyer. This example contains a junior tranche (Class B) and two mezzanine tranches (Class M-1 and M-2). Credit losses are allocated to tranches starting with the most subordinated tranche, while repayments are allocated starting from the most senior tranche. A vertical slice of each of the tranches is retained by the Government-Sponsored Enterprises (GSEs), while the remaining credit risk is sold to investors. The most senior tranche (Class A) is fully retained by the GSEs. [Color figure can be viewed at wileyonlinelibrary.com]

the next tranche in seniority starts to be paid. The losses on mortgages in the reference pool reduce the principal balance starting with the most subordinated tranches ("cash flow waterfall"). On the contrary, prepayments of the mortgages in the pool are first absorbed by the most senior tranche.

CRTs pay as interest one-month US Dollar Libor plus a floater spread. The fluctuations of the spread signal what private capital markets would charge for sharing the credit risk supported by the GSEs (Wachter, 2018).

4 | DATA

We assemble a unique database by combining information at the security level from multiple data sources. First, we collect data of the mortgages in the CRTs reference pool from the GSEs (Fannie Mae, 2021; Freddie Mac, 2021a). Specifically, for all CRTs issued up to August 15, 2017, we collect the LTVs, geographical composition and delinquencies of the mortgages in the reference pool. We also collect the supplementary data made public by the GSEs showing the share of the principal balance of the CRT deals that was potentially affected by the hurricanes. Then, from Bloomberg, we gather data of all CRT issuances. We record issuance dates, the seniority of the tranches, the principal balance per tranche, and the floater spread paid by each tranche. Our sample contains 163 CRT securities. Table 1 summarizes the main characteristics of the CRTs. Table 2 presents summary statistics of the key variables for the junior CRT tranches, and Table A1 in the online appendix for the mezzanine tranches.

We also collect the complete history of yields in the secondary CRT market from Refinitiv Eikon, which we merge with the CRT characteristics. We collect the daily transaction volume of CRTs in

TABLE 1 Summary statistics: CRT securities in the sample.

		Number of securities		
		Fannie Mae	**Freddie Mac**	**All**
Tranches	Junior	15	23	38
	Mezzanine	54	71	125
Loan-to-value (LTV) ratio	60.01–80%	42	49	91
	80.01–97%	27	45	72
Issuance year	2013	2	4	6
	2014	9	17	26
	2015	8	26	34
	2016	29	31	60
	2017	21	16	37
Total		**69**	**94**	**163**

Note: The Credit Risk Transfer (CRT) securities in our sample are all the Fannie Mae's and Freddie Mac's CRT securities traded in the secondary market. These CRTs were issued from July 23, 2013 to August 15, 2017.

TABLE 2 Summary statistics: Junior tranches.

	Obs.	Mean	SD	Min	Max
Spread daily (pp)	1575	7.064	1.710	4.521	13.008
Geographical exposure (%)	1575	5.510	2.816	1.840	9.600
Trading volume ($ million)	1575	0.598	2.620	0	36.500
Hurricane dummy	1575	0.357	0.479	0	1
Ten-year treasury rate (%)	1575	2.203	0.066	2.050	2.330
Two-year treasury rate (%)	1575	1.359	0.054	1.270	1.470

Note: The table presents summary statistics of the key variables in the diff-in-diff specification for junior tranches of Credit Risk Transfers (CRTs). The daily spread is the yield to maturity minus the one-month US Dollar Libor. The hurricane dummy takes the value of one from the first trading date after the first landfall in the US coast of Hurricane Irma on September 11, 2017 onward, and zero otherwise. Geographical exposure is the exposure to the areas affected by Harvey and Irma. The exposure is estimated by Fannie Mae and Freddie Mac as the percentage of unpaid principal balance in the reference pools of mortgages in the counties affected by the hurricanes. The statistics are calculated for the window of 30 days before and 30 days after Hurricane Harvey.

the secondary market from TRACE. We use the one-month US Dollar Libor rates from Refinitiv Eikon to calculate the spread over Libor. We use these panel data of daily CRT spreads for the diff-in-diff estimations, over different time windows around the dates of the hurricanes.

For the logistic regressions and model simulations, we use extra data sources that we discuss in those sections.

5 | EMPIRICAL ANALYSIS

On August 26, 2017, Hurricane Harvey made landfall on the US coast. Harvey was followed by Hurricane Irma, making a landfall on the US coast on September 10, 2017. Harvey hit mostly Houston, while Irma hit the southern part of Florida. Harvey and Irma were large and unexpected shocks to local mortgage markets.

Hurricanes Harvey and Irma were substantially impactful for the areas of the underlying mortgages. The two hurricanes combined affected up to 10% of loans in some mortgage pools. Thus,

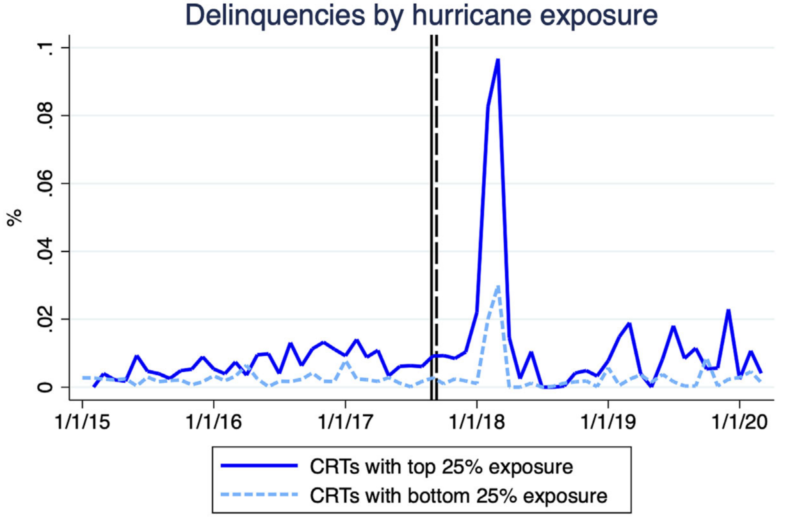

FIGURE 2 Monthly delinquencies in pools of mortgages for Credit Risk Transfers (CRTs) with different geographical exposure to Harvey and Irma. The figure plots the average share of the current unpaid principal balance delinquent for more than 120 days for CRT mortgage pools that had the highest and lowest geographical exposures to the hurricane-hit areas. Geographical exposure is the share of unpaid principal balance in the mortgage pools located in one of the counties listed by Federal Emergency Management Agency (FEMA) as a major disaster area and in which FEMA has authorized individual assistance following Hurricanes Harvey or Irma. The solid vertical line indicates August 28, 2017, which is the first trading day after Hurricane Harvey's landfall in Texas. The dashed vertical line is September 11, 2017, which is the first trading day after Hurricane Irma's landfall in Florida. [Color figure can be viewed at wileyonlinelibrary.com]

although the hurricanes were local events and the mortgage pools were geographically diversified, these hurricanes affected a large enough part of the mortgage pool to upset investors. The losses are allocated first to the junior tranches and this magnifies their exposure. For example, 0.5% default in the mortgage pool, translates to 50% ($\frac{0.5\%}{1\%}$) default in a junior tranche that is allocated 1% of the principal balance.

5.1 | Identification strategy

Our identification strategy exploits differences in the CRT securities that create heterogeneous exposure to default risk induced by the hurricanes.

Geographical exposure. CRT mortgage pools are geographically diversified since they are backed by mortgages from all US states. However, we find that the hurricanes created heterogeneity in expected CRT losses, based on the geographical composition of the mortgage pools. Days after the landfalls, investors had information about the geographical concentration of their holdings in hurricane-affected areas. Specifically, the GSEs made public the share of unpaid principal balance in the CRT mortgage pools located in the counties listed by FEMA as major disaster areas following Hurricanes Harvey or Irma. We use this share as the measure of geographical exposure to the hurricanes.

Fannie Mae's CRTs had between 1.8% and 2.6% balance affected by the two hurricanes, whereas Freddie Mac's CRTs had between 3.6% and 9.6%. In the econometric analysis, we use a continuous

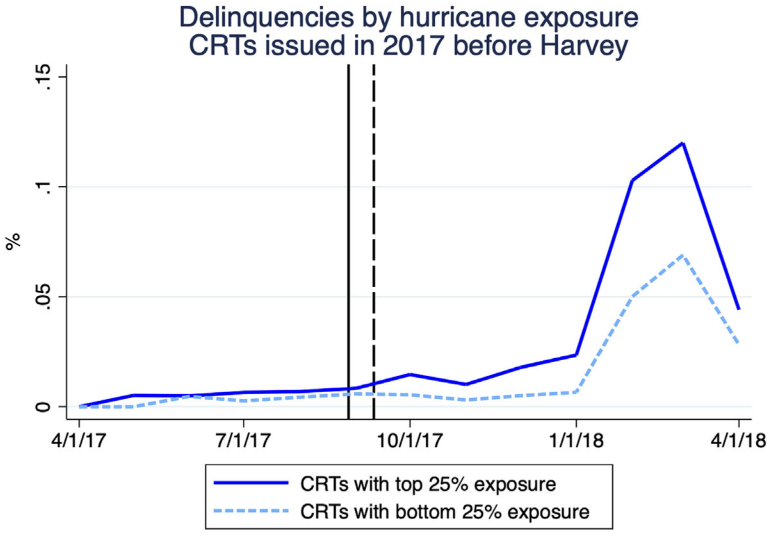

FIGURE 3 Monthly delinquencies in pools of mortgages for Credit Risk Transfers (CRTs) issued in 2017 with different geographical exposure to Harvey and Irma. The figure plots the average share of current unpaid principal balance delinquent for more than 120 days for CRT mortgage pools that had the highest and lowest geographical exposures to the hurricane-hit areas, for the CRTs issued between January and July 2017. Geographical exposure is the share of unpaid principal balance in the mortgage pools located in one of the counties listed by Federal Emergency Management Agency (FEMA) as a major disaster area and in which FEMA has authorized individual assistance following Hurricanes Harvey or Irma. The solid vertical line indicates August 28, 2017, which is the first trading day after Hurricane Harvey's landfall in Texas. The dashed vertical line is September 11, 2017, which is the first trading day after Hurricane Irma's landfall in Florida. [Color figure can be viewed at wileyonlinelibrary.com]

measure of geographical exposure, and use the full sample of CRTs, both from Fannie and Freddie. For illustration purposes, in some of the figures in this section, we focus on Freddie as Freddie's CRTs had more geographical heterogeneity in the hurricane affected areas. This allows for a better visualization of the article's mechanics. Moreover, by plotting only CRTs from Freddie, we plot groups that are homogeneous in other dimensions, except their exposure to hurricanes.[6]

Figure 2 plots the monthly 120-day delinquency rate for Freddie's CRT mortgage pools with the top 25% and bottom 25% hurricane exposure. The delinquency rates for the two groups were moving in parallel before the hurricanes made landfall at the US coast. Right after the hurricanes, those CRTs with a higher share of mortgages in the hurricane damaged areas (counties in Houston and Southern Florida) experienced substantially higher delinquencies.

Figure 3 focuses on Freddie's CRTs with the longest time to maturity, that is, the securities that were issued shortly before the hurricanes hit the US coast, between January and July 2017. The worst scenario for investors would be to suffer losses in newly issued CRTs, which made only few expected payments of principal and interest. By focusing on these CRTs, we make the two groups shown in the figure to be homogeneous, as they have similar time to maturity. Like in the previous figure, we see a surge in mortgage delinquencies after the landfall of Hurricanes Harvey and Irma. Before the landfall, the two groups, with high and low geographical exposure to the hurricane-

[6] For example, Fannie and Freddie use different tranching, which affects the prices of each tranche.

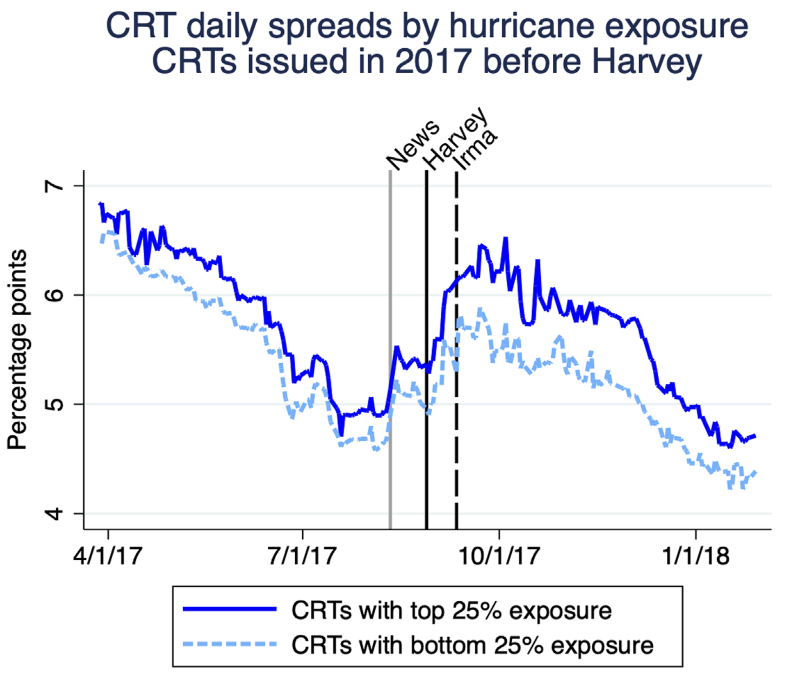

FIGURE 4 Spreads for Credit Risk Transfers (CRTs) issued in 2017 by hurricane exposure. The figure plots the average daily spread (yield to maturity minus one-month US Dollar Libor) in the secondary market of Freddie Mac's junior CRT tranches, issued between January and July 2017, with mortgage pools that have the top 25% and the bottom 25% geographical exposure to the hurricanes. The first solid vertical line indicates August 15, 2017, when the first warnings about Harvey came out. The second solid vertical line indicates August 28, 2017, which is the trading day after Harvey's landfall, and the dashed vertical line is September 11, 2017, which is the first trading day after Irma's landfall. [Color figure can be viewed at wileyonlinelibrary.com]

hit areas, had similar dynamics of delinquencies. After the landfalls, the securities with a higher share of mortgages in the hurricane-damaged areas have a higher surge in delinquency rates.

Figure 4 continues to focus on the groups shown in Figure 3, that is, CRTs that were issued shortly before the hurricanes' landfalls. This figure shows that the parallel trends assumption for the diff-in-diff identification is satisfied. The spreads of the two CRT groups, with low and high geographical exposure to the hurricanes, show similar dynamics before the first landfall. The spreads have been decreasing since the beginning of 2017. This can be explained by various factors: investors getting more familiar with the CRT market, a sound housing market, and strong demand for credit. The hurricanes disrupted this decreasing trend, as there was a sudden jump in spreads of about 1 pp at the moment the hurricanes hit the US coast. Spreads of CRTs that were more geographically exposed to the hurricanes reacted more than those of less exposed CRTs. The investors are very exposed to credit risk when holding these recently issued CRTs. This figure shows an announcement effect as spreads react to the first news of Hurricane Harvey and even more after the landfalls. The recently issued CRTs took about 3 months to recover their pre-hurricane levels.

Figure 5 plots the spreads by high and low exposure for the full sample of CRTs, from Fannie and Freddie, consistent with the regression analysis.[7] Clearly, the spreads move in parallel from the

[7] Figure A3 in the online appendix shows how the average spreads from Freddie's junior CRTs compare with Fannie's junior CRTs.

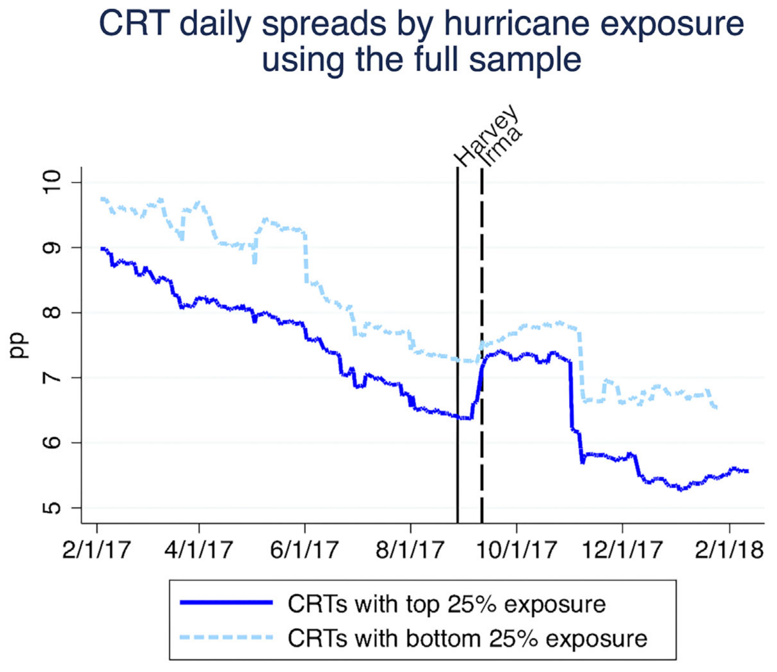

FIGURE 5 Spreads for Credit Risk Transfers (CRTs) by hurricane exposure. The figure plots the average daily spread (yield to maturity minus one-month US Dollar Libor) in the secondary market of Fannie Mae's and Freddie Mac's junior CRT tranches, with mortgage pools that have the top 25% and the bottom 25% geographical exposure to the hurricanes. The bottom 25% exposure ranges between 1.8% and 2.6% of the mortgage pool, which only includes Fannie Mae's CRTs. The top 25% exposure ranges between 8.6% and 9.6% of the mortgage pool, which only includes Freddie Mac's CRTs. The first solid vertical line indicates August 15, 2017, when the first warnings about Harvey came out. The second solid vertical line indicates August 28, 2017, which is the trading day after Harvey's landfall, and the dashed vertical line is September 11, 2017, which is the first trading day after Irma's landfall. [Color figure can be viewed at wileyonlinelibrary.com]

inception of the CRTs until the summer of 2017. There is a constant spread between the pools prior to the hurricanes due to differences in risk across locations that we control for with fixed effects. Then, following the landfalls of Harvey and Irma, there is a sudden surge in the spreads. The surge is larger for those CRTs that had the top exposure to the hurricane-affected areas. On average, there does not seem to be an anticipation effect, as the spreads did not react to the news about the hurricanes. Moreover, the recovery of the spreads on average was more abrupt compared to the spreads of the CRTs issued in 2017. The spreads remained high from September 2017 for about 2 months, and then dropped substantially in November 2017. At that time, there were several news from the GSEs and FEMA on disaster relief and this explains the drop in spreads.

Tranche seniority. Another source of heterogeneous exposure to credit risk is tranching because losses are allocated inversely to the seniority of the tranche. Figure 6 shows that investors in junior tranches reacted immediately when Hurricane Harvey made landfall and asked for higher compensation for taking the credit risk. The spreads stayed high after the landfall of Hurricane Irma. It took about 2 months for spreads to revert back to the pre-hurricane levels. Although the junior tranches showed an average increase in spreads close to 1 pp, the mezzanine tranches showed an increase in spreads of 0.2 pp on average. Junior tranches are the riskiest ones and therefore the more sensitive to changes in expectations and new information. Thus, they have more drastic movements.

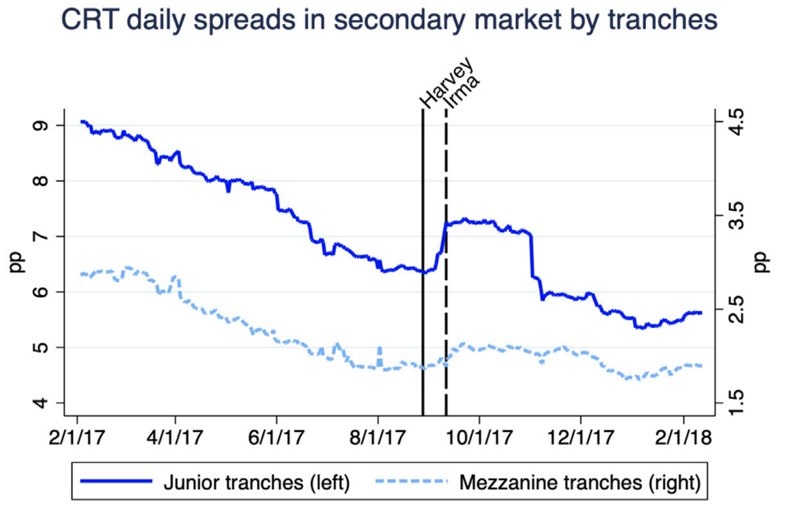

FIGURE 6 Spreads for Credit Risk Transfers (CRTs) by tranches. The figure plots the average daily spread (yield to maturity minus one-month US Dollar Libor) in the secondary market of the junior and mezzanine tranches of Freddie Mac's CRTs, issued between July 2013 and July 2017. The solid vertical line indicates August 28, 2017, which is the trading day after Harvey's landfall, and the dashed vertical line is September 11, 2017, which is the first trading day after Irma's landfall. [Color figure can be viewed at wileyonlinelibrary.com]

Moreover, the junior tranches are the ones that absorb first the losses from default, whereas the mezzanine tranches absorb first the losses due to prepayments. This creates the different dynamics we observe in Figure 6. The reaction of junior CRT spreads to expectations of default was a sudden, large increase in spreads. The reaction of mezzanine CRT spreads to risk of prepayments was more gradual and lasted longer than the junior spread reaction.

Loan-to-value. In addition to the geographical composition of their reference pool, and the different tranche seniority, CRTs are heterogeneous in the LTV ratio of the mortgages in the pool. Figure A1 shows that, following the hurricanes, CRTs whose underlying pools had higher LTV ratios (80.01–97%) suffered higher delinquencies than CRTs whose pools had low LTV ratios (60.01–80%).

Figure A2 plots the spreads of the junior CRTs, by the two groups of high and low LTV. The trends were parallel before the news about Hurricane Harvey. As expected, the high-LTV CRTs had on average higher spreads, due to higher credit risk. At the time of the first news about Hurricane Harvey, there was a sharp increase in the spread of both groups, with the high LTV group increasing the most. Markets priced higher credit risk initially. However, about a month after the hurricanes, the high LTV spreads dropped to the levels of the low LTV spreads. The reason for that is the private mortgage insurance that all mortgages with LTV above 80% have to be guaranteed by the GSEs. Hence, although there was an initial reaction to the default risk right after the hurricanes that was stronger for the high LTV securities, this risk was mitigated by private insurance and the CRT market narrowed the spreads between high and low LTVs.

5.2 | Specification

We do a difference-in-difference analysis with panel data of daily CRT spreads. The treatment is the first trading date after the landfall of Hurricane Irma on September 11, 2017. This specification aims to capture the combined effects of the two hurricanes, since Irma hit the United States 2 weeks after Harvey. The treatment group comprises those CRTs with high geographical exposure to the hurricane-affected areas. The control group are those CRTs with low geographical exposure. We perform the analyses separately for junior and mezzanine tranches. Thus, we study different dimensions (geographical exposure and tranche seniority) that generate heterogeneity in CRT exposure to credit risk.[8]

Our identification assumption is that, prior to the 2017 hurricanes, the geographical exposure of the CRT mortgage pools to counties in major disaster areas was not correlated with the perceived credit risk of the CRT notes. The parallel trends discussed in Section 5.1 validate the assumption. We estimate:

$$S_{i,t} = \beta_0 + \beta_1 H_t E_i + C_i + D_t + V_{i,t} + u_{i,t}, \tag{1}$$

where i indexes securities and t denotes days. $S_{i,t}$ is the spread of CRT i on day t calculated as the yield to maturity minus the one-month US Dollar Libor. H_t is the treatment variable that takes the value of one for t on and after the first trading date after Irma's landfall, and zero otherwise. The treatment captures the effect of both Harvey and Irma, after both hurricanes made landfall in the United States. E_i is the percentage of CRT unpaid principal balance geographically exposed to Harvey and Irma combined. Thus, our exposure variable is continuous. C_i are the CRT security fixed effects and D_t are the day fixed effects. $V_{i,t}$ is the trading volume of security i on day t that allows us to control for liquidity. We estimate the model for time windows of 15–45 days before and after the treatment date. In our estimation, we cluster the standard errors by CRT security (Abadie et al., 2023; Bertrand et al., 2004).

5.3 | Results

Table 3 presents the estimates of specification (1) for the junior tranches. The geographical exposure to hurricanes after the landfall has a significant positive effect on the spreads in all time windows from 15 to 45 days. One more percentage point of exposure increases the spread after landfall by 0.064 pp in the 25-day window. In our sample, the CRT with the most exposed mortgage pool had an increase in spread of 0.50 pp higher than the least exposed CRT in the same window ($0.064 \times (9.6\% - 1.84\%)$). The level effects of the landfall and the geographical exposure are absorbed by the CRT fixed effects.

Table A2 shows the results for a specification without the time fixed effects. Instead, this specification includes the following time-series controls: the 10-year treasury rates (the initial time to maturity of the CRTs), and the 2-year treasury rates to control for other short-term factors. In addition, it controls for the time interval between the first trading day after Harvey's landfall until the day before Irma's landfall. These controls isolate the effect of the timing of the hurricanes from other potential influences happening at the same time.[9]

[8] Our results are not driven by salience like in Dessaint and Matray (2017) because all CRTs are exposed to areas that may potentially be hit by hurricanes. Thus, higher sensitivity to hurricanes is a level shock affecting all CRTs. Here, we measure the reaction to the Harvey and Irma shocks. That is, expectations of higher defaults in the areas hit by those two hurricanes.

[9] We also estimated dynamic treatment effects using an event study design, and the results are consistent with what we discuss in this section.

TABLE 3 Spreads after hurricanes by geographical exposure: Junior tranches.

Window (days)	±15	±20	±25	±30	±35	±40	±45
	Spread						
Hurricane × exposure	0.066***	0.067***	0.064***	0.059***	0.050***	0.046***	0.043**
	(0.011)	(0.012)	(0.013)	(0.013)	(0.015)	(0.016)	(0.017)
CRT fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	812	1067	1356	1575	1870	2124	2378
R^2	0.992	0.992	0.990	0.988	0.985	0.983	0.982
Within R^2	0.214	0.252	0.220	0.166	0.108	0.078	0.067

Note: Standard errors clustered by Credit Risk Transfer (CRT) security are in parentheses. The spread is measured in percentage points. Hurricane is the treatment variable that takes the value of one from the first trading date after Hurricane Irma's landfall in the US coast, and zero otherwise. It captures the combined effect of both hurricanes. Exposure is the geographical exposure to the areas affected by Harvey and Irma. Controls are CRT security fixed effects, time fixed effects, and trading volume. The window shows the number of days before and after Hurricane Harvey. $^{***}p < 0.01$; $^{**}p < 0.05$.

The results in Table A2 show that the interaction effect of the geographical exposure and the post-hurricane period is similar to the previous results. The highest exposure CRT has a total increase in spreads of 0.90 pp in the 25-day window.[10] To put this into perspective, the increase in spreads is 13.1% of the initial spread level of 6.85% of junior CRTs 25 days before Hurricane Harvey.

Table A3 shows the results from the diff-in-diff analysis of the mezzanine tranches. The magnitudes of the effects are smaller than for the junior tranches. Spreads of the mezzanine tranches increase by 0.116 pp on average due to the hurricanes in the 25-day window, while the variation in geographical exposure does not significantly affect the spreads. To put this result into perspective, the increase in spreads is 5.9% of the initial spread level of 1.96% during the 25-day period before Hurricane Harvey for mezzanine CRTs.

Overall, the results show that markets increase the pricing of credit risk during a period of market stress. This increase is statistically and economically significant, and it depends on the level of risk of the CRT securities.

The previous results are robust to concerns about liquidity risk since we are controlling for it. Moreover, the overall transaction volume (Figure A4) shows higher trading volume during the months of the hurricanes, July and August 2017. That is, not only was there no sign of illiquidity at the time of the hurricanes, but in fact, trading volume increased.

Another concern might be that the risk premia of junior CRTs increase not because of higher default risk but because of higher prepayment risk. For example, as insurance contracts pay out for damaged homes in the areas affected by a hurricane, households might use the insurance payment to prepay their mortgages. If the junior CRT market was pricing prepayment risk, we would expect the risk premium to increase over time, as insurance pays out, like we observe for the mezzanine tranches (prepayments are absorbed by the most senior tranche first). However, we observe the opposite trend in the spreads of junior tranches: a sharp increase in the risk premium post-hurricanes and then a gradual decrease, consistent with the observed pattern of delinquencies. This pattern shows that the increased spreads are due to increased credit risk and not due to increased prepayment risk.

[10] 0.064 (from Table A2) × 9.60 (from Table 2) + 0.286 (from Table A2) = 0.90 pp.

Finally, the results are robust to nonsymmetric intervals and different controls. Table A4 shows that the results are robust to estimating a triple interaction with a dummy variable for the high-LTV CRTs. The LTV does not change the spreads significantly as private mortgage insurance for the high LTVs mitigates the losses from credit risk, like we explained earlier. Also, the results do not change when we remove from the sample the days between the two landfalls, or when we set the treatment date 5–10 days earlier to capture announcement effects.

5.4 | Interpretation of results

It is important to highlight that CRT investors were stressed over the period we study. Ultimately, the hurricanes did not cause a major ex post surge in defaults as the Federal Government and the GSEs granted extraordinary mortgage and foreclosure relief options to the hurricane-affected counties (see, e.g., Bakel, 2017). As a result, finally, most of the increase in delinquencies we show in the article did not translate into foreclosures.

CRT investors had reasons to be stressed. CRT investors were facing the first credit shock since the creation of the market. Delinquencies were up and they did not know how much relief the government would provide to prevent their losses. In fact, in October 2017, as the impact of the hurricanes was assessed, the Association of Mortgage Investors sent a letter to the GSEs and the FHFA asking to remove natural catastrophe risk from CRTs (Yoon, 2017). Thus, investors made expectations about a new negative shock in a context of high uncertainty and with rising delinquencies hinting at future losses. This evidence shows rational behavior in the investors, and we can use the episode to calibrate a pricing model.

6 | HURRICANE RISK AND DEFAULTS ACROSS US COUNTIES

The previous section quantified the interest rate reaction to a shock to expectations of mortgage delinquencies. The second step is to quantify the expected mortgage delinquencies due to the hurricanes. To do so, first we collect data on the number of hurricanes and tropical storms in each US county each month. Then, we merge this data set with monthly performance and characteristics of mortgages in each county. The goal is to estimate the probability of mortgage delinquencies due to hurricane risk for each county. We then input the estimated probabilities into the model we study in the next section.

The hurricane data come from FEMA from 1999 to 2019. Figure 7 shows the average number of hurricanes and tropical storms that hit each county in our 21-year interval. These storms are especially frequent in Florida, Louisiana, and North Carolina, where storms hit with frequency 0.5 to 0.8 per year. The rest of the Atlantic coast has experienced a hurricane with frequency 0.2 to 0.5 per year. Adjacent counties experienced a hurricane with less than 0.2 frequency per year, while the rest of the US counties did not experience any hurricane.

The mortgage data come from Freddie Mac. Our sample contains 265,956 single-family mortgage loans originated from 1999 to 2019 (random sample of about 12,600 mortgages per origination year), covering all the United States. The loan performance is monthly and includes a code every month that indicates whether a loan has made the required payment or it is n-day delinquent (in increments of 30 days). The performance data set is complete without any gaps between months. Table 4 summarizes the characteristics and performance of the Freddie mortgages. In the sample, 0.72% of the loans per year become delinquent for 180 days or more, that is, they miss at least six

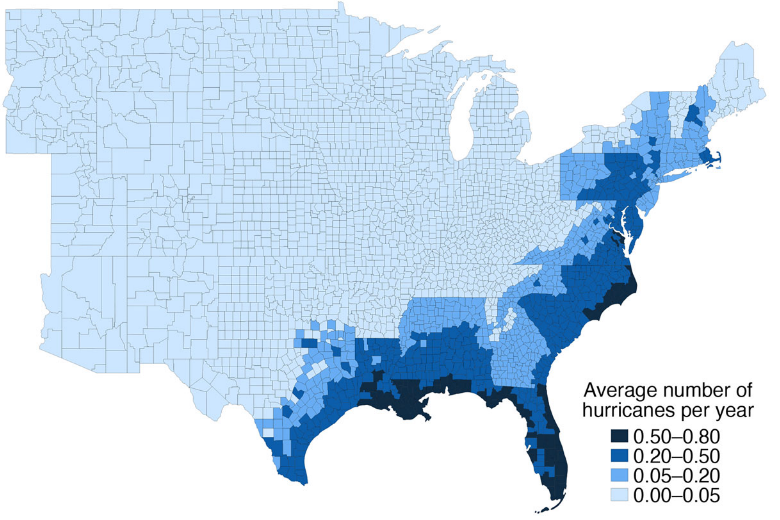

FIGURE 7 Occurrence of hurricane events in US counties. The map shows the average number of hurricanes or tropical cyclones declared by Federal Emergency Management Agency (FEMA) between 1999 and 2019. [Color figure can be viewed at wileyonlinelibrary.com]

TABLE 4 Summary statistics of Freddie Mac single-family loans.

	Mean	SD	Min	Max
Default	0.0072	0.085	0	1
Hurricane	0.067	0.250	0	1
Credit score	734.4	54.3	300	850
Debt-to-income ratio	33.3	11.6	1	65
Loan-to-value ratio	68.9	17.7	6	100
Primary residence	0.911	0.285	0	1
Secondary residence	0.028	0.164	0	1
Investment	0.062	0.241	0	1
Purchase	0.327	0.469	0	1
Cash-out refinance	0.335	0.472	0	1
No cash-out refinance	0.338	0.473	0	1
First-time buyer	0.096	0.294	0	1
One-unit	0.967	0.178	0	1
Two-unit	0.024	0.154	0	1
Three-unit	0.0044	0.066	0	1
Four-unit	0.0038	0.061	0	1
Single borrower	0.412	0.492	0	1

Note: Number of observations is 1,283,235. Number of loans is 265,956. This table shows the summary statistics of key variables used in the logistic regressions. The sample consists of Freddie Mac single-family mortgages originated between January 1999 and December 2019, covering geographically all the United States. Each observation is a mortgage-year.

consecutive monthly payments. The date of delinquency is the date of the required payment that brings the loan into 180 days delinquent. Once a loan becomes 180 days delinquent, we remove it from the database. We use 180+ day delinquency as our definition of default. This definition makes it possible to link defaults to the hurricanes because we know the exact timing and location of the hurricanes and the exact timing a borrower defaults in the same location. Later we discuss alternative definitions of default.

To be consistent with the annual frequency of the mortgage payments and the annual mortgage rate in our model in the next section, we aggregate delinquencies and hurricane occurrences to annual. Our goal is to link the occurrence of a hurricane in a given year to the mortgages missing six or more consecutive monthly payments in that given year or the subsequent years. In the interval between 1999 and 2019, the average hurricane occurrence was 0.067 per year. In case a county was hit by multiple hurricanes per year, the hurricane dummy still gets the value of one for that county-year. Regarding loan characteristics, the average credit score is 734, while the average LTV ratio is 68.9.

Based on the hurricane occurrence and an extensive list of mortgage characteristics and fixed effects, we estimate a logit model of the probability of mortgage default. We use panel data at the county-year level to estimate the following logistic regression:

$$\ln\left(\frac{P_{m,t+i}}{1-P_{m,t+i}}\right) = \beta_0 + \beta_1 H_{m,t} + L_m + Y_t + C + u_{m,t}, \tag{2}$$

where m indicates the mortgage loan and t the year. $P_{m,t+i}$ is the probability a mortgage m defaults in the year $t+i$, $i = 0, 1, 2, 3, 4$. $H_{m,t}$ indicates a hurricane or tropical cyclone that hit the location of the mortgage m in year t. L_m summarizes the controls for a comprehensive list of loan-level characteristics: credit score, debt-to-income ratio, LTV ratio, the occupancy purpose (primary residence, secondary residence, or investment), loan purpose (purchase, refinance with cash out, or refinance with no cash out), whether the borrower is a first-time buyer or not, whether the property consists of 1, 2, 3, or 4 units, whether there is one or multiple borrowers, and origination year fixed effects. Y_t summarizes year dummies, to control for any annual influences that might affect loan performance and hurricanes. C summarizes the county dummies to control for fixed influences due to the geographical location of the property. We adjust the standard errors for clustering by county (Abadie et al., 2023). Clustering by loan does not change the results.

Table 5 shows the result of the estimation of (2). The occurrence of a hurricane in a given year leads to a significant increase in defaults (180+ days delinquencies) in that same year ($i = 0$), and the 2 years that follow ($i = 1, 2$). From the third year onward after the hurricane, the given hurricane has no significant effect on defaults. The marginal effects show that the occurrence of a hurricane in a given year increases the probability of default by 0.09 pp the same year, 0.27 pp the year after, and 0.26 pp the following year, from the baseline probability of 0.7%. Overall, following a hurricane the probability of default per hurricane increases by 0.62 pp (ignoring the slight change in the loan sample each year). These results are in line with Rossi (2021). Table 6 repeats the analysis in Table 5 for loan performance up to the end of 2016. We use the results from Table 6 for the calcibration of our model in the next section.

As a robustness check, we created an alternative delinquency variable with a different definition of delinquency. In this new variable, a mortgage is considered delinquent if it missed payments for six consecutive months and it did not cure later. With this stricter definition of delinquency, the conclusions from the analysis remain the same.

TABLE 5 Logistic regression: Probability of default 1999–2019.

	Probability of missing six consecutive monthly payments $_{m,t+i}$				
Lead years (i) :	**0**	**1**	**2**	**3**	**4**
Hurricane $_{m,t}$	0.123**	0.281***	0.233***	0.045	0.077
	(0.049)	(0.045)	(0.047)	(0.063)	(0.059)
Loan characteristics	Yes	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	1,283,235	1,017,279	773,947	580,187	433,673
Marginal effect: Increase in probability of default					
Increase (pp)	0.088	0.269	0.263	not sig.	not sig.

Note: Standard errors clustered by county are in parentheses. This table shows the results of logistic regressions for the probability a mortgage loan defaults, that is, becomes delinquent for more than 180 days. The lead time is the number of years after the hurricane for which the probability is estimated. The variable Hurricane is a dummy that takes the value of one if one or more hurricanes hit a given county in a given year, and zero otherwise. The regression controls for county and year fixed effects. It also controls for the following loan characteristics: credit score, debt-to-income ratio, loan-to-value ratio, the occupancy purpose (primary residence, secondary residence or investment), loan purpose (purchase, refinance with cash out, or refinance with no cash out), whether the borrower is a first-time buyer or not, whether the property consists of 1, 2, 3, or 4 units, whether there is one or multiple borrowers, and origination year dummies. The sample consists of the annual performance of Freddie Mac single-family mortgages issued between January 1999 and December 2019, covering geographically all the United States. Summary statistics are in Table 4. The marginal effects show the increase in the regression model prediction of the 180-day delinquency probability, when the hurricane dummy changes from zero to one. $^{***}p < 0.01$; $^{**}p < 0.05$.

TABLE 6 Logistic regression: Probability of default 1999–2016.

	Probability of missing six consecutive monthly payments $_{m,t+i}$				
Lead years (i) :	**0**	**1**	**2**	**3**	**4**
Hurricane $_{m,t}$	0.190***	0.268***	0.248***	0.0784	0.108*
	(0.051)	(0.047)	(0.053)	(0.065)	(0.061)
Loan characteristics	Yes	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	1,027,298	812,384	607,471	448,416	329,494
Marginal effect: Increase in probability of default					
Increase (pp)	0.163	0.295	0.333	not sig.	not sig.

Note: Standard errors clustered by county are in parentheses. This table shows the results of logistic regressions for the probability a mortgage loan defaults, that is, becomes delinquent for more than 180 days. The lead time is the number of years after the hurricane for which the probability is estimated. The variable Hurricane is a dummy that takes the value of one if one or more hurricanes hit a given county in a given year, and zero otherwise. The regression controls for county and year fixed effects. It also controls for the following loan characteristics: credit score, debt-to-income ratio, loan-to-value ratio, the occupancy purpose (primary residence, secondary residence, or investment), loan purpose (purchase, refinance with cash out, or refinance with no cash out), whether the borrower is a first-time buyer or not, whether the property consists of 1, 2, 3, or 4 units, whether there is one or multiple borrowers, and origination year dummies. The sample consists of the annual performance of Freddie Mac single-family mortgages issued between January 1999 and December 2016, covering geographically all the United States. The marginal effects show the increase in the regression model prediction of the 180-day delinquency probability, when the hurricane dummy changes from zero to one. Total increase in probability of default $= 0.163 + 0.295 + 0.333 = 0.791$ pp. $^{***}p < 0.01$; $^{*}p < 0.10$.

7 | MARKET-IMPLIED MORTGAGE RATES

In the previous sections, we analyzed how markets price mortgage credit risk following major hurricanes, and how exposed is each county to hurricanes and defaults. We build on those estimates to calibrate a model that maps cross-sectional differences across counties in hurricane risk into mortgage rates. We refer to these rates as market-implied mortgage rates since the model is calibrated to replicate how the CRT market prices credit risk. Finally, we compute the difference between how the GSEs price credit risk and how markets would do it.

7.1 | Setup

We model mortgages as long-term, fixed-rate annuity loans, as in Campbell and Cocco (2003) and Garriga et al. (2017). Mortgage lenders are risk-neutral and compete loan by loan.[11] They originate mortgages at time $t = 0$, with a fixed term k. We denote by M_t the loan size, by r^m the mortgage rate and by x the fixed payment. Thus, the annuity formula implies

$$M_0 = \frac{x}{r^m}\left(1 - \frac{1}{(1+r^m)^k}\right). \tag{3}$$

Borrowers default each period with exogenous probability $0 \leq \pi_t \leq 1$. In case of default, the borrower makes no more payments and the lender recovers a fraction $0 \leq (1-\delta) \leq 1$ of the value of the house posted as collateral (PH). The parameter δ is the expected deadweight loss from default. We can write recursively the value at t of an outstanding mortgage right after a payment is been made as

$$V_t = \frac{1-\pi_t}{1+r^f}(x + V_{t+1}) + \frac{\pi_t}{1+r^f}\min\{(1-\delta)PH, (1+r^m)M_t\}, \tag{4}$$

where the first term on the right-hand side is the expected revenue if the borrower makes the next payment. That is the probability of repayment $(1-\pi_t)$, multiplied by the discounted value of next period payment (x) and the value of the mortgage the following period (V_{t+1}). We discount using the risk-free rate r^f. The second term is the discounted probability of borrower's default multiplied by the recovery value of the house $(1-\delta)PH$. Since the recovery value of the house might be larger than the remaining principal, the minimum operator ensures that borrowers in default do not overpay. In other words, in case of default the maximum received by the lender is the discounted value of the outstanding mortgage principal.

We assume that lenders need to cover every period a constant funding cost r^d (e.g., deposits or warehouse funding) and constant operating costs r^w (e.g., origination and servicing costs) that are proportional to the original loan. We denote the present value of such costs as

$$C_0 = \sum_{j=1}^{k} \frac{\left(r^d + r^w\right)M_0}{\left(1+r^f\right)^j}. \tag{5}$$

[11] The risk-neutrality assumption is relaxed because risk aversion will be captured in the calibration of the loan recovery parameter that we discuss below. These assumptions are standard in the macrofinance literature, see, for example, Garriga and Hedlund (2020).

Competition among lenders ensures that mortgage rates adjust so the expected revenue from lending covers the lender's costs. This is the expected zero profit condition:

$$V_0 = C_0. \tag{6}$$

The goal of the model is to solve endogenously for mortgage rates. We assume as exogenous the mortgage size, default probabilities, home values, and discount rates. Once we have mortgage rates, then we can define the market-implied guarantee fees (g-fees or r^g) as the excess of the mortgage rate over the cost of funds and operating cost of the lender. That is,

$$r^g = r^m - r^d - r^w. \tag{7}$$

In other words, the g-fee is the part of the mortgage rate that compensates for the credit risk. If there is no credit risk then the g-fee is zero and mortgage rates equal lenders' cost of funds and operations. Our definition assumes that the total g-fees are ongoing and there are no upfront g-fees.

The model ensures that, when there is zero probability of default ($\pi = 0$), the mortgage payment equals the funding annuity payment ($x = (r^d + r^w)M_0$), the mortgage rate equals the funding and operating costs ($r^m = r^d + r^w$), and the implied guarantee fee is zero ($r^g = 0$).

7.2 | Calibration

We split the model parameters into two groups: parameters that we calibrate exogenously, and parameters that we select such that the model targets the empirical estimates from Section 5. Table 7 summarizes the calibration.

We set $k = 10$ years as households often move or refinance their 30 year mortgages. In any case, our key results are robust to the maturity of the mortgage. Lenders' costs (r^d and r^w) are constant as these costs are likely not affected by the hurricanes. Keeping them constant allows us to isolate and focus on the cost of credit risk. We set the cost of funds $r^d = 2.21\%$ that is the 10-year US government bond yield in August 2017, the month of the first landfall. We also set the risk-free rate to be constant and $r^f = 2.21\%$. We set the LTV ratio to be 80%, which is the median ratio for agency mortgages originated in 2017.

We endogenously select the deadweight loss δ and the operating cost r^w to match the diff-in-diff analysis. First, we set the pre-hurricane mortgage rate to be $r^m = 3.93\%$, the average 30-year fixed mortgage rate in August 2017 (Freddie Mac, 2021b). Then we target this rate to increase by $\Delta r^m = 0.064$ pp when a mortgage is hit by a hurricane. This increase is estimated from equation (1) $\beta_1 = 0.064$ pp, that is, the average increase in the price of credit risk caused by the hurricanes for a 1 pp increase in exposure of the mortgage pool (Table 3). This is equivalent to the most junior tranche going from zero exposure to becoming fully exposed, that is, all mortgages in the tranche are hit by a hurricane. This increase shows how much additional compensation investors demand to take on the increased credit risk caused by their exposure to the hurricanes.

We select the level of default probability pre-hurricanes to be constant each period and equal to $\pi = 0.83\%$. This is consistent with the average defaults of fixed-rate agency mortgages originated between 1999 and 2016. Then, we target the change in the expected probability of default caused by the hurricanes to equal the mortgage default rates caused by previous hurricane landfalls. This is the kind of exercise investors perform to revise their cash flow projections for CRTs. To estimate the increase in the mortgage default probability, we replicate Table 5 using the mortgage perfor-

TABLE 7 Calibration strategy.

Parameter	Value	Description
Exogenous parameters		
k	10	Mortgage term in years
ltv	0.80	Loan-to-value ratio
r^d	2.21%	Lender's cost of funds: 10y government bond rate in 2017
r^f	2.21%	Risk-free rate: 10y government bond rate in 2017
π	0.83%	Default probability before landfall
r^m	3.93%	Mortgage rate before landfall
Endogenous parameters		
δ	86.50%	Deadweight loss
r^w	1.07%	Lender's operating cost
Targets		
$\Delta\pi$	0.79 pp	Default probability increase from hurricanes pre-2017 from Table 6
Δr^m	0.64 pp	Mortgage rate increase estimated in Table 3

Note: This table lists the parameters (exogenous and endogenous) and targets used in Section 7.1.

mance data up to 2016. The idea is to include data that were available at the time of the landfall in 2017, since these were arguably shaping the investors' expectations. Table 6 shows that defaults increase on average by 0.79 pp after a hurricane hits, thus we target $\Delta\pi = 0.79$ pp.

Figure A6 shows the amortization and recovery implied by the model. In the first 8 years from origination, the lenders incur losses greater than zero, while in the last 2 years, if the mortgage defaults, the recovery value of the collateral is sufficient to cover the outstanding loan amount. The endogenous parameter for deadweight losses is calibrated to a loss of 83.13% of the original loan amount. There are several reasons why this value is larger than the literature that finds losses given default of about 40% on average for outstanding loans (Higgins et al., 2022).[12] First, the original loan amounts are larger than outstanding loans. Thus, we need larger percentage losses to recover the same amount. Second, we assume zero depreciation. Thus, we need larger percentage losses to recover the same amount as in depreciated homes. Third, our calibration focuses on the riskiest investors, those exposed to junior tranches.[13] Fourth, it is a way to introduce risk aversion in the model as the deadweight loss parameter affects the mortgage spread over the risk-free rate and only bites when there is default risk. Thus, having risk-averse investors is very similar to having risk-neutral investors with a higher deadweight loss parameter.

7.3 | Market pricing of hurricane risk

In Section 6, we estimated the probability of mortgage default due to hurricane exposure for each US county. We input these probabilities into the calibrated model to compute the mortgage rates and g-fees that correspond to each county. Figure 8 and Table 8 contain the results.

[12] We define deadweight loss as a percentage of the original house price, instead of the outstanding loan amount like in Higgins et al. (2022).

[13] Investors in junior tranches of CRTs are much more exposed to defaults and losses compared to a single mortgage. Tranching increases significantly the probability of losses in the part of the mortgage pool allocated to the junior tranche, and thus the total deadweight losses.

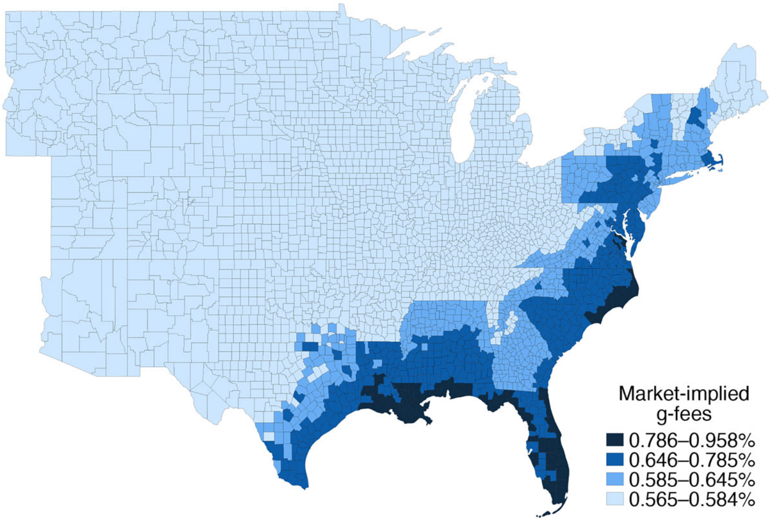

FIGURE 8 Market-implied guarantee fees. The map shows the county average market-implied g-fees computed as described in Section 7.1. [Color figure can be viewed at wileyonlinelibrary.com]

TABLE 8 Simulation results.

Hurricanes per year (frequency)	Default probability (%) π	Market-implied mortgage rate (%) r^m	Market-implied g-fee (%) r^g
0.0	0.718	3.845	0.565
0.2	0.818	3.925	0.645
0.5	0.993	4.065	0.785
0.8	1.207	4.238	0.958
1.0	1.373	4.373	1.093

Note: This table shows the results of the simulation using the model with the probability of defaults as inputs as described in Section 7.1 and the calibration from Table 7.

Table 8 shows model-implied mortgage rates for different hurricane frequencies. The baseline frequency is zero. Then, as we simulate the hurricane frequency of locations from the central United States to the Atlantic coast, the frequencies increase gradually and reach a maximum of 0.8. For the simulations, we also include a frequency of 1, that is, one hurricane or tropical storm per year. These frequencies correspond to default probabilities from 0.72% to 1.37%. The last two columns of Table 8 show how the market-based pricing would increase mortgage rates and g-fees in risky coastal locations. We find that market-implied mortgage rates range from 3.85% in the less risky counties to 4.37% in the simulated areas with a hurricane every year.

Figure 8 plots the market-implied g-fees for each county. Counties that are on the path of a tropical storm or hurricane every 2 years or more often (frequency 0.5–0.8) have market-implied g-fees between 0.79% and 0.96%. G-fees for most inland counties are 0.57%. That is, the market-implied g-fee of the most exposed counties is 39 basis points, or 70% higher than the g-fee of the counties not exposed to hurricanes.

To understand the economic magnitude of this effect, we look at the statutory g-fees that the GSEs charge for mortgages with heterogeneous risk characteristics. The statutory g-fees are the same across locations, although they differ based on borrower characteristics. For example, in our baseline year, 2017, the statutory g-fees for the lowest credit score band (< 660) was 28 basis points higher from the highest credit score band (≥720) (FHFA, 2018). Our model finds 11 basis points higher difference between the counties least exposed to hurricanes and the counties most exposed to hurricanes, compared to the difference between low and high credit score bands.

What are the implicit subsidies relative to the market-implied rate? The average statutory g-fee for 30-year fixed rate mortgages was 59 basis points in 2017 (FHFA, 2018). Hence, our results suggest that counties with zero hurricane risk are paying 4% (3 basis points) higher g-fees relative to the market-implied level. In contrast, counties with the highest hurricane risk are paying 38% (37 basis points) lower g-fees relative to the market-implied level.

The current policy is such that g-fees across counties do not show much heterogeneity. There is uniform g-fee policy across locations. According to Hurst et al. (2016), this increases welfare because it provides mortgage insurance across locations.[14] However, Figure 8 shows that with the current policies, inland locations subsidize the mortgages of risky coastal locations. Thus, the GSEs provide incentives for households in some locations to take on hurricane risk.

A key policy argument for keeping uniform pricing of g-fees is that most of the burden of higher mortgage rates will likely be borne by low-income households. To assess this argument, we explored whether economic factors in the areas that are frequently hit by hurricanes are different from the areas that have low hurricane risk. We find that the hurricane frequency is negatively correlated with the median individual salary and business income. It is also negatively correlated with house prices, especially for low-tier houses, and positively correlated with unemployment rate (see Table A7 in the online appendix). The evidence shows that the areas more exposed to hurricane risk (hence to increases in market based g-fees relative to statutory g-fees) are low income. Therefore, moving from the current system to a market-based one would have effects on inequality. Gete and Zecchetto (2018) analyze a similar topic in a paper studying the removal of the credit-risk guarantees by the GSEs.

In a hypothetical world without any home or mortgage insurance, our results would be stronger. Even with the presence of home and mortgage insurance, the hurricanes cause losses that are not fully covered (see Kousky, 2014, for a review of the economic costs of natural disasters). For example, the hurricanes cause labor income losses from missing days from work or destroyed businesses and working locations. In addition, there are many repair expenses not covered by insurance. For example, the experience from Hurricane Ian in 2022 shows that even for insured damages, insurance companies can make the repayment process grueling to avoid covering the costs. Oh et al. (2021) show that homeowners' insurance in risky areas does not provide households with sufficient financial protection from climate losses.

It can be argued that, since we are calibrating the model to match the estimates from Table 3, our exercise in Section 7.1 priced mortgages based on the short-run reaction of financial markets to hurricane risk (time windows from 15 to 45 days). That is, we focused on the period of maximum stress around the arrival of the hurricanes. If CRT investors were new to major hurricanes in 2017 and underestimated the amount of support that the government would provide, then our article provides upper-bound estimates as we study an episode of extreme market reaction. However, it is likely that investors may question how much government support the US government will provide in the future as government debt is high, FEMA is in a weak financial position, and major

[14] The current GSE policy is to offer forbearance in hurricane-hit areas and not to raise g-fees in response to geographical divergence in risks. Maintaining access to mortgages may stabilize markets and prevent an increase in foreclosures. See Bi et al. (2024) and Lacour-Little et al. (2024).

disasters happen more often. In addition, insurance companies are reducing coverage on natural disasters. Thus, it seems realistic to think that the CRT stress that we study can happen again.

7.4 | Robustness checks

To assess the robustness of the model, we use a different calibration strategy for the probabilities of default that the investors expected when Hurricanes Harvey and Irma hit the United States. In our previous calibration exercise, we used the average increase in the default probability after any hurricane or tropical storm hits the location of the mortgage. However, one could argue that Harvey and Irma were not typical hurricanes, thus the investors calibrated their expectations on the most destructive hurricanes in history.

For this robustness check, we use historical mortgage-level data from Freddie for the areas affected by Hurricane Katrina, which hit New Orleans and neighboring areas in 2005. Katrina ranked in the top five of the costliest storms on record, like Harvey and Irma. Moreover, Katrina affected areas with similar pre-hurricane default probabilities as the areas hit by Harvey and Irma. Our estimations coincide with industry analyses. We find that after Hurricane Katrina, the defaults increased by 1.21 pp in the following years for mortgages in the affected areas (see Figure A5). Thus, for this sensitivity test, we use a target $\Delta\pi = 1.21$ pp. Table A5 summarizes the calibration based on Hurricane Katrina.

Table A6 shows the results. Using hurricane Katrina to calibrate the target defaults yields lower market-implied g-fees, compared to the baseline simulation. These results set a lower bound for the market-implied g-fees. If the investors' pricing of credit risk was based on expected defaults of the magnitude of the most catastrophic hurricane, then more moderate default probabilities would cause smaller increases in the market-implied g-fees.

In this model, we have imposed partial equilibrium assumptions, such as no response by home buyers to the price of credit, in house prices, default rates, or mortgage size. In a general equilibrium setting, increasing mortgage rates may decrease house prices, which then may increase defaults generating amplification. Moreover, home buyers may opt for smaller mortgage sizes when credit becomes more expensive. In this scenario, the LTV ratio drops and very risky investors are priced out of the market. In equilibrium, the average mortgagor is less risky and default rates drop, especially in the climate-exposed areas that have the highest mortgage rates. However, the pricing out of risky households may increase inequality.

The model can be generalized to capture other sources of credit risk, for example, credit score or LTV ratio. However, these borrower and loan characteristics may interact with home and mortgage insurance, as we showed for LTV ratio and CRT spreads. In a related paper, Sastry (2022) shows that banks decrease LTV ratios in areas with heightened flood risk, which changes the composition of mortgages in risky areas with distributional consequences.

8 | CONCLUSIONS

In this article, we gather a new database of the market for CRTs and study the impact of Hurricanes Harvey and Irma. The CRT market trades mortgage credit risk and allows us to infer how investors price hurricane risk. We find significant results. For the riskiest CRTs, the hurricanes increased spreads by 13% of the average spreads before the landfall. Then, we infer market-based mortgage rates across US counties using a model calibrated to match the previous estimates. Our results show that the immediate market pricing, if incorporated into g-fees, would make the g-fees up to 70% more expensive in the counties most exposed to hurricanes, compared to inland counties. The inland counties subsidize mortgage rates of the risky coastal locations. By preventing markets from pricing mortgage credit risk heterogeneously across locations, the GSEs prevent the internalization of climate risks.

Our findings help to inform the debate about US housing finance reform. First, the CRT market remained liquid during two of the most catastrophic hurricanes. This suggests that mortgage private markets can absorb credit risk even under stress. Second, CRT markets provide information on the immediate perception and pricing of hurricane risk. Third, it may be worthy to make explicit what is the catastrophe risk that the government would take and when would such guarantee apply. Finally, housing reform is linked to inequality debates as areas more exposed to hurricane risk, and thus more exposed to higher rates in a market system, are usually low income.

Future work is required to address implications for broader policy issues. How much insurance should the GSEs require from areas more exposed to climate change? In the absence of such insurance, should the GSEs adjust the terms of mortgages to reflect heightened climate risk, as private markets would? The answer requires additional research. A full treatment of the distributional and efficiency effects goes beyond the scope of this article. Maintaining constant g-fees may stabilize markets and reduce foreclosures. Future research should explore the extent to which GSE policies could encourage adaptation measures and building innovations that could improve climate resilience.

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