Climate Risk and Mortgage Markets: Evidence from Hurricanes Harvey and Irma*

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Abstract

This paper quantifies the extent to which government-sponsored enterprises (GSEs) subsidize credit risk from natural disasters in U.S. mortgages. We study a unique, hand-collected database of the new mortgage Credit Risk Transfers (CRTs). First, we estimate diff-in-diff regressions that exploit heterogeneous geographical exposure of CRTs to Hurricanes Harvey and Irma, as well as heterogeneity in risk exposure across CRT tranches. The parallel trends identifying assumption is satisfied. Yields of CRTs with different exposure to the hurricanes' default risk move in parallel until shortly before the landfall of the hurricanes. We find significant increases in the yields, up to 9%, for those CRTs more exposed to hurricane credit risk. Second, we estimate logistic regressions to quantify hurricane-induced mortgage defaults in U.S. counties. Finally, we use a model of mortgage credit supply calibrated to match the diff-in-diff estimates. Using the logistic regression results as inputs to the model, we derive the market price of mortgage credit risk (the g-fees) for every U.S. county. We find that g-fees in counties most exposed to hurricanes would be 72% higher than in inland counties if they were priced by the market. The GSEs give g-fee subsidies that prevent internalizing climate risk.

Keywords: Climate Risk, CRT, Credit Risk, GSEs, Hurricanes, Mortgages.

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1 Introduction

How do mortgage markets price credit risk from natural disasters? What would the market price of mortgage rates be in locations with different exposure to climate risk? These questions are unexplored even though an increasingly large literature shows that climate risk is priced in housing markets.[1] The barrier for studying market-pricing of mortgages has been that the U.S. mortgage markets have had strong government intervention. For example, nearly half of the mortgage debt outstanding (\$5.7 trillion) is owned or guaranteed by Fannie Mae and Freddie Mac (agencies, Government Sponsored Enterprises or GSEs), which have been in conservatorship since 2008 (Lucas and McDonald 2010). Moreover, Ginnie Mae, a federal government corporation, guarantees about \$2.1 trillion mortgages.[2] Thus, most mortgage credit risk in the U.S. has been directly or indirectly priced by the government. In this paper we overcome that barrier, analyzing a hand-collected database of the new market of Credit Risk Transfers (CRTs), which was created in 2013.

Potential underpricing of mortgage credit risk provides incentives for lenders to originate risky mortgages as Elenev, Landvoigt and Van Nieuwerburgh (2016) theorize. GSE subsidies to mortgage rates may encourage households to live in areas exposed to climate risk. Moreover, mispricing entails potential fiscal costs for taxpayers. Such costs can be especially high in mortgage markets because securitization may create incentives for lenders to sell their riskiest loans (Willen 2014). In fact, Ouazad and Kahn (2019) show that lenders sell their mortgages with the worst climate risk to the GSEs.

The CRTs are structured securities that the GSEs issue to bring private capital to mortgage markets (Levitin and Wachter 2020).[3] The GSEs pay interest plus the invested principal to the buyers of the CRTs. However, both payments depend on the credit performance of an underlying pool of agency mortgages. 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.

We proceed in three steps. First, we do a difference-in-difference analysis to estimate the extent to which markets price mortgage credit risk. Our identification exploits the fact that different CRT securities have heterogeneous geographical exposure to a positive shock to default risk, caused by Hurricanes Harvey and Irma. The hurricanes were unforeseen events that

[1] See Giglio, Kelly and Stroebel (2021) for a survey.

[2] As of December 31, 2019. (FHFA 2020; Ginnie Mae 2020).

[3] 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, Strzodka and Vickery (2018), Lai and Van Order (2019) and Echeverry (2020) study different aspects of the CRT market.

suddenly generated large expectations of local mortgage defaults.[4] Second, we estimate the probability of mortgage default due to hurricanes with logistic regressions. Third, we analyze a model of credit supply calibrated to match our diff-in-diff estimates. 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 simulations use the inputs from the logistic regressions. Also, we use the model to estimate the implicit subsidy to credit risk that the GSEs provide. This subsidy is the difference between the market-implied cost of credit risk predicted by the model and the statutory guarantee fees (g-fees) that the GSEs charge.

Our unique database combines 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-level characteristics and credit performance data from Freddie Mac that we merge with data of hurricane occurrences from the Federal Emergency Management Agency (FEMA).

CRTs have heterogeneous exposure to the hurricanes because CRTs differ in the geographical composition of their reference pool. Moreover, different tranches of the same CRT deal have different exposure to the default risk of the underlying mortgage pool. This is the first paper to show and exploit these heterogeneities. For example, even though all CRTs are backed by pools of mortgages from all U.S. states, some CRTs had a higher share of mortgages in hurricane damaged areas and these mortgages suffered larger delinquency rates. Markets were able to price higher credit risk exposure as investors had all the information about the characteristics of the mortgages underlying the CRTs.

The parallel trends identifying assumption for the diff-in-diff analysis is satisfied. Yields of CRTs with different exposure to the hurricanes' default risk move in parallel until shortly before the landfall of the hurricanes. Then, we find significant increases in the yields (that is, decreases in prices) for those CRTs more exposed to the credit risk caused by Harvey and Irma. For the riskiest CRT tranches, the yield spread to Libor is 9% higher than average.[5] Yield spreads for the mezzanine tranches increase by 5% relative to the average spreads. These results are 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.

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

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

The results are not affected by the government intervention that prevented a surge in mortgage defaults once the hurricanes hit. Our identification is anchored on the fact that, when the hurricanes made landfall, markets expected large mortgage losses. A signal of these heightened loss expectations is that, a month after these hurricanes, the Association of Mortgage Investors asked the GSEs to remove natural catastrophe risk from the CRTs because they were afraid of large spikes in mortgage defaults (Yoon 2017).

In the second part of the paper we estimate logistic regressions for the probability of mortgage delinquencies and defaults due to hurricanes. That is, we quantify to what extent the frequency of hurricanes in U.S. counties affects default rates. For this exercise we use the timing of all Atlantic hurricanes reported in the U.S. between the years 1999 and 2019, and the monthly performance of 700,000 mortgages across the U.S. We find that the loans in counties that are most frequently hit by hurricanes, 0.8 times per year on average, have 0.9 percentage points higher probability of default, compared to the loans in counties not affected by hurricanes. This is a substantial increase of 40% higher probability of default.

In the last part of the paper we employ a model of mortgage credit supply. This model derives the price of mortgage credit risk given probabilities of default. We calibrate the model to match the estimates obtained from the CRT market. We use the results of our logistic regressions as inputs to derive the market price of mortgage credit risk for every U.S. county. In other words, our simulation studies differences in the exposure to hurricanes across U.S. counties. The market-implied guarantee fee (g-fee) is what the GSEs would charge to insure credit losses, if the risk was priced by the market. It is the part of the mortgage rate that compensates for credit risk. We find that market-implied g-fees in counties that are hit most frequently by a tropical storm or hurricane would be 72% higher than in counties far from the Atlantic coast.

The previous result implies that the mortgage g-fees currently charged are not enough to cover the potential credit risks in hurricane-exposed areas. Moreover, by preventing markets from pricing mortgage credit risk heterogeneously across U.S. counties, the GSEs reduce the internalization of the risk of natural disasters. In other words, existing mortgage rates in the U.S. do not reflect the climate risks that markets would price. This result brings a novel risk-dimension to Hurst et al. (2016), who show that lack of risk-based pricing provides insurance across locations. We show that lack of risk-based pricing may encourage climate risk-taking. Inland locations are subsidizing the mortgages of risky coastal locations.

This paper contributes to two main strands in the literature. The first focuses on the financial consequences of climate risk. Recent papers have shown the impact of natural disasters on mortgage markets (see for example, Morse 2011; Berg and Schrader 2012; Chavaz 2016; Cortés and Strahan 2017 and Ouazad and Kahn 2019). By exploiting geographical heterogeneity due to hurricanes, the literature has shown effects of hurricanes on bank stability (Schüwer, Lambert and Noth 2019), on Real Estate Investment Trusts trading (Rehse et al. 2019), on stock returns (Lanfear, Lioui and Siebert 2019), on housing prices (Ortega and Taspinar 2018), on managers perception of disaster risk (Dessaint and Matray 2017) and on household debt (Billings, Gallagher and Ricketts 2019). Deryugina (2017) show the fiscal cost and Deryugina, Kawano and Levitt (2018) show the economic effects on households of hurricanes that hit the U.S. The climate finance literature has shown that geographical exposure to climate risk is priced in municipal bonds (Goldsmith-Pinkham et al. 2021), house prices (Bernstein, Gustafson and Lewis 2019), corporate loans (Correa et al. 2021) and long-term interest rates (Giglio et al. 2021). Exposure to climate risk of wildfires causes more delinquencies and foreclosures (Issler et al. 2021). Oh, Sen and Tenekedjieva (2021) show that homeowners' insurance fails to accurately price climate risk. Our contribution is to implement the first study of the effects of default risk due to hurricanes on mortgage pricing.

This paper also contributes more broadly to the housing finance literature. Paper like Lucas and McDonald (2010), Jeske, Krueger and Mitman (2013), Frame, Wall and White (2013), Elenev, Landvoigt and Van Nieuwerburgh (2016), Hurst et al. (2016) and Gete and Zecchetto (2018) have analyzed different topics related to the role and future of the GSEs. Pavlov, Schwartz and Wachter (2020) 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. We contribute to this literature by estimating the GSE implicit subsidies to mortgage rates in areas exposed to hurricane risk.

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

2 Overview of Credit Risk Transfers

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).

2.1 CRT structure

The CRTs are notes with final maturity of 10 or 12.5 years. CRTs offer investors the rights to cashflows from a reference pool of mortgages that underlie recently securitized agency MBS. The principal balance of a CRT note is a percentage of the total outstanding principal balance of the reference pool. 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 U.S. 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 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 GSE's moral hazard in the selection of mortgages (Lai and Van Order 2019).

The CRT performance is directly linked to the risk of default of the underlying mortgages. The cashflows from the mortgages in the reference pool are used to repay the tranches according to the seniority pecking order. Once the outstanding principal balance of the most senior tranche is paid, 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. On the contrary, prepayments of the mortgages in the pool are absorbed by the most senior tranche first.

CRTs pay as interest one month U.S. 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).

3 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 2020; Freddie Mac 2020). 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 in total. Table 1 summarizes the main characteristics of the CRTs. Table 2 presents summary statistics of the key variables for the junior CRTs.

We also collect the complete history of yields in the secondary CRT market from Thomson Reuters Eikon, which we merge with the CRT characteristics. We collect the daily transaction volume of CRTs in the secondary market from TRACE. We use the 1-month US Dollar Libor rates from Thomson Reuters Eikon to calculate the spread over Libor. We use these panel data of daily CRT yields for the diff-in-diff estimations, over different time windows around the dates of the hurricanes.

For the model simulation we use extra data sources that we discuss in that section.

4 Empirical Analysis

On August 26, 2017 Hurricane Harvey made landfall on the U.S. coast. Harvey was followed by Hurricane Irma, making a landfall on the U.S. 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.[6]

Hurricanes Harvey and Irma were substantially impactful for the areas of the underlying mortgages. The two hurricanes combined affected up to 10% of the loans in the mortgage pools. Thus, 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. Moreover, the losses are allocated first to the junior tranches, which magnifies their exposure.

[6] Papers such as Cortés and Strahan (2017), Dessaint and Matray (2017), Schüwer, Lambert and Noth (2019) and Rehse et al. (2019) also use hurricanes as exogenous shocks.

For example, 0.5% default in the mortgage pool, translates to 5% ($\frac{0.5\%}{10\%}$) default in a junior tranche that is allocated 10% of the principal balance.

4.1 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 U.S. states. However, Figure 2 shows that those CRTs with a higher share of mortgages in the hurricane damaged areas (counties in Houston and Southern Florida) experienced substantially higher delinquencies. Thus the hurricanes created heterogeneity in expected CRT losses. Days after the landfalls investors had information about the geographical concentration of their holdings in hurricane-affected areas.

Figure 3 shows that the parallel trends assumption for the difference-in-difference 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 were decreasing since the beginning of 2017, and, in fact, since mid-2015. 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 one percentage point at the moment the hurricanes hit the U.S. coast. Spreads of CRTs that were more geographically exposed to the hurricanes reacted more than those of less exposed CRTs.

Tranche seniority Another source of heterogeneous exposure to credit risk is tranching because losses are allocated inversely to the seniority of the tranche. Figure 4 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 two months for spreads to revert back to the pre-hurricane levels. Although the junior tranches showed an average increase in spreads close to one percentage point, the mezzanine tranches showed an increase in spreads of 0.2 percentage points on average. 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 4. 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 of the mortgages in the pool. Figure 5 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 6 plots the spreads of the junior CRTs, by the two groups of high and low LTV. The trends were broadly 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 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.

Remaining term Finally, a fourth dimension of exposure to risk is the remaining life of the CRT. Investors are more exposed to credit risk when holding those CRTs with the largest time to maturity. Figure 7 plots the spreads of CRTs that were issued less than seven months before the hurricanes. The CRT spreads react to the first news of Hurricane Harvey and even more after the landfalls, that is, there is an announcement effect. The worst scenario for investors would be to suffer losses in newly issued CRTs which did not yet make the expected payments of principal and interest. The recently issued CRTs took about three months to recover their pre-hurricane levels.

Most of the increase in delinquencies we show above finally did not translate into defaults and foreclosures. The federal government and the GSEs granted extraordinary mortgage and foreclosure relief options to the households living in the hurricane affected counties (see for example, Bakel 2017; Freddie Mac 2017a; Freddie Mac 2017b). Thus, cumulative delinquencies peaked in April 2018 and then decreased. Many delinquent mortgagors resumed their payments after some months. Nevertheless, even if the hurricanes did not cause a major ex-post surge in defaults, ex-ante markets were stressed as we discussed in Figures 2 to 7.[7]

4.2 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 Hurricane Irma hit the U.S. two weeks after Hurricane 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 compare different dimensions (geographical exposure and tranche seniority) that generate heterogeneity in CRT exposure to credit risk.

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 4.1 validate the assumption. We estimate:

$$S_{i,t} = \beta_0 + \beta_1 T_t + \beta_2 E_i + \beta_3 T_t E_i + C_i + D_t + u_{i,t}, \tag{1}$$

where i indexes securities and t denotes days. $S_{i,t}$ is the spread of CRT i at time t calculated as the yield to maturity minus the one month U.S. Dollar Libor. T_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 U.S. E_i is the percentage of CRT unpaid principal balance geographically exposed to Hurricanes Harvey and Irma combined. Thus, our exposure variable is continuous.

C_i are the CRT security fixed effects. The time series controls D_t are the daily trading volume of the CRTs (this allows us to control for liquidity), the 10-year treasury rates (the initial time to maturity of the CRTs), and 2-year treasury rates to control for other short-term factors. Additionally, we control 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. We estimate the model for time windows of 20 to 40 days before and after the treatment date.

[7]The figures in this section plot the CRTs from Freddie Mac, as they all have higher geographical exposure to the hurricanes compared to the CRTs from Fannie Mae. Figure A1 in the Online Appendix shows how the average spreads from Freddie's junior CRTs compare with Fannie's junior CRTs.

In our estimation we cluster the standard errors by CRT security, to allow for serial correlation within each CRT (Bertrand, Duflo and Mullainathan 2004).

4.3 Results

Table 3 presents the estimates of specification (1) for the junior tranches. The landfall has a significant positive effect on the spreads in all time windows from 20 to 40 days. For example, the junior CRTs increase their spreads by 0.28 percentage points (pp) on average 25 days after the landfall, compared to 15 days before the landfall. In addition, the results show a positive and significant interaction between the landfall and the hurricane exposure. The more exposure to the hurricanes a CRT has, the more the spreads increase. One more percentage point of exposure increases the spread after landfall by 0.065 pp in the 25-day window. The level effect of the geographical exposure is absorbed by the CRT fixed effects. Overall, the spreads of the junior CRT tranche and average exposure to hurricanes increase on average by 0.637 percentage points (pp) in the 25-day window.[8]

Table 4 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 0.092 pp on average due to the hurricanes, while the variation in geographical exposure does not significantly affect the spreads.

Table 5 summarizes the key takeaways from the empirical exercise. The junior CRTs increase the spreads on average by 0.639 pp, while the mezzanine CRTs increase the spreads on average by 0.099 pp. To put these results into perspective, the increase in spreads is 9.38% of the initial spread level before the hurricanes for junior CRTs, and 5.02% of the initial spread level before the hurricanes 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 A2) 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

[8] $(0.065 \text{ (fromTable 3)} \times 5.460 \text{ (fromTable 2)}) + 0.282 \text{ (fromTable 3)} = 0.637\ pp.$

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. However, we observe the opposite trend, 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.

Finally, the results are robust to symmetric intervals and different controls. Tables A1, A2 and A3 show that the results are robust to including date fixed effects and estimating a triple interaction with high and low LTV. 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 5-12 days earlier to capture announcement effects.

5 Hurricane risk and defaults across U.S. counties

The previous section quantified the interest rate reaction to a shock to expected mortgage defaults. The second piece of the puzzle we need is to quantify the expected mortgage defaults due to the hurricanes. To do so, first we measure the number of hurricanes and tropical storms in each U.S. county each month. Then, we merge those data with monthly performance and characteristics of mortgages in each county. The goal is to estimate the probability of mortgage delinquency and default due to hurricane risk for each county. We will input the estimated probabilities into the credit supply model we study in the next section.

The hurricane data come from the Federal Emergency Management Agency (FEMA) from 1999 to 2019. Figure 8 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 probability 50% to 80% per year. The rest of the Atlantic coast has experienced a hurricane with probability 20% to 50% per year. Adjacent counties experienced a hurricane with less than 20% probability per year, while the rest of the U.S. counties did not experience any hurricane.

The mortgage data come from Freddie Mac. Our sample contains nearly 700,000 single-family mortgage loans originated from 1999 to 2019 (random sample of about 33,000 mortgages per origination year), covering all the U.S. Table 6 summarizes the characteristics and performance of the Freddie Mac mortgages. In the sample, 3.3% of the loans became delinquent for

180 days or more, that is, they missed at least six consecutive monthly payments, and 2.3% of the loans defaulted. In the interval between 1999 and 2019, the average hurricane frequency was 0.062 per year, while the maximum times a loan's county was hit by a hurricane was 3 times per year. The hurricane frequency depends not only on the county of the location of the loan, but also on the year and month of origination and the total term of the loan. Regarding loan characteristics, the average credit score is 736, while the average loan-to-value ratio is 70.3.

Based on the hurricane frequency and an extensive list of mortgage characteristics, we estimate a logit model of the probability of mortgage default. We use cross-sectional data at the county level to estimate the logit model. Later on, we do robustness checks by analyzing monthly panel data. We estimate the following logistic regression:

$$\ln(\frac{P_m}{1-P_m}) = \beta_0 + \beta_1 F_m + C_m + u_m, \tag{2}$$

where P_m is the probability a mortgage m defaults. We run alternative regressions in which P_m is the probability of delinquency of at least 90, 120, 150 or 180 days. F_m is the number of hurricanes or tropical storms per year that hit the location of the mortgage. C_m summarizes the controls for a comprehensive list of loan-level 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 fixed effects. We cluster the errors by county to allow for within-county correlations.

Table 7 shows the result of estimating (2). The marginal effects show that one more hurricane every year increases the probability of default from 2.29% to 3.34%. This is a substantial increase in default of 46%. One hurricane per year increases the probability of delinquency of at least 180 days from 3.12% to 5.52%, and the probability of delinquency of at least 90 days from 4.27% to 8.36%. These results are in line with Rossi (2021).

Alternative logit specification To show more evidence that the defaults are due to the hurricanes and not due to some unobservable features of the counties more exposed to the Atlantic hurricanes and the mortgages in those counties, we perform additional analyses using data at the monthly level. This analysis allows us to track the timing of the delinquency, that is, to show that the borrowers begin to miss payments right after a hurricane hits.

We take a 50% random sample of the previous mortgages, to make the number of observations more manageable. The panel data consists of loan characteristics and monthly performance from January 1999 to December 2019. There are about 13 million loan-month observations in our sample.

The 90-day delinquency dummy is defined as follows: A mortgage that is making regular payments each month gets a zero. The first time it misses a payment for 3 consecutive months, the dummy becomes 1. Then this loan's performance in the months that follow is removed from the sample that analyses 90-day delinquencies. That is, the loan survives up until the first month it becomes delinquent for 90 days.

We set up the logit model as follows:

$$\ln(\frac{P_{m,t+i}}{1-P_{m,t+i}}) = \beta_0 + \beta_1 F_{m,t} + C_m + M + R + u_m, \tag{3}$$

where m indicates the mortgage loan and t the year-month. $P_{m,t+i}$ is the probability a mortgage m becomes 90-days delinquent in the month $t+i$. $i = 1, 2, 3, etc.$ counts the months after t. We run alternative regressions in which $P_{m,t+i}$ is the probability of delinquency of 180 days, or $P_{m,t+i}$ is the probability of default. $F_{m,t}$ is the number of hurricanes or tropical storms that hit the location of the mortgage in year-month t. C_m is a list of loan-level characteristics controls, the same as in (2): 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 fixed effects. M summarizes month dummies, to control for any seasonal influences that might affect loan performance and hurricanes. R summarizes the county dummies to control for fixed influences due to the geographical location of the property. We cluster the errors by loan, to allow for serial correlation of errors within each loan.

Let's assume that a hurricane hits the loan location in August 2017. We would expect (with some probability) the borrower to miss her first payment in August or in September, depending on the particular dates of the hurricane and the mortgage payments. Then, the borrower might miss a second payment in September or October, and a third payment in October or November of 2017. In other words, the loan is likely to become 90-day delinquent (to miss 3 consecutive payments) 2 to 3 months after the month of the hurricane. This is exactly what we test with the logistic regression. The probability of 90-day delinquency in 2 to 3 months following a hurricane. We also expect not to find any effect of hurricanes on 90-day delinquencies in the first month after the hurricane or more than 3 months later.

Table 8 shows the result of estimating (3) for $P_{m,t+i}$ the probability of 90-days delinquency, and $i = 1, ..., 5$. The results confirm the expectations we just described. Significant 3 month delinquencies happen between the second and fourth month after the hurricane. As additional evidence, the hurricane events are not significantly related to delinquencies that happened in other months unrelated to hurricanes, for example in months $t + 1$ and $t + 5$.

Table 9 shows the results of a similar estimation for 180-days delinquency. Overall, the dynamics of delinquencies are consistent with the timing of the hurricanes.

6 Credit Supply Model

In the previous sections we analyzed how markets price mortgage credit risk following major hurricanes, and how exposed each county is to hurricanes and defaults. In this section we build on those estimates to compute mortgage rates implied by the CRT market and hurricane risk. We set up a model of credit supply that we calibrate to be consistent with the diff-in-diff estimations of the rates in the CRT market. Then, we study cross-sectional differences in the exposure to hurricane risk. We estimate mortgage rates for each county. 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 in areas with different exposure to hurricane risk.

6.1 Setup

We model mortgages as long-term loans, as in Campbell and Cocco (2003) and Garriga, Kydland and Šustek (2017). Regular payments are real, that is, we abstract from the inflation channels studied in the previous papers. Mortgage lenders are risk neutral and compete loan by loan.[9]

We denote by r_t^d the cost of funds for lenders (e.g. deposits or warehouse funding) at time t, and by r_t^w the operating costs (e.g. origination and servicing costs) per mortgage. Both costs are proportional to the mortgage size (M_t). We denote mortgage rates by r_t^m.

The outstanding loan amount M_t decays geometrically at rate $\lambda < 1$. The parameter λ proxies for the duration of the mortgage. That is, the mortgage amount outstanding in period

[9]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 macro-finance literature, see for example Garriga and Hedlund (2020).

t is a fraction λ of last period,

$$M_t = \lambda M_{t-1}. \tag{4}$$

For example, if $\lambda = 0$ then the mortgage is a one-period contract. The mortgage payment (x_t) that the borrower makes every period covers both the part of the principal that has to be repaid, $(1-\lambda)M_{t-1}$, plus the interest on the outstanding mortgage ($r_t^m M_{t-1}$). That is,

$$x_t = (1 - \lambda + r_t^m)M_{t-1}. \tag{5}$$

Borrowers default every period with exogenous probability $0 \leq \pi_t \leq 1$. In case of default the lender recovers a fraction $0 < \gamma_t < 1$ of the value of the house ($P_h H_t$) posted as collateral. The parameter γ_t is the recovery rate. Therefore, the value V_t of a long-term mortgage is the present discounted sum of the future expected revenue generated by the mortgage. That is,

$$V_t = (1-\pi_t)(x_t + \frac{1}{1+r_t^d}V_{t+1}) + \pi_t \min\left(\gamma_t P_h H_t, x_t + \frac{1}{1+r_t^d}V_{t+1}\right), \tag{6}$$

where the first term on the right-hand side is the expected revenue if the borrower pays the loan. That is, the probability of repayment $(1-\pi_t)$, multiplied by the payment (x_t) and the discounted value of the mortgage the following period $\left(\frac{1}{1+r_t^d}V_{t+1}\right)$. We use the deposit rate r_t^d as the discount rate. The second term is the probability of the borrower's default multiplied by the recovery value of the house. Since the recovery value of the house might be larger than the value of the mortgage, the minimum operator ensures that borrowers in default do not overpay. That is, in case of borrower's default the maximum received by the lender is the discounted value of the outstanding mortgage.

Competition among lenders ensures that mortgage rates adjust so the expected revenue from lending covers the lender's costs. That is,

$$V_t = (1 + r_t^d + r_t^w)M_{t-1} \tag{7}$$

Mortgage rates ensure that the future expected revenue generated by the mortgage covers the costs of funds for the lenders (deposit costs) plus operating costs.

Solving endogenously for mortgage rates is the goal of the model. That is why we refer to it as a model of credit supply. We will assume as exogenous the mortgage size, default probability, recovery fraction, home values and discount rates.

Once we have mortgage rates, then we can define the market implied guarantee fees (g-fees) (r_t^g) as the excess of the mortgage rate over the cost of funds and operating cost of the lender.

That is,

$$r_t^g = r_t^m - r_t^d - r_t^w. \tag{8}$$

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.

6.2 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 4. Table 10 summarizes the calibration.

We set as $t = 0$ the time of the shock of the hurricanes' landfall. We denote the pre-hurricane values with $t = -1$ and the post-hurricane values with $t = 0$. We assume that lenders' costs are constant, that is, $r_t^d = r^d$ and $r_t^w = r^w$. This is a reasonable assumption since likely these costs were not affected by the hurricanes. We set $r^d = 0.91\%$ that is the average five-year CD rate in July 2017, the month before the landfalls. We assume that per period operating costs (r^w) equal the prorated equivalent of the origination costs of a 30 year mortgage. Since these costs were 1.17% as of July 2017 we set $r^w = 0.074\%$. We set the mortgage amortization rate $\lambda = 0.95$ to match the amortization path of a 30-year fixed-rate, fixed-payment mortgage.

It is useful to divide both sides of (6) by V_t to eliminate loan values and work with the inverse of the loan-to-value ratio, which we assume to be constant, $\frac{P_h H_t}{V_t} \equiv l \;\; \forall t$. Then we set the loan-to-value ratio to be 80%, which is the median ratio for GSE guaranteed mortgages in 2017.

We select both the level of default probability pre-hurricanes (π_{-1}) and the change caused by the hurricanes ($\pi_0 - \pi_{-1}$) to be consistent with the experience of the junior tranches of CRTs with high LTV. We do as market participants and infer defaults from data on delinquencies since actual default data take months to be available. In the single-family loan dataset of Freddie Mac, 50% of the delinquent loans resume the payments at some point in time and 50% become owned by the lender or remain delinquent for more than 18 months. Guren and McQuade (2020) show similar patterns. Thus, we assume that the expected default rate is 50% of the delinquency rate. According to Figure 5 the average annual delinquency rate was 0.0356% before the hurricanes. Thus we assume that the expected default rate is 0.0178% (or 50% of 0.0356%) of the total mortgage pool. Junior tranches are on average 1% of the mortgage pool and absorb the credit losses in the mortgage pool until they are wiped out. Thus, we set the default rate on junior tranches of CRTs to be π_{-1} =1.78% ($\frac{0.0178\%}{1\%}$). According to Figure 5 the hurricanes caused delinquencies to increase annually by 0.0292 pp between July 2017 and July 2019, above the expected annual increase. Thus, following the same logic as before the equivalent increase in the default rate in the mortgage pool is 0.0146 pp and the corresponding increase for the junior tranches is 1.462 pp. That is, CRT investors of junior tranches with high LTV expect that the hurricanes would cause $\pi_0 - \pi_{-1} = 1.462$ pp increase in the default rate. We set the pre-hurricane mortgage rate to be $r^m_{-1} = 6.812\%$, the average spread of junior CRTs right before the first landfall (from Table 5).

So far we have described the parameters that we select exogenously. We select endogenously the recovery parameters. We follow the GSEs' methodology and assume a link between recovery and default probabilities. Freddie Mac (2015) uses a step-function that we approximate with

$$\gamma_t = 1 - a\pi_t^b. \tag{9}$$

Thus, $a > 0$ and $0 < b < 1$ are the parameters to calibrate. The exponent b is smaller than one to ensure a convex function.

Our first calibration target is the change in the market implied mortgage rate that we obtain from Table 5. The estimates show an average increase in the mortgage rate of $r^m_0 - r^m_{-1} = 0.639$ pp. This increase shows how much additional compensation investors demand to take on the increased credit risk.

As second target we ask that the slope of (9), that is

$$\frac{d\gamma_t}{d\pi_t} = -ab\pi_t^{b-1}, \tag{10}$$

before the hurricanes ($t = 0$) matches the slope reported in Freddie Mac (2015).

6.3 Market pricing of hurricane risk

The estimates of the logistic regressions quantify the probability of mortgage default due to hurricane exposure. Using our credit supply model, we derive the mortgage rates and g-fees that correspond to the hurricane exposure of each county. For this simulation exercise we start from the past hurricane frequency from Figure 8. The baseline frequency is zero. Then, as we move from the central U.S. to the Atlantic coast, the frequency increases gradually and reaches a maximum of 0.8. These frequencies correspond to default probabilities from 2.29% to 3.22%. Table 11 summarizes the results of the simulation exercise.

Figure 9 shows the market-implied g-fees for each county. Counties that are on the path of a tropical storm or hurricane every two years or more often (frequency 0.5-0.8) have market-implied g-fees between 0.73% and 0.88%. G-fees for most inland counties fluctuate between 0.51% and 0.53%. That is, the market-implied g-fee of the most exposed counties is 72% higher than the g-fee of the counties not exposed to hurricanes.

Effective g-fees across counties do not show much heterogeneity, as discussed by Hurst et al. (2016). Thus, Figure 9 shows that the GSEs, by applying a uniform g-fee policy across locations, push inland locations to subsidize the mortgages of some risky coastal locations. Hurst et al. (2016) emphasize that lack of risk-based pricing provides insurance across locations. That is a positive effect of a uniform g-fee policy across locations. However, our results show a negative consequence of such lack of market-based pricing. Individuals in areas exposed to hurricanes face subsidized mortgage borrowing costs that overexpose them to climate risk.

7 Conclusions

In this paper we analyzed how markets price mortgage credit risk. To do so we gathered a new database of the market for Credit Risk Transfers (CRTs) and studied the impact of Hurricanes Harvey and Irma. We exploited that CRTs are heterogeneous in their credit risk exposure to the hurricanes. We found that for the riskiest CRTs the hurricanes increased spreads by 9% of the average spreads before the landfall.

Then, we calibrated a model of credit supply to match the previous estimates. We used the model to infer mortgage rates across counties if these rates were purely priced by the markets without government intervention through the GSEs. Our results show that the GSEs are mispricing hurricane risk across geographical locations. Market pricing would make the g-fees up to 72% more expensive in the counties most exposed to hurricanes. Thus, the GSEs are preventing the internalization of climate risks.

A uniform g-fee policy across locations prevents discrimination across borrowers. However, a negative consequence of such lack of market-based pricing is that the inland counties subsidize the mortgage rates of the risky coastal locations. By preventing markets from pricing mortgage credit risk heterogeneously across U.S. counties, the GSEs reduce the internalization of the risk of natural disasters.

Our results inform the literature that studies credit risk in private markets, as well as the literature on the financial effects of climate risk. Also, our findings inform the debate of the U.S. housing finance reform. The GSEs and the taxpayers might continue to guarantee mortgage payments, or more risk might be transferred to private markets. In either case, our results suggest that reforms may want to allow more market pricing of risk across geographical locations.

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Figures

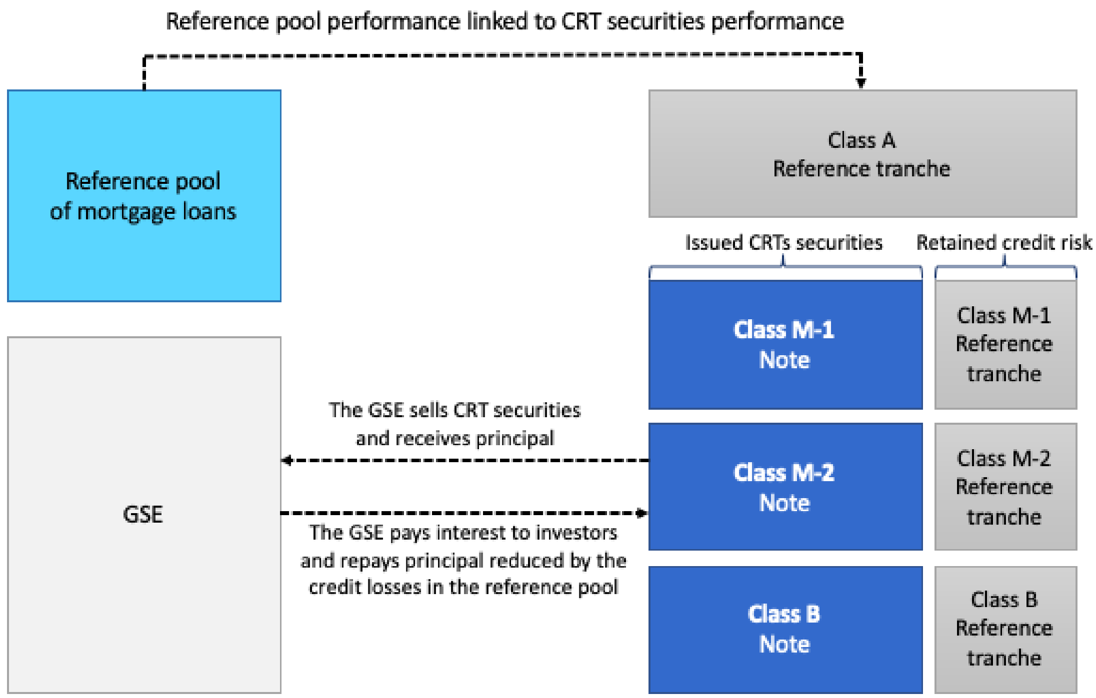

Figure 1. Example Credit Risk Transfer transaction. The figure shows an example of a CRT transaction linked to a reference pool of loans. Credit losses on the reference pool reduce the obligation of the GSE to pay interest and repay principal on the CRT securities. This example contains a junior tranche (Class B) and two mezzanine tranches (Class M-1 and M-2). The credit losses are allocated to tranches starting with the most subordinate tranche, while repayments are allocated starting from the most senior tranche. A vertical slice of each of the tranches is retained by the GSEs, while the remaining credit risk is sold to investors. The most senior tranche (Class A) is a reference tranche and is fully retained by the GSEs.

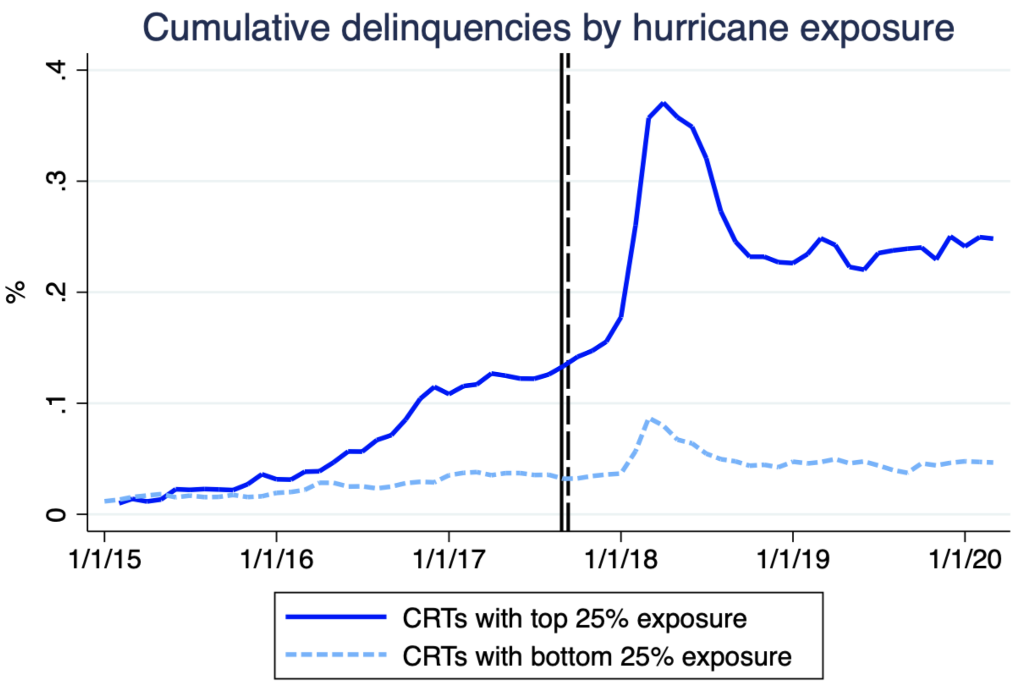

Figure 2. Cumulative delinquencies in pools of mortgages for CRTs with different geographical exposure to Harvey and Irma. The figure plots the average share of unpaid principal balance (delinquent for more than 120 days) for CRT mortgage pools that had the highest and lowest geographical exposures to 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 the Federal Emergency Management Agency ("FEMA") as a major disaster area and in which FEMA has authorized individual assistance to assist homeowners as a result of Hurricane Harvey or Hurricane 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 first landfall in Florida.

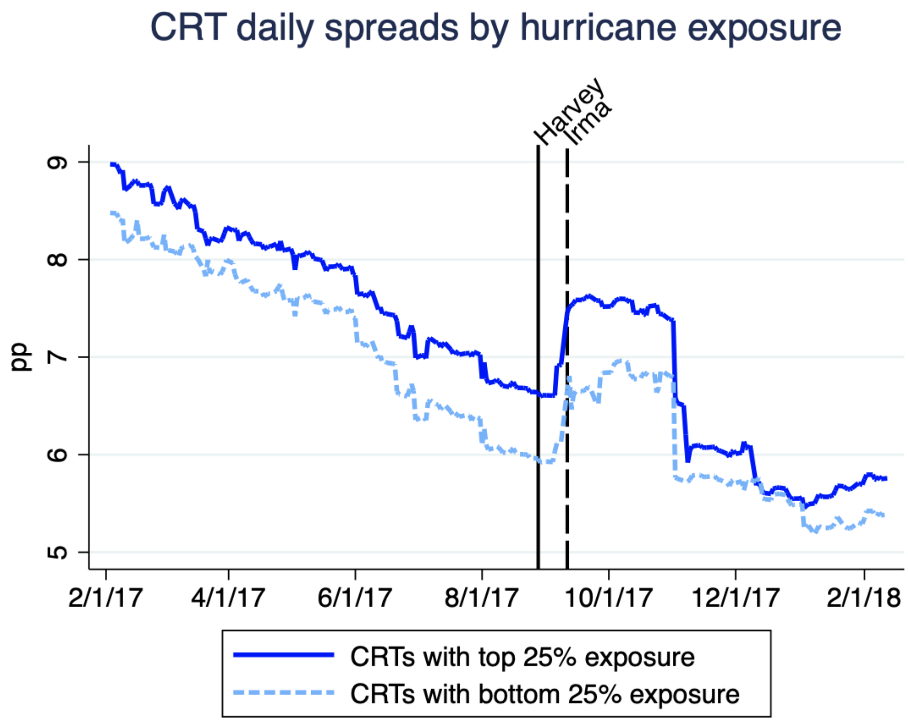

Figure 3. Spreads for CRTs by hurricane exposure. The figure plots the average daily spread (yield to maturity minus one month U.S. Dollar Libor) in the secondary market of Freddie Mac's junior CRT tranches, with mortgage pools that have the top 25% and the bottom 25% geographical exposure to the hurricanes. 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.

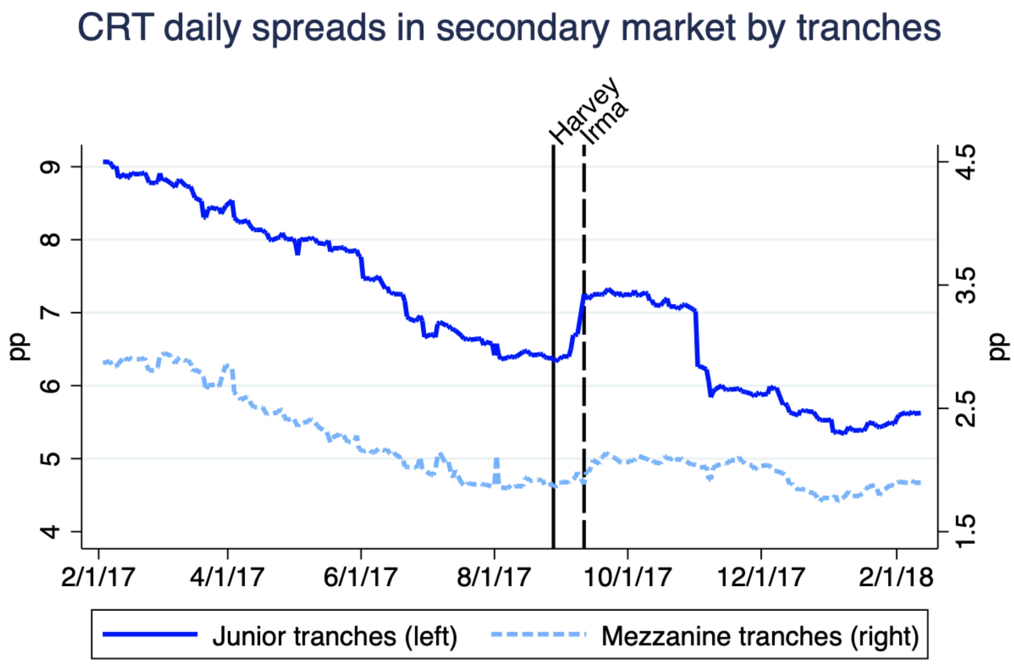

Figure 4. Spreads for CRTs by tranches. The figure plots the average daily spread (yield to maturity minus one month U.S. Dollar Libor) in the secondary market of the junior and mezzanine tranches of Freddie Mac's CRTs. The solid vertical line indicates August 28, 2017, which is the trading day after Harvey's landfall, and the dashed vertical line is September 11, 2017, which is the first trading day after Irma's landfall.

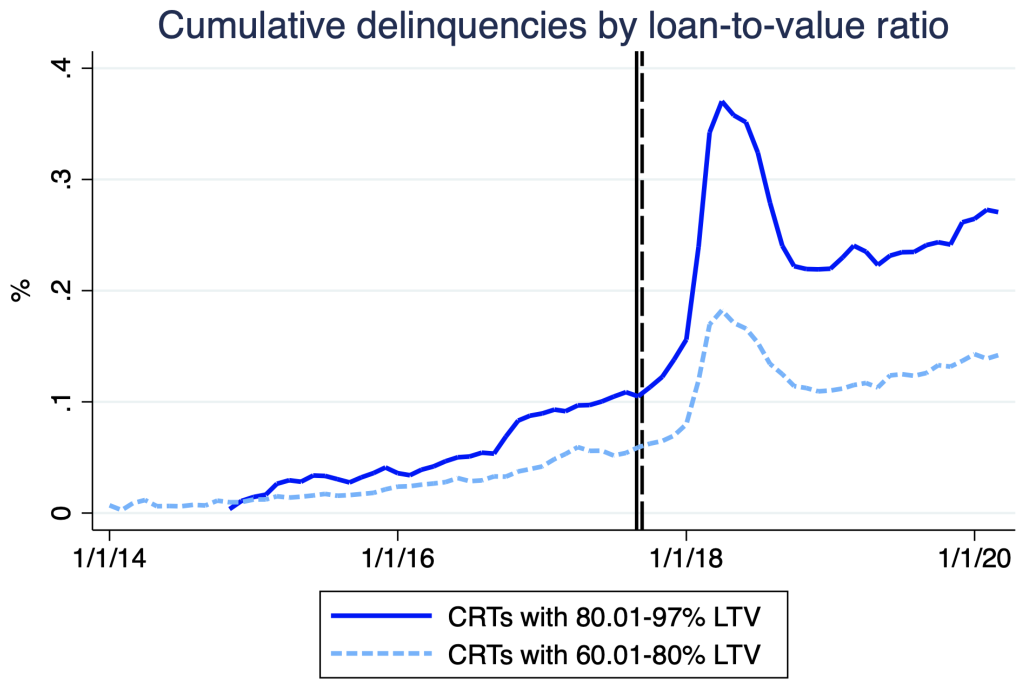

Figure 5. Cumulative delinquencies in pools of mortgages for CRTs with different loan-to-value. The figure plots the average share of unpaid principal balance (delinquent for more than 120 days) for CRT mortgage pools with different LTVs. The solid vertical line indicates August 28, 2017, which is the 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 first landfall in Florida.

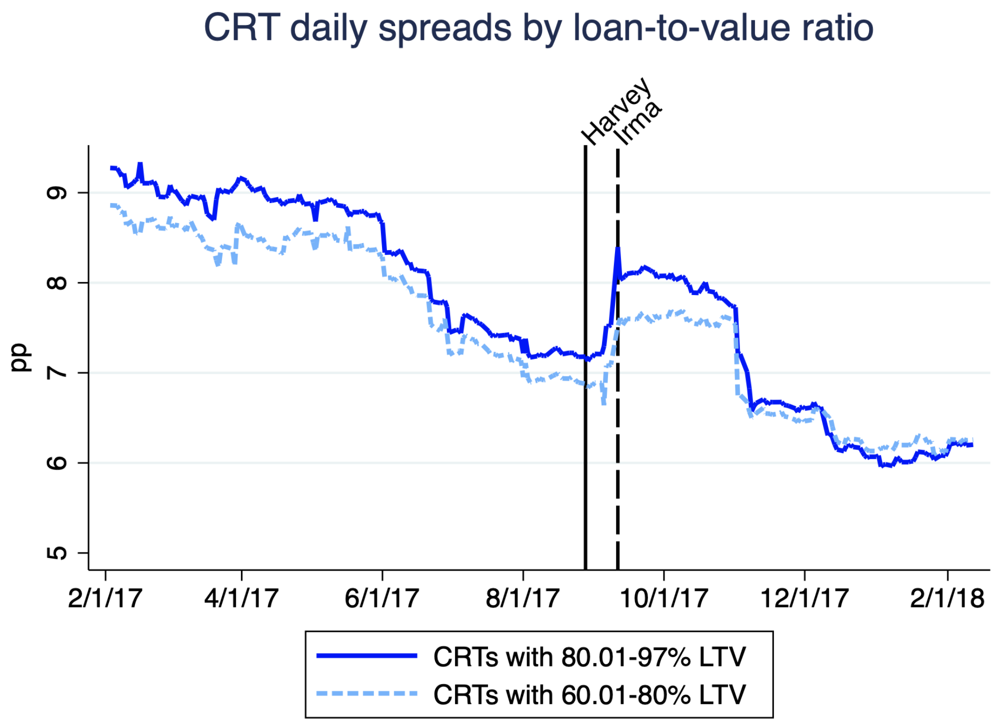

Figure 6. Spreads for CRTs by loan-to-value ratios. The figure plots the average daily spread (yield to maturity minus one month U.S. Dollar Libor) in the secondary market for Freddie Mac's junior CRT tranches issued in 2017 before Hurricanes Harvey and Irma, with high and low loan-to-value ratios. The 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.

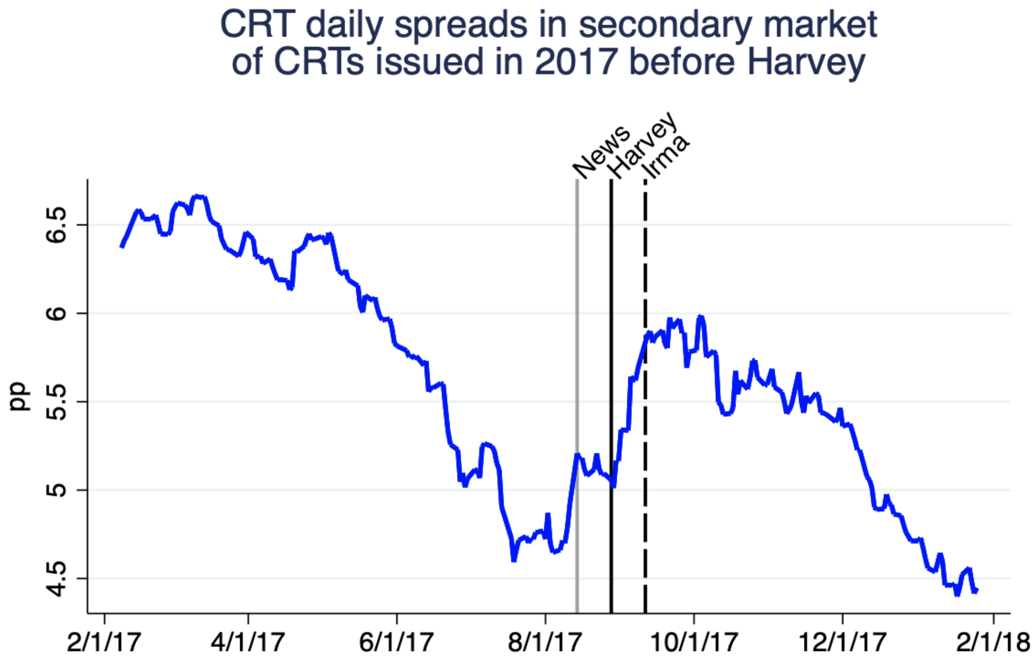

Figure 7. Spread of CRTs during Hurricanes Harvey and Irma. The top figure plots the average daily spreads (yield to maturity minus one month U.S. Dollar Libor) in the secondary market of Freddie Mac's junior CRT tranches issued between January and July 2017. The first solid vertical line indicates August 15, 2017, when the first warnings about Harvey came out. The second solid vertical line indicates August 28, 2017, which is the first 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.

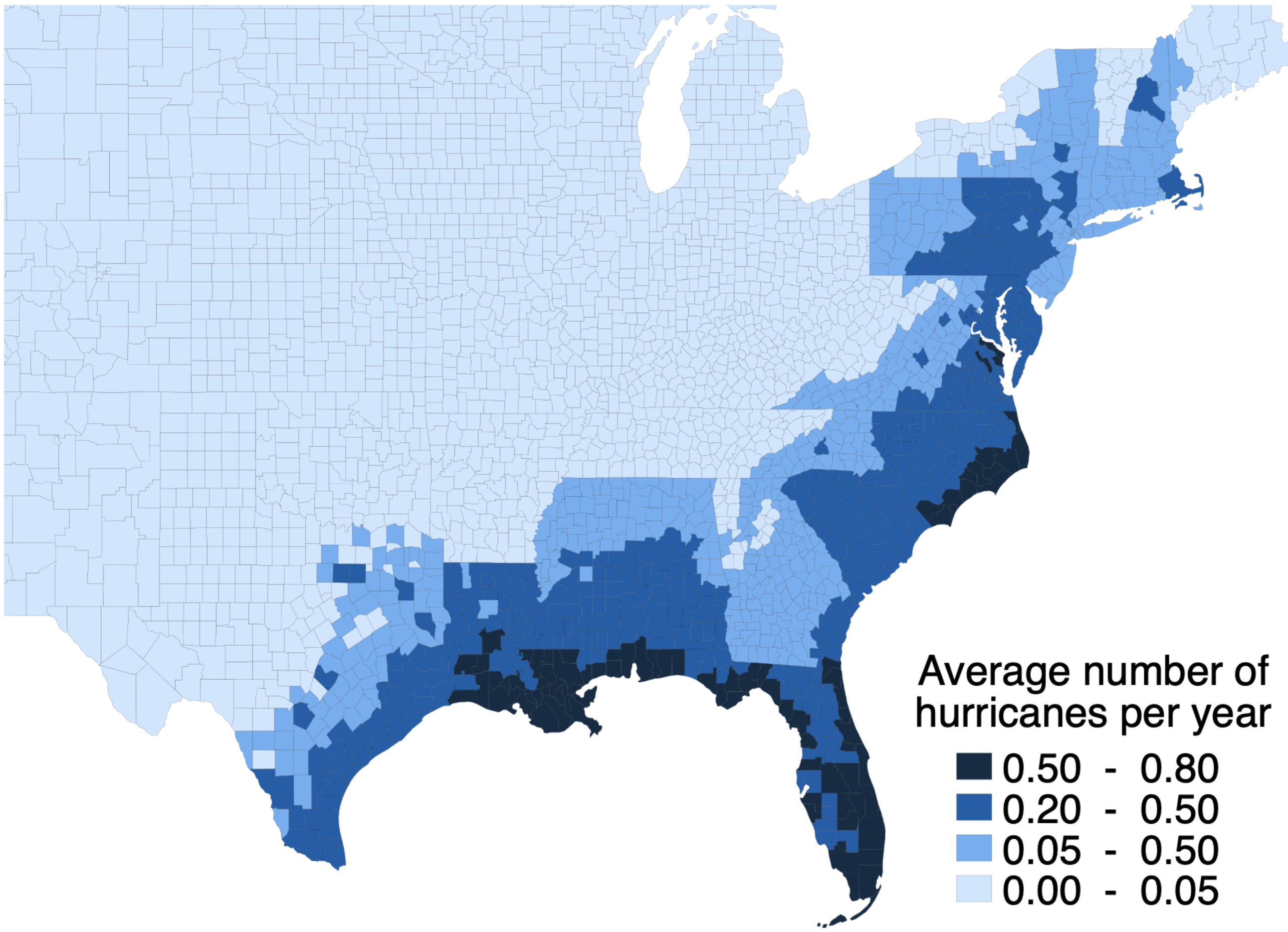

Figure 8. Occurrence of hurricane events in U.S. counties. The map shows the average number of hurricanes or tropical cyclones declared in FEMA during the years 1999 to 2019.

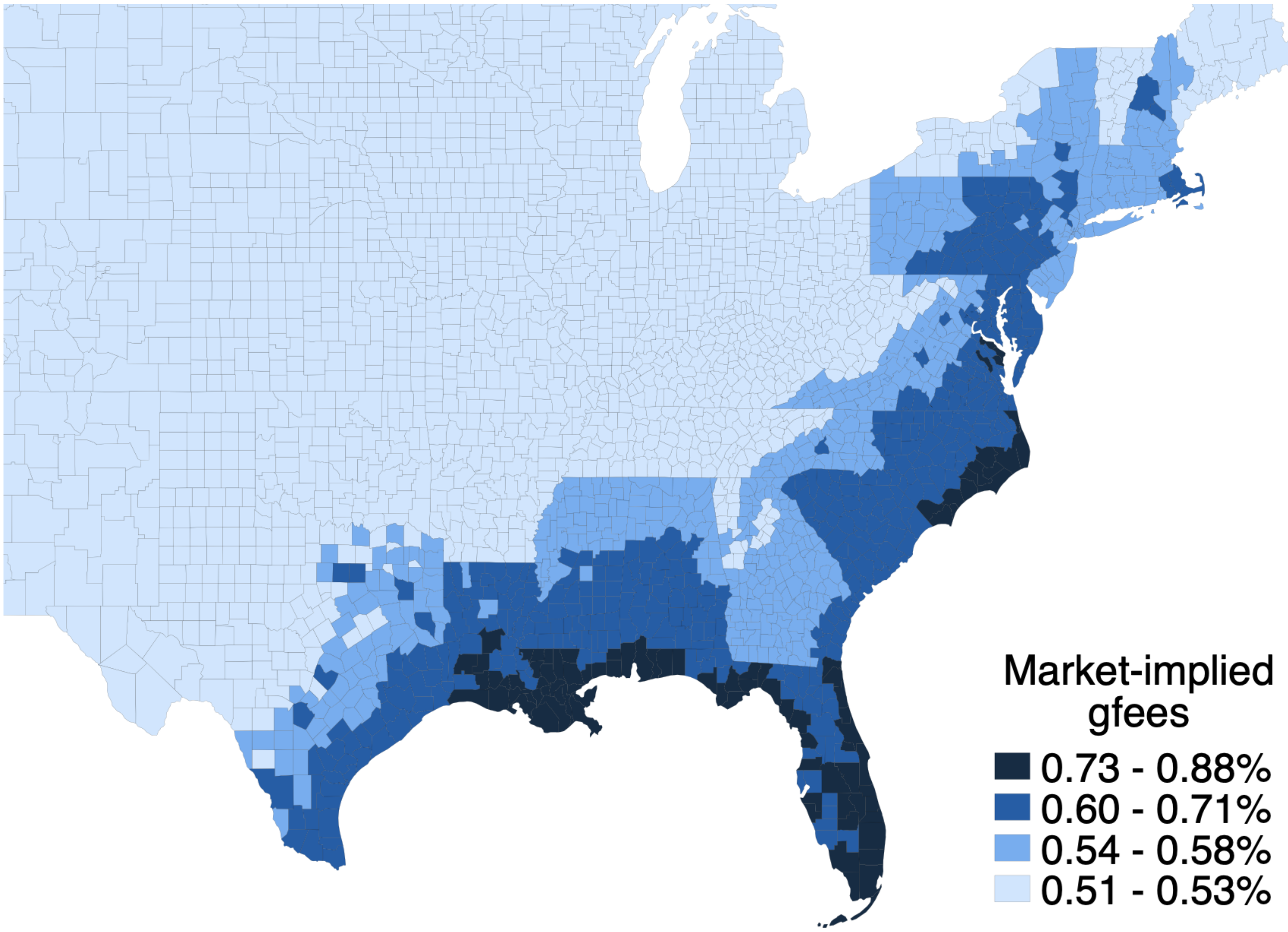

Figure 9. Market-implied guarantee fees. The map shows the county-wide average market-implied g-fees based on our model and the historical hurricane frequency and mortgage defaults. The mortgage rate equals the g-fee plus operating costs and cost of funds.

Tables

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**

The table presents the distribution of the CRT securities in our sample. These 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. The junior tranche is named B, or if there are multiple junior tranches they are denoted B1 and B2. Mezzanine tranches are named M1, M2 and M3.

Table 2. Summary statistics

	Obs.	Mean	SD	Min	Max
Junior tranches B, B1, B2					
Spread daily (pp)	1,076	7.082	1.679	4.791	13.008
Geographical exposure (%)	1,076	5.460	2.826	1.840	9.600
Trading volume daily ($ million)	1,076	0.509	2.247	0	28.854
Hurricane dummy	1,076	0.417	0.493	0	1
Ten year treasury rate (%)	1,076	2.177	0.059	2.050	2.280
Two year treasury rate (%)	1,076	1.355	0.053	1.270	1.460
Mezzanine tranches M1, M2, M3					
Spread daily (pp)	3,450	2.045	1.019	0.456	3.933
Geographical exposure (%)	3,450	5.007	2.856	1.090	9.600
Trading volume daily ($ million)	3,450	1.080	3.632	0	40.000

The table presents summary statistics of the key variables in the diff-in-diff specification for CRTs based on junior tranches, with different loan-to-value ratios. The daily spread is the yield to maturity minus the one month U.S. Dollar Libor. The hurricane dummy takes the value of 1 from the first trading date after the first landfall in the U.S. coast of Hurricane Irma on September 11, 2017 onwards, and 0 otherwise. Geographical exposure is the exposure to the areas affected by Hurricanes 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 15 days before and 25 days after Hurricane Harvey.

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

Window (days)	+15	+20	+25	+30	+35	+40
	Spread					
Hurricane	0.284***	0.281***	0.282***	0.297***	0.339***	0.351***
	(0.080)	(0.081)	(0.080)	(0.078)	(0.081)	(0.082)
Hurricane × exposure	0.066***	0.066***	0.065***	0.062***	0.054***	0.053***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.012)	(0.012)
Observations	812	962	1,076	1,190	1,380	1,494
R-squared	0.990	0.990	0.989	0.988	0.987	0.986
Within R-squared	0.706	0.757	0.766	0.756	0.735	0.721

Standard errors clustered by CRT security are in parentheses. The spread is measured in percentage points. Hurricane is the treatment variable that takes the value of 1 from the first trading date after Hurricane Irma's landfall in the U.S. coast, and 0 otherwise. It captures the combined effect of both hurricanes. Exposure is the geographical exposure to the areas affected by Hurricanes Harvey and Irma. Controls are CRT security fixed effects, daily transaction volume, a dummy that controls for the interval between the two hurricanes, and the 10-year and 2-year treasury rates. The window begins 15 days before Hurricane Harvey and ends the number of dates indicated in each column. The sample and all variables are as defined in Table 2. *** $p<0.01$.

Table 4. Spreads after hurricanes by geographical exposure: Mezzanine tranches

Window (days)	+15	+20	+25	+30	+35	+40
			Spread			
Hurricane	0.092***	0.096***	0.092***	0.097***	0.105***	0.112***
	(0.022)	(0.023)	(0.024)	(0.024)	(0.024)	(0.024)
Hurricane × exposure	-0.0005	-0.0005	0.0002	-0.0002	-0.001	-0.001
	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Observations	2,604	3,087	3,450	3,813	4,417	4,784
R-squared	0.985	0.985	0.985	0.985	0.986	0.986
Within R-squared	0.080	0.209	0.252	0.252	0.279	0.284

Standard errors clustered by CRT security are in parentheses. The spread is measured in percentage points. Hurricane is the treatment variable that takes the value of 1 from the first trading date after Hurricane Irma's landfall in the U.S. coast, and 0 otherwise. It captures the combined effect of both hurricanes. Exposure is the geographical exposure to the areas affected by Hurricanes Harvey and Irma. Controls are CRT security fixed effects, daily transaction volume, a dummy that controls for the interval between the two hurricanes, and the 10-year and 2-year treasury rates. The window begins 15 days before Hurricane Harvey and ends the number of dates indicated in each column. The sample and all variables are as defined in Table 2. *** $p<0.01$.

Table 5. Impact of hurricanes on CRT spreads: Junior tranches

Window (weeks)	+15	+20	+25	+30	+35	+40	Average
Junior tranches B, B1, B2							
Spread increase (pp)	0.644	0.641	0.637	0.636	0.634	0.640	0.639
Initial level of spread (pp)							6.812
Percentage increase (%)							9.376
Mezzanine tranches M1, M2, M3							
Spread increase (pp)	0.092	0.096	0.092	0.097	0.105	0.112	0.099
Initial level of spread (pp)							1.974
Percentage increase (%)							5.015

This table shows the marginal change in CRT spreads after the landfall, for the average geographical exposure from Table 2. The calculations use the coefficients from Tables 3 and 4. For example, for a window of 25 days after Harvey's landfall the junior tranches had an increase in spread equal to $0.282 + (0.065 \times 5.460) = 0.637$ *pp*. The percentage increase in the spread is calculated as the average increase from the regressions of different time windows, over the average level of the CRT spread fifteen days before the landfall.

Table 6. Summary statistics of Freddie Mac loans

	Mean	SD	Min	Max
90-day delinquent	0.045	0.207	0	1
120-day delinquent	0.039	0.195	0	1
150-day delinquent	0.036	0.186	0	1
180-day delinquent	0.033	0.177	0	1
Defaulted loan	0.023	0.149	0	1
Hurricane frequency	0.062	0.166	0	3
Credit score	736.4	53.1	300	850
Debt-to-income ratio	33.4	11.3	1	65
Loan-to-value ratio	70.3	17.5	4	103
Primary residence	0.911	0.284	0	1
Secondary residence	0.031	0.174	0	1
Investment	0.058	0.233	0	1
Purchase	0.374	0.484	0	1
Cash-out refinance	0.311	0.463	0	1
No cash-out refinance	0.315	0.465	0	1
First-time buyer	0.110	0.313	0	1
One-unit	0.972	0.165	0	1
Two-unit	0.021	0.143	0	1
Three-unit	0.004	0.063	0	1
Four-unit	0.003	0.058	0	1
Single borrower	0.407	0.491	0	1

Number of observations is 696,198. This table shows the summary statistics of key variables used in the logistic regressions. The sample consists of Freddie Mac single-family mortgages issued between January 1999 and December 2019, thirty three thousand randomly selected mortgages per year covering geographically all the U.S. Each observation is a mortgage loan.

Table 7. Logistic regression: Probability of mortgage default

	Delinquency				Default
	90-day	120-day	150-day	180-day	
Hurricane frequency	0.857***	0.801***	0.746***	0.698***	0.438***
	(0.100)	(0.110)	(0.115)	(0.121)	(0.165)
Observations	696,198	696,198	696,198	696,198	667,922
Marginal effects: Probability of default					
Hurricane frequency=0	0.0427	0.0375	0.0342	0.0312	0.0229
Hurricane frequency=0.5	0.0604	0.0520	0.0465	0.0418	0.0277
Hurricane frequency=1	0.0836	0.0710	0.0624	0.0552	0.0334

Standard errors clustered by county are in parentheses. This table shows the results of the logistic regression for the probability a mortgage loan becomes delinquent for more than 90, 120, 150 or 180 days, and the probability of default during the loan lifetime. The regression 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 fixed effects. The sample consists of Freddie Mac single-family mortgages issued between January 1999 and December 2019, thirty three thousand randomly selected mortgages per year covering geographically all the U.S. *** $p<0.01$.

Table 8. Logistic regression with panel data: 90-day delinquency

	Probability of missing 3 consecutive mortgage payments$_{m,t+i}$				
Lead time (i) :	1 month	2 months	3 months	4 months	5 months
Hurricanes per month$_{m,t}$	0.0783	0.393***	0.458***	0.195***	0.0111
	(0.073)	(0.052)	(0.047)	(0.065)	(0.079)
Loan characteristics controls	Yes	Yes	Yes	Yes	Yes
Origination year fixed effects	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	13,203,463	12,922,530	12,643,688	12,367,020	12,093,096

Standard errors clustered by loan are in parentheses. This table shows the results of the logistic regression with panel data for the probability a mortgage loan becomes delinquent for more than 90 days. The lead time is the number of months after the hurricane for which we estimate the probability. The regression controls for month and county 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 fixed effects. The sample consists of Freddie Mac single-family mortgages issued between January 1999 and December 2019, sixteen thousand randomly selected mortgages per year covering geographically all the U.S. *** p<0.01.

Table 9. Logistic regression with panel data: 180-day delinquency

	Probability of missing 6 consecutive mortgage payments$_{m,t+i}$						
Lead months (i)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Hurricanes$_{m,t}$	0.0391	0.115	0.228***	0.157**	0.203**	0.158*	0.099
	(0.092)	(0.086)	(0.075)	(0.078)	(0.083)	(0.094)	(0.094)
Loan characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Origination year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,099,040	11,838,313	11,580,110	11,324,961	11,073,400	10,820,945	10,579,823

Standard errors clustered by loan are in parentheses. This table shows the results of the logistic regression with panel data for the probability a mortgage loan becomes delinquent for more than 180 days. The lead time is the number of months after the hurricane for which we estimate the probability. The regression controls for month and county 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 fixed effects. The sample consists of Freddie Mac single-family mortgages issued between January 1999 and December 2019, sixteen thousand randomly selected mortgages per year covering geographically all the U.S. *** $p<0.01$; ** $p<0.05$; * $p<0.1$.

Table 10. Calibration strategy

Parameter	Value	Description
		Exogenous parameters
l	1.250	Inverse of 80% loan-to-value ratio
λ	0.950	Mortgage amortization parameter
r^d	0.910%	Lender's cost of funds: 5y CD rate
r^w	0.074%	Lender's operating cost
π_{-1}	1.780%	Avg default probability 2 weeks before landfall
$\pi_0 - \pi_{-1}$	1.462 pp	Change in default probability due to landfall
r^m_{-1}	6.812%	Avg mortgage rate 2 weeks before landfall
		Endogenous parameters
a	0.887	Value of a in equation (9)
b	0.214	Value of b in equation (9)
		Targets
$r^m_0 - r^m_{-1}$	0.639 pp	Mortgage rate change estimated in Table 5
$\frac{d\gamma_t}{d\pi_t}\Big\|_{t=0}$	-4.5	Avg slope of equation (9)

This table lists the parameters (exogenous and endogenous) and targets used in Section 6. The equation (9) is the relation between the market expectation of the recovery rate γ and the default probability π.

Table 11. Simulation results

Hurricanes per year F	Default probability π	Recovery rate γ	Market-implied mortgage rate (%) r^m	Market-implied g-fee (%) r^g
0	0.0229	0.605	1.493	0.509
0.2	0.0250	0.597	1.570	0.586
0.5	0.0284	0.586	1.703	0.719
0.8	0.0322	0.575	1.861	0.877
1	0.0351	0.567	1.984	1.000

This table shows the results of the simulation using the credit supply model and probability of defaults as inputs. The lenders' cost of funds is $r^d = 0.910\%$ and the operating cost is $r^w = 0.074\%$. The g-fee is calculated from $r^g = r^m - r^d - r^w$. Figure 9 shows the market-implied g-fees on the map.

NOT FOR PUBLICATION
ONLINE APPENDIX

A Detailed Description of Database

We assemble a unique database of CRTs, by combining information from multiple data sources:

1. We collect data about the mortgages in the reference pool for the CRTs from the web pages of the GSEs (Fannie Mae 2020; Freddie Mac 2020). The GSEs make public the features and performance over time of the mortgage loans in the reference pool of CRTs. Specifically, for all CRTs issued up to August 15, 2017, we collect the LTV ratios of the mortgages in the reference pool of the securities, the delinquencies over time, and the geographical composition of the reference pools.

2. There are in total 163 CRT securities in the sample, which is the universe of CRTs from the time of the first issuance up to the month before the hurricanes we study. We restricted the sample before the hurricanes, so the results are not affected by new issuances.

3. We build a database of all CRT issuances from Bloomberg, including issuance dates, the tranches determining the seniority of credit protection and the ones retained by the GSEs, the original principal balance per tranche, and the floater spread paid by each tranche.

4. We collect the time series of prices and yields in the secondary market of CRTs from Thomson Reuters Eikon.[10] We also use the 1-month US Dollar LIBOR benchmark from Thomson Reuters Eikon, to calculate the spread over LIBOR we use in the analysis.

5. We collect the size of the daily transactions of CRTs from TRACE. The reported trade size per transaction is capped at $5 million.

Table A4 shows the process of merging the above datasets.

For the simulations we put together the following data:

[10] We cross-checked the prices with data from TRACE.

1. We obtain disaster declaration data from the Federal Emergency Management Agency (FEMA). This dataset contains the date of the declaration, the incident type, the declaration title, the state and the FIPS county code. To filter the hurricanes and tropical cyclones, we keep the following incident types: "Severe Storm(s)", "Hurricane", "Flood" and "Coastal Storm". We then go through the declaration titles, which are more detailed than the incident types, and delete the ones unrelated to hurricanes. The declarations in our final database are straightforward and ensure that we pick up only hurricane-related disasters, e.g. "HURRICANE DORIAN", "TROPICAL STORM FRANCES". We keep only the years 1999 to 2019, as the history of hurricanes is reportedly changing rapidly due to climate change. The most recent years are more representative of the future expectations, However, we also need a long-enough time frame, since hurricanes hit the same county in the U.S. at most once a year. These hurricanes in the final database affected 1,201 counties in total, in the following 19 states: Alabama, Connecticut, Delaware, Florida, Georgia, Louisiana, Maine, Maryland, Massachusetts, Mississippi, New Hampshire, New Jersey, New York, North Carolina, Pennsylvania, Rhode Island, South Carolina, Texas and Virginia.

2. We use the loan-level origination and credit performance data from Freddie Mac' portfolio of single family loans. Specifically, we use a random sample of 33,000 single-family mortgage loans originated per year, for the years 1999 to 2019. That is, a total of 700,000 loans nationwide. The dataset contains the following data that we use to estimate probabilities of default: Monthly performance, including days that the loan is delinquent, and loan characteristics: origination month, credit score, debt-to-income ratio, loan-to-value ratio, the occupancy purpose (primary residence, secondary residence or investment), the type of property (single-family, condominium, planned unit development, manufactured housing or cooperative), loan purpose (purchase, refinance with cash out, or refinance with no cash out), whether the borrower is a first-time buyer or not, number of units of the property, and whether there is one or multiple borrowers. Moreover, we have available the 3-digit zip code prefixes of the loans.

3. We merge the loan zipcode with the FIPS codes of all U.S. counties and the previous disaster declaration dataset, using the HUD USPS zip-to-county crosswalk file, from Q1 2014.

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FIGURES FOR THE ONLINE APPENDIX

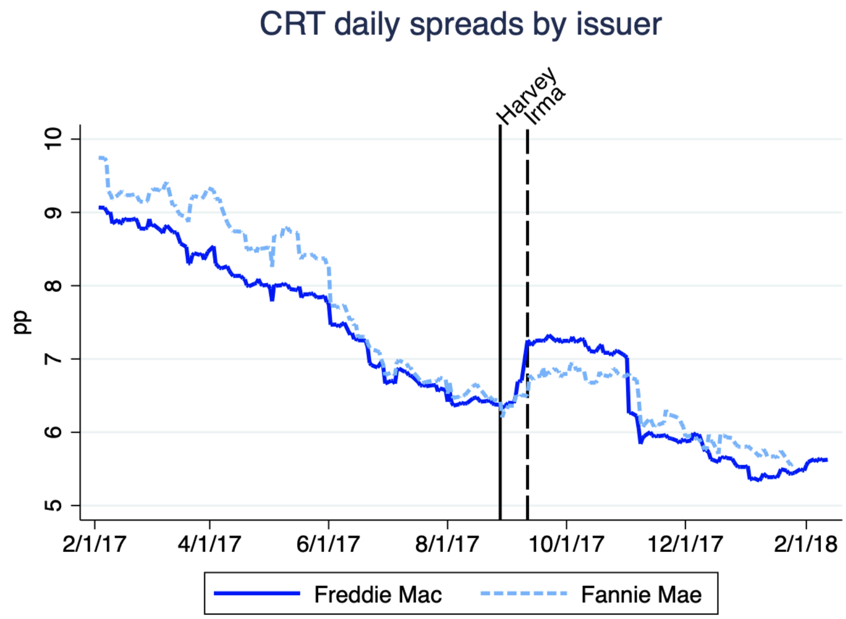

Figure A1. Spreads for CRTs by issuer. The figure plots the average daily spread (yield to maturity minus one month U.S. Dollar Libor) in the secondary market of all CRT risky tranches by the GSE issuer. The hurricane exposure of Freddie Mac's CRTs is between 3.60 and 9.60 percent, whereas the hurricane exposure of Fannie Mae's CRTs is between 1.92 and 2.56 percent. 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.

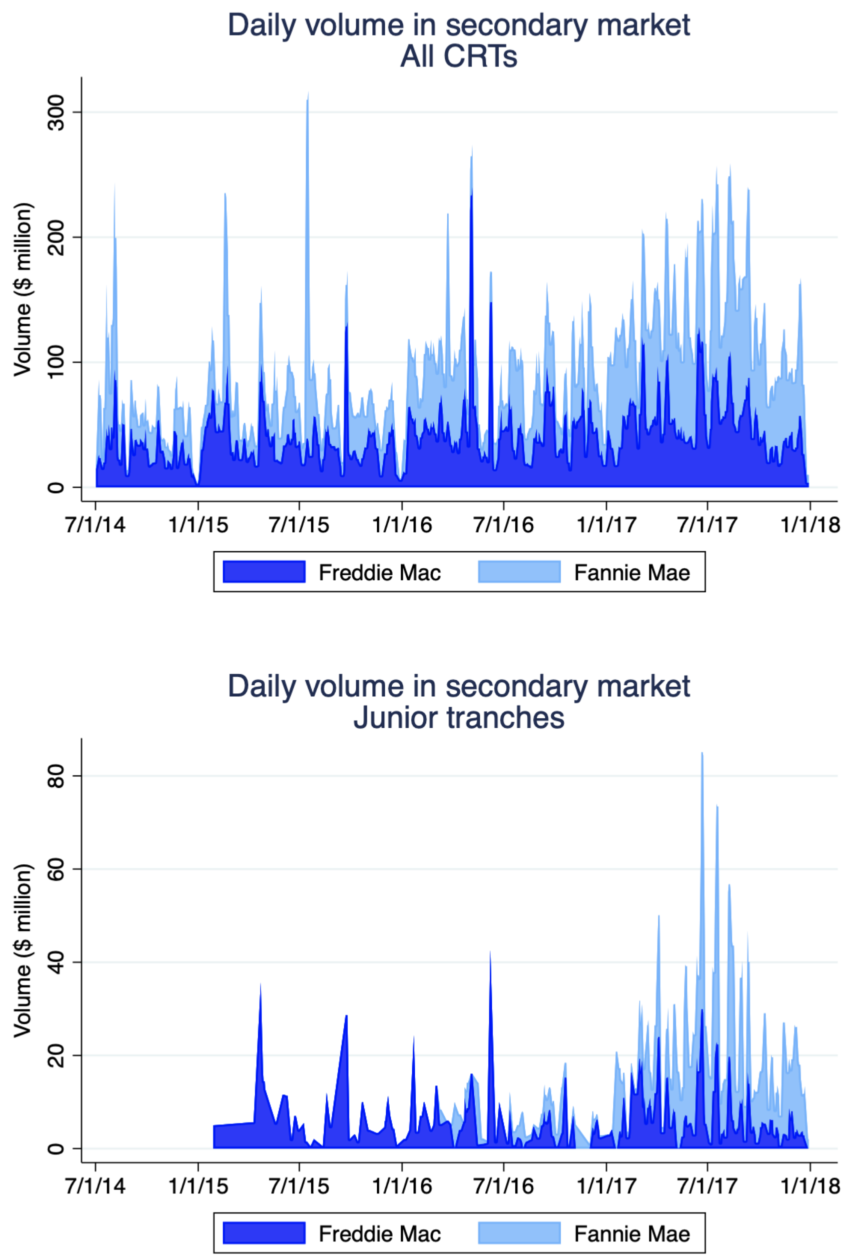

Figure A2. Trading volume of CRTs. The figures plot the time series of the total daily volume (7 days moving average) of the transactions in the secondary market of all CRTs, and only the junior tranches, from Fannie Mae and Freddie Mac. The reported trade size per transaction is capped at $5 million. Source: TRACE.

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TABLES FOR THE ONLINE APPENDIX

Table A1. Robustness: Time Fixed Effects

Window (days)	+15	+20	+25	+30	+35	+40
			Spread			
Hurricane × exposure	0.066***	0.067***	0.065***	0.062***	0.054***	0.053***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.012)	(0.012)
Observations	812	962	1,076	1,190	1,380	1,494
R-squared	0.992	0.991	0.991	0.990	0.988	0.987
Within R-squared	0.214	0.250	0.239	0.207	0.145	0.131

Standard errors clustered by CRT security are in parentheses. The spread is measured in percentage points. The variables are as in Table 36. Controls are CRT security fixed effects, time fixed effects and daily transaction volume. The window begins 15 days before Hurricane Harvey and ends the number of dates indicated in each column. *** p<0.01.

Table A2. Robustness: Loan-to-value ratio controls. Junior tranches

Window (days)	+15	+20	+25	+30	+35	+40
	Spread					
Hurricane	0.330***	0.313***	0.296***	0.290***	0.307***	0.314***
	(0.078)	(0.081)	(0.086)	(0.086)	(0.089)	(0.091)
Hurricane × exposure	0.051***	0.053***	0.053***	0.053***	0.050***	0.050***
	(0.015)	(0.015)	(0.016)	(0.016)	(0.017)	(0.017)
Hurricane × high LTV	-0.091	-0.056	-0.008	0.043	0.106	0.114
	(0.177)	(0.180)	(0.175)	(0.175)	(0.186)	(0.185)
Hurricane × exposure × high LTV	0.030	0.025	0.019	0.013	0.003	0.001
	(0.024)	(0.025)	(0.024)	(0.024)	(0.026)	(0.026)
Observations	812	962	1,076	1,190	1,380	1,494
R-squared	0.991	0.990	0.989	0.989	0.987	0.986
Within R-squared	0.712	0.763	0.771	0.761	0.740	0.725

Standard errors clustered by CRT security are in parentheses. The spread is measured in percentage points. Hurricane is the treatment variable that takes the value of 1 from the first trading date after Hurricane Irma's landfall in the U.S. coast, and 0 otherwise. It captures the combined effect of both hurricanes. Exposure is the geographical exposure to the areas affected by Hurricanes Harvey and Irma. Controls are CRT security fixed effects, daily transaction volume, a dummy that controls for the interval between the two hurricanes, and the 10-year and 2-year treasury rates. The window begins 15 days before Hurricane Harvey and ends the number of dates indicated in each column. The sample and all variables are as defined in Table 2. *** p<0.01.

Table A3. Robustness: Loan-to-value ratio controls. Mezzanine tranches

Window (days)	+15	+20	+25	+30	+35	+40
			Spread			
Hurricane	0.080**	0.079**	0.074**	0.075**	0.075**	0.077**
	(0.031)	(0.033)	(0.033)	(0.034)	(0.034)	(0.034)
Hurricane × exposure	0.004	0.003	0.004	0.003	0.003	0.004
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Hurricane × high LTV	0.018	0.036	0.041	0.049	0.070	0.079
	(0.045)	(0.049)	(0.049)	(0.049)	(0.049)	(0.048)
Hurricane × exposure × high LTV	-0.007	-0.007	-0.007	-0.007	-0.010	-0.012
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Observations	2,604	3,087	3,450	3,813	4,417	4,784
R-squared	0.985	0.985	0.985	0.985	0.986	0.986
Within R-squared	0.083	0.210	0.253	0.253	0.282	0.288

Standard errors clustered by CRT security are in parentheses. The spread is measured in percentage points. Hurricane is the treatment variable that takes the value of 1 from the first trading date after Hurricane Irma's landfall in the U.S. coast, and 0 otherwise. It captures the combined effect of both hurricanes. Exposure is the geographical exposure to the areas affected by Hurricanes Harvey and Irma. Controls are CRT security fixed effects, daily transaction volume, a dummy that controls for the interval between the two hurricanes, and the 10-year and 2-year treasury rates. The window begins 15 days before Hurricane Harvey and ends the number of dates indicated in each column. The sample and all variables are as defined in Table 2. *** $p<0.01$; ** $p<0.05$.

Table A4. Credit Risk Transfers database construction

Action to construct database	Number of observations	Source
Database: All CRT deals, names and features	163 securities	Freddie Mac and Fannie Mae websites
Database: Daily CRT yields	75,687	For the 163 securities we downloaded the historical prices from 2013 from Refinitiv Eikon
Merge with origination data using CUSIP code	75,687	Bloomberg
Merge with hurricane exposure using CRT names	75,687	Freddie Mac and Fannie Mae official reports

This table describes step-by-step the construction of the database of the daily yields of CRT securities. From this database we plot the figures showing the time series of yields. We also estimate various differences-in-differences regressions, using groups of CRTs, based on their risk characteristics.