Mortgage Stress without Government Guarantees. Lessons from Hurricanes and the Credit Risk Transfers.*

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Abstract

We use the new market for Credit Risk Transfers (CRTs) and the landfall of two major hurricanes to study both how markets price default risk from natural disasters, and how U.S. mortgage rates would change in absence of government-backed guarantees. First, we exploit that CRTs differ in the geographical and loan-to-value composition of their reference pool and in subordination. Thus, CRTs differ in exposure to the risk of mortgage defaults caused by the hurricanes. We estimate that for the riskiest CRTs the hurricanes increased spreads by 10% of the average spreads before the landfall. Second, we calibrate a model of credit supply to match the previous estimates. We use the model to estimate how changes in default probabilities change the market price of mortgage credit. For example, during the Global Financial Crisis mortgage rates would have increased by 29% absent government guarantees and monetary policy interventions.

Keywords: Credit Risk, Mortgages, GSEs, Hurricanes, Financial Crises.

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1 Introduction

Most of the credit risk from U.S. mortgages is borne by the American taxpayers through Fannie Mae and Freddie Mac, the two Government-Sponsored Enterprises (GSEs) in conservatorship since 2008, and through Ginnie Mae, which is a federal government corporation. Thus, in the U.S., directly or indirectly, mortgage credit risk is basically priced by the government. In this paper we study how markets would price such risk. To do so, we also answer a related question: how would markets price default risk from natural disasters? We proceed in two steps. First, we study default risk due to hurricanes in the market for Credit Risk Transfers (CRTs). Second, we use the estimates to calibrate a model of credit supply and run simulations.

The CRTs are structured securities that the GSEs started to issue in 2013 to bring private capital to mortgage markets (Levitin and Wachter 2020).[1] The GSEs pay interest plus the principal invested to the buyers of the CRTs. However, both payments depend on the credit performance of an underlying pool of mortgages. If the mortgages default, the CRT investors suffer those losses as they receive smaller payments. Hence, the GSEs are transferring the credit risk of such mortgages to the investors who buy the CRTs.

Our identification exploits that different CRTs have heterogeneous exposure to the mortgage defaults caused by a local, large and unexpected shock, that is, Hurricanes Harvey and Irma that hit the U.S. in late August and early September 2017. The hurricanes were unexpected events that suddenly generated large expectations of credit losses. These two hurricanes 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).

The heterogeneous exposure is due to CRTs differing in the loan-to-value (LTV) ratio and 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. Showing the heterogeneity in geographical exposure is a first novelty of this paper. All CRTs are backed by pools of mortgages that in principle are geographically diversified as they include mortgages from all U.S. states. However, this paper shows that such diversification is not perfect. Some CRTs had a higher share of mortgages in the hurricane damaged areas and suffered larger delinquency rates. Markets discovered such fact once the hurricanes hit. Investors have available all information about the characteristics of mortgages underlying the CRTs. Importantly, days after the hurricanes' landfalls, the GSEs published supplementary disclosures about the loans

[1] 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.

in the CRT mortgage pools that are in the hurricane affected areas. Thus, markets were able to price higher exposure to mortgage credit risk.

To do the analysis, we hand-collected a unique database of CRTs by combining information from different data sources. From Bloomberg, we obtained data on all issuances of CRTs. We merged such data, at the individual security level, with price data from the secondary CRT market from Thomson Reuters Eikon, and with data on defaults in each CRT reference pool from the GSEs.

We perform a difference-in-difference analysis. We measure how markets change the price of those CRTs with higher exposure to the mortgage default expected to be caused by the hurricanes. Harvey hit mostly in Houston and Irma in the southern part of Florida. The hurricanes impacted thousands of households and led to a considerable surge in mortgage delinquencies. Later-on, government intervention prevented a surge in mortgage defaults, but, our identification is anchored on the fact that when the hurricanes made landfall markets expected large mortgage losses. For example, right after the hurricanes, in October 2017, 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).[2]

Our identification is valid as the parallel trends identifying assumption is perfectly satisfied in our setting. CRTs with different exposure to the hurricanes' default risk behaved similarly until shortly before the landfall of the hurricanes.

We find significant increases in the yields (that is, decreases in prices) for those CRTs more exposed to credit risk, that is, junior tranches from those CRTs geographically more exposed to the hurricanes whose underlying mortgages have LTVs above 80. For these tranches and CRTs, we find that the hurricanes increase spreads relative to Libor by 72.9 basis points. This is a 10% increase relative to the average spreads in the pre-hurricane period. Consistent with the theory, the results weaken as we look into those tranches less exposed to risk. For example, we find no significant effect of the hurricanes on mezzanine tranches. This shows that tranching is a great way to generate default-free assets. We check that the results are not driven by increased liquidity risk.

We use the previous results to calibrate a model of mortgage credit supply. This allows us to have a structural way to extrapolate from mortgage defaults into the market price of mortgage credit risk for any historical period. Thus, we can study how markets would price default risk

[2] There is an increasingly large literature that also uses hurricanes as exogenous shocks because it is impossible to predict well in advance the exact location, timing and severity of individual hurricanes. See for example, Rehse et al. (2019), Schüwer, Lambert and Noth (2019), Cortés and Strahan (2017), or Dessaint and Matray (2017).

from natural disasters and simulate time series of market implied mortgage rates and implied guarantee fees (g-fees), given historical default rates, in the absence of government guarantees.

This paper contributes to two literatures. First, it contributes to the literature on housing finance. Second, it contributes to the literature on the financial consequences of natural disaster risk. The reform of the American housing finance system is a topic of great importance for financial markets and the economy. Papers like Jeske, Krueger and Mitman (2013), Frame, Wall and White (2013), Elenev, Landvoigt and Van Nieuwerburgh (2016), Hurst et al. (2016), Gete and Zecchetto (2018) and Fieldhouse, Mertens and Ravn (2018) have analyzed different topics related to the GSEs. To our knowledge, this is the first paper to estimate the pricing of mortgage credit risk without the GSEs. Our estimates also speak more broadly to the literature that studies the macroeconomic effects of credit risk (e.g. Campbell and Cocco 2015; Garriga and Hedlund 2020).

This paper contributes the growing literature that studies the implications of natural disasters for credit markets. Recent examples include Morse (2011), Berg and Schrader (2012), Cortés and Strahan (2017), Ouazad and Kahn (2019), Schüwer, Lambert and Noth (2019), and Rehse et al. (2019). Our contribution is to implement the first study of the effects of default risk due to hurricanes on mortgage pricing.

The rest of the paper is organized as follows: Section 2 provides the background of CRT transactions and describes the CRT debt security structure. Section 3 describes 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 analyzes a model of credit supply calibrated to match the results from Section 4. Section 6 concludes.

2 Overview of Credit Risk Transfers

2.1 Background

The GSEs have historically been exposed to significant mortgage credit risk, mainly because they provide a credit guarantee of timely payment of principal and interest to investors of the agency mortgage-backed securities (MBS) they issue. The 2008 financial crisis resulted in high mortgage credit losses for the GSEs, which led to their conservatorship by the FHFA in September 2008.[3] Under this conservatorship, the MBS that the GSEs issue are effectively

[3] At the time of the 2008 finiancial crisis the GSEs were managing credit risk by charging guarantee fees to the MBS investors, by requiring private mortgage insurance or additional credit enhancement for mortages with

guaranteed by the federal government. The guarantee exposes the government and the U.S. taxpayers to the risk of significant mortgage defaults.

Directed by the FHFA, the GSEs developed credit risk transfer (CRT) transactions, and brought the first securities to the market in July 2013. These transactions are loss sharing agreements with private investors who would share the credit risk on mortgage loans underlying agency MBS. The CRT debt securities are Freddie Mac's Structured Agency Credit Risk (STACR) securities and Fannie Mae's Connecticut Avenue Securities (CAS). The STACR and CAS debt securities have been the most widely used from the credit risk mitigation instruments, for example, accounting for 70% of the risk in force shed from the GSEs' balance sheets in the second quarter of 2017 (FHFA 2017).[4] CRT transactions currently are being executed in a fully functioning liquid market, and have gained a broad investor base. Since their inception and up to the second quarter of 2017, which is the period we are focusing on, the CRT securities provided GSEs with loss protection on about $1.3 trillion of mortgage loans (FHFA 2017).

The use of CRTs is likely to be expanded, as other financial institutions, such as JP Morgan Chase & Co., are exploring CRT issuance as a mechanism for regulatory capital relief (Bloomberg 2019).

2.2 CRT structure

The CRTs are notes with final maturity 10 or 12.5 years that offer to investors rights to cashflows from a reference pool of mortgages that individually may underlie recently securitized agency MBS. The notes pay monthly a share of the mortgage principal to the investors as this gets repaid, plus interest. By contrast, in a traditional MBS structure, there is true sale of a specific pool of mortgages to move specific assets off-balance sheet. To date, the CRTs have referenced 30-year fixed rate mortgages, which represent the majority of mortgages securitized into MBS. The principal balance of a CRT note is a percentage of the total outstanding principal balance of the reference pool. Each reference pool consists of around 139 million mortgages, with total unpaid principal of approximately $30 billion at the time of issuance.

The mortgage reference pools have two characteristics that are key to our subsequent analysis. First, all reference pools are geographically diversified. They contain mortgages on houses in all U.S. states. The highest concentration is commonly in the states of California, Texas,

loan-to-value ratios exceeding 80%, by setting minimum undewriting standards, by requiring representations and warranties from the loan sellers, and by keeping equity capital as additional buffer against insolvency. These credit risk management tools did not prevent the high mortgage losses during the crisis.

[4] Alternative risk sharing mechanisms include risk sharing with mortgage originators, credit insurance and credit enhancement contracts.

Florida, Illinois, Georgia or Virginia. There is variation within the shared of principal balance in each state across CRTs. Second, the reference pools are split into two groups: high or low LTV. The high LTV pools contain exclusively mortgage loans with LTV ratios from 81% and up to 97%. The low LTV pools contain exclusively mortgage loan with LTV ratios between 61% and 80%. The first CRT contracts were based on a fixed severity schedule, that is, the recovery value of the foreclosed houses were calculated based on a step function. The fixed severity schedule expedited the procedure of calculating the losses, without waiting for the formal foreclosure processes. From the second quarter of 2015 the GSEs started issuing CRTs based on actual severity.

Figure 1 shows a sample CRT transaction. The outstanding principal balance at issuance is divided into tranches with different levels of seniority. The most senior tranche is retained entirely by the GSEs. Next in seniority are typically two or three "mezzanine" tranches, and immediately lower in seniority is the subordinate tranche, which are sold to investors. The most subordinate tranche, or "first loss", was retained by the GSEs in the early CRT transactions, but it is sold to investors after 2016. A typical allocation of the outstanding principal balance is 94.5%-96.0% to the most senior tranche retained by the GSEs, 3.5%-4.0% to the mezzanine tranches, and 0.5%-1.5% to the subordinate and first loss tranches. Higher percentage of losses is allocated to the subordinated tranches when the first loss is sold to investors. The GSEs also retain a vertical slice of each of the tranches sold to investors, as a mechanism to reduce the GSE's moral hazard in the selection of mortgages (Lai and Van Order 2019).

Appendix A1 contains detailed calculations of the CRT cash flows. The cashflows from the scheduled principal payments (mortgage repayments) and unscheduled principal payments (early repayments) from the borrowers on mortgages in the reference pool are used to repay the most senior tranche owned by investors still outstanding at any given point. The principal balance of the CRT notes is reduced by the amount of these payments. Once the principal balance of most senior tranche outstanding is eliminated, the next tranche in seniority starts getting repaid and having its principal balance reduced by the scheduled and unscheduled principal payments. The losses on mortgages in the reference pool are used to reduce the principal balance of the most subordinate tranche outstanding. Once the principal balance of most subordinate tranche outstanding is eliminated, the next most subordinate tranche starts having its principal balance reduced by the mortgage losses.

The monthly interest paid to the investors is a floating rate on the outstanding principal balance equal to one month U.S. Dollar Libor plus a "floater spread" determined at the time of the primary market issuance. The floater spread is higher for the subordinate tranches. For example up to December 2018, the subordinate tranche of Fannie Mae's CRTs paid a spread of

8 percentage points on average, whereas the mezzanine tranches paid a spread of 3 percentage points on average. The floater spreads are generally set to ensure that the CRT notes are priced at par, that is, investors pay $1 for every $1 of principal of the CRT note. Figure A1 shows the historical spreads of the CRTs in the primary market. The credit spreads at issuance on the higher rated CRT mezzanine tranches (M-1) seem to be correlated with the corporate BBB index, while the credit spreads at issuance on the lower rated CRT mezzanine tranches (M-2) seem to be correlated with the high yield Credit Default Swap Index (FHFA 2017: 14).

The price fluctuations of CRTs in the secondary market provide information about what private capital markets would charge for sharing the credit risk generated by the credit guarantee business of the GSEs (Wachter 2018). The CRT performance is directly linked to the risk of the default of the underlying mortgages. Importantly, Freddie Mac and Fannie Mae made available to investors the characteristics and performance over time of the underlying mortgage pools as well as of the individual loans. Investors have complete information of the underlying securitized credit, in a way that is standardized and transparent. Thus, CRT pricing identifies the investors' perceptions of the riskiness of mortgage lending based on the GSEs' portfolios. Knowledge of credit conditions informs the market perception of credit risk, which is indicated in the market pricing of CRTs.

3 Data

We assemble a unique database of CRTs by combining information at the security level from multiple data sources. First, we collect data about the mortgages in the CRTs reference pool from the web pages of the GSEs (Fannie Mae 2020; Freddie Mac 2020). The GSEs disclose 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, geographical composition and delinquencies of the mortgages in the reference pool of the CRTs. Second, from Bloomberg, we gather data of all CRT issuances. We record issuance dates, the tranches determining the seniority of credit protection and those retained by the GSEs, the original principal balance per tranche, and the floater spread paid by each tranche. Third, from Thomson Reuters Eikon we collect the time series of prices and yields in the secondary CRT market. We cross-validated these data with data on CRT secondary prices from TRACE. We also use the 1-month US Dollar Libor rates from Thomson Reuters Eikon to calculate the spread over Libor. Table 1 presents the distribution of CRTs in our sample based on risk characteristics.

Moreover, for the model simulations, we use the time series of the effective single-family guarantee fees from 1991 to 2018 from the FHFA Monthly Interest rate Survey (FHFA 2020), and the historical delinquency rates for single-family residential mortgages from FRED. We also collect the time series of the average 5-year certificate of deposits (CD) rates from 1991 to 2020 Bankrate[5], and origination costs at specific dates from the FHFA Monthly Interest rate Survey (FHFA 2020).

4 Empirical Analysis

Since the birth of the CRT market in 2013, there were no major shocks to credit risk until August 2017, when Hurricane Harvey was approaching the U.S. coast. Harvey was soon followed by Hurricane Irma in September 2017. Harvey hit mostly the metropolitan area of Houston, while Irma hit in the southern part of Florida. The exact timing of the hurricanes and the exact location of the landfalls were largely unexpected. Thus, we can think of Harvey and Irma as a large and unexpected shock to local mortgage markets. Various 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 to local markets.

4.1 Heterogeneities in exposure to mortgage default caused by the hurricanes

In theory, CRTs are geographically diversified as they are backed by mortgages from all U.S. states. However, Figure 2 shows that such diversification is not perfect. The geographical distribution of the CRT mortgage pools was a determining factor for the share of delinquencies when the hurricanes hit. Those CRTs with a higher share of mortgages in the hurricane damaged areas (Houston and Southern Florida) experienced a substantially higher share of delinquencies. Markets were able to price this heterogeneity since, days after the hurricanes' landfalls, the GSEs published supplementary disclosures about the loans in the CRT mortgage pools that were in the hurricane affected areas.

In addition to the geographical composition of their reference pool, CRTs are also heterogeneous in the loan-to-value (LTV) of the mortgages in the pool. Figure 3 shows that those CRTs whose underlying mortgage pools have higher LTV ratios (81-97%) suffered higher delinquen-

[5] Bankrate is an American consumer financial services company. (https://www.bankrate.com/banking/cds/historical-cd-interest-rates/).

cies following the hurricanes than CRTs whose mortgage pools had low LTV ratios (61-80%). This fact is consistent with the LTV ratio being a key driver of credit risk.

Finally, a third cause of heterogenous exposure to credit risk is tranching. Different tranches of the same CRT deal have different exposure to the default risk of the underlying mortgage pool because losses are allocated inversely to the seniority of the tranche.

It is important to stress that most of the increase in delinquencies shown above did not translate into defaults and foreclosures (see for example Bakel 2017; Freddie Mac 2017a; Freddie Mac 2017b). This is because policymakers reacted to the hurricanes and implemented extraordinary relief options for the mortgagors. However, even if ex-post the hurricanes caused no major surge in defaults, ex-ante markets were stressed as we show next in Figures 4 to 6. Because of this reason, in October 2017, 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).

Figure 4 shows spreads in the junior tranches of CRTs. The yield spreads are the compensation the investors demand for taking on credit risk. The top panel plots the average in the whole market. The bottom panel reports those CRTs recently issued and thus with a larger set of promised cashflows outstanding. These are arguably the CRT notes with the highest risk everything else constant, since, compared to other CRTs, they have the maximum time remaining until their final maturity. Both plots show that investors reacted to the first warnings about Hurricane Harvey forming in the Atlantic, by demanding higher spreads for taking on credit risk. The jump in spreads was larger for the younger CRTs both at the news of the hurricanes and once they hit. In other words, junior investors, who are the first to take on the losses, reacted to higher credit risk by demanding higher spreads. The spreads reverted back to the pre-hurricane trend in December 2017, although for the young CRTs it took two months longer to recover their pre-hurricane levels.

Figure 5 shows that the spreads for CRTs that were more geographically exposed to the hurricane reacted more than the ones for less exposed CRTs. Ex-ante the investors did not know exactly the extend of the damages in each CRT pool. However, they had information about the geographical concentration of the mortgage loans' principal balance within the U.S. Moreover, Figure 5 shows that the parallel trends assumption for the diff-in-diff identification is satisfied. The spreads of the two CRTs show similar dynamics before the first landfall.

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 have 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 clearly priced higher credit risk.

From the previous figures we can conclude that stress in the markets lasted up to about eight weeks and subsided afterwards. Likely, the daily announcements by the GSEs and the government of the disaster assistance programs contributed to the revision of the initial beliefs. So far our analysis was mostly graphical. Next, we formally present our empirical specification.

4.2 Specification

We study a difference-in difference methodology with panel data of daily CRT spreads in the secondary market. The treatment group are those CRT notes with the highest geographical exposure to the hurricane-affected areas, and the control group are those CRTs with the lowest geographical exposure. The “treatment” is the first trading date after the landfall of Hurricane Irma on September 11th 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 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 in the figures 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 Hurricane Irma’s landfall, and zero otherwise. E_i is the percentage of CRT unpaid principal balance geographically exposed to Hurricane Harvey and Hurricane Irma combined, as reported by the GSEs. We include as cross-sectional controls C_i, the floater spread to account for the riskiness of the security; an indicator for the issuer, Fannie Mae or Freddie Mac; and issuance year dummies to capture both differences in the spread of the issuance year cohorts of CRTs and different time to maturity as discussed in Figure 4. We include time series controls D_t to isolate the effect of the timing of the hurricanes from other potential economic influences happening at the same time. The time series controls are the 10-year treasury rates, in line with the original time to maturity of the CRTs, and 2-year treasury rates to reflect shorter maturities. We estimate the model for time windows of 2 to 7 weeks before and after the treatment date.

CRTs differ substantially in their exposure to credit risk based on the LTV ratios in the mortgage reference pool, and the claims to losses depending on tranche subordination. To isolate the effect of the hurricanes based on the geographical exposure, we perform the diff-in-diff analysis on different samples, that is, for high and low LTVs, and for subordinated and mezzanine tranches. In the next section we specifically turn our focus on the riskiest sample, junior CRTs with high LTVs, to develop a credit risk model.

Table 2 presents summary statistics of the key variables for the junior CRTs. The high-LTV CRTs have higher floater spreads (spreads at issuance) and higher yield spreads in the secondary market, consistent with higher credit risk.

4.3 Results

Table 3 presents the estimates of specification (1) for the subordinated tranches and different LTVs. Spreads increase significantly after the hurricanes for CRTs with larger exposure to the hurricanes for time windows between 2 and 7 weeks after Hurricane Irma's landfall. To put the results into perspective, two weeks after the landfalls the yield spreads of the junior CRT tranche with high LTV and the maximum exposure to the hurricane affected areas increase on average by 0.76 percentage points more compared to the junior CRT tranche with the minimum exposure.[6]

To address concerns that the results might be affected by liquidity risk, we control in the previous specification for the daily trading volume of the junior CRTs.[7] Table A1 shows that the results remain broadly unchanged compared to the baseline results in Table 3. Any changes in trading volume are not driving the changes in credit spreads. Moreover, qualitative evidence from the overall transaction volume (Figure A2) does not show any sign of illiquidity at the time of the hurricanes.

Table 4 shows that the mezzanine tranches reacted very little to the landfall, and the geographical exposure to the hurricanes did not matter for the jump in spreads. The small reaction of the mezzanine tranches to increased credit risk is in line with the credit protection of the CRT structure. The junior tranches would need to absorb on average 0.5% to 1.5% of losses in the underlying principal balance, before the mezzanine tranches begin to absorb losses. Being local shocks, the hurricanes did not wipe out substantial value from the CRTs, since the underlying mortgage pools are well diversified. However, the CRT market priced the ex-ante

[6] 0.106 (from Table 3) x (9.30-2.16) (from Table 2) = 0.76 pp.

[7] Due to data limitations, we do not have available bid-ask spreads for the CRTs. Specifically, debt securities issued by the GSEs are not eligible for reporting in Trade Reporting and Compliance Engine (TRACE).

credit risk at the time of the landfalls of the catastrophic hurricanes Harvey and Irma.

Our results provide a baseline of the pricing of credit risk by the markets during a period of market stress. Overall, we find that credit risk exposure increases the price of credit risk in CRTs during a period of market stress. The magnitude of default expectations due to the hurricanes only affected the securities with the junior claim to losses.

Table 5 summarizes the key takeaway from the empirical exercise. This table shows the estimated change in the spread of junior CRTs with average geographical exposure to the hurricanes, after the hurricanes' landfall, for time windows 2 to 7 weeks before and after the landfall. For example, for a 2-week window the junior tranche with high LTV had an increase in spread equal to 0.729 percentage points (pp). That is, 0.106 (interaction coefficient from Table 3)$\times$6.47 (average exposure from Table 2)+0.043 (landfall coefficient from Table 3). Table 5 also shows the change in the one month U.S. Dollar Libor. We use the change in the CRT yields due to the hurricanes, that is, the change in spreads adjusted for Libor changes, to calibrate our model in the next section.

5 Simulations in a Model of Credit Supply

In the previous section we analyzed how markets price mortgage credit risk following major hurricanes. In this section we want to build on those estimations to study how U.S. mortgage rates would change after a shock to credit risk in absence of government-backed guarantees. To do so, first we setup a model of mortgage credit supply standard in the literature. Then we calibrate such model to be consistent with the empirical results from Section 4. Finally, we use the calibrated model to run simulations of mortgage rates under different scenarios of stress in mortgage markets, which we proxy with the probability of mortgage default.

5.1 Setup

Mortgage lenders are risk neutral and compete loan by loan. The risk assumption is not an important one because risk-aversion will be captured in the calibration of the loan recovery parameter we discuss below. We denote by r_t^d the cost of funds for lenders (e.g. deposits or warehouse funding) and by r_t^w the origination costs per mortgage, at time t. Positive origination costs, $r_t^w > 0$, ensure a positive mortgage spread over the lenders' cost of funds. Lenders will originate any mortgage (L) that in expectation allows them to cover their costs of funds and origination. For simplicity we work with one-period mortgages.

Lenders take into account that the mortgage loan can default with probability $0 \leq \pi_t \leq 1$. In the case of default the lender would recover a fraction $\gamma_t < 1$ of the value of the house posted as collateral. We refer to the parameter γ_t as the recovery rate. We denote by P_h the value of the house, which we assume constant. Thus, in the absence of government's credit guarantees, lenders price mortgages (r_t^m is the mortgage rate) to ensure that their costs equal the expected revenue from the mortgage. That is, for a loan size L originated at time t,

$$(1 + r_t^d + r_t^w)L = (1 - \pi_t)(1 + r_t^m)L + \pi_t \gamma_t P_h. \tag{2}$$

The first term in the right-hand side is the expected revenue if the borrower pays the loan. The second term in the right-hand side is the expected revenue for the lender if the borrower defaults and the lender obtains the share γ_t of the value of the house.

We define the market implied guarantee fees r_t^g as:

$$r_t^g = r_t^m - r_t^d - r_t^w. \tag{3}$$

That is, the market implied guarantee fees, are the excess of the mortgage rate over the cost of funds and origination cost of the lender. In other words, the guarantee fee is the part of the mortgage rate that compensates for the credit risk.

5.2 Calibration

Before parameterizing the model, it is useful to divide both sides of (2) by L to eliminate loan sizes and instead work with the inverse of the loan-to-value ratio $\frac{P_h}{L}$. That is, equation (2) becomes:

$$1 + r_t^d + r_t^w = (1 - \pi_t)(1 + r_t^m) + \pi_t \gamma_t \frac{P_h}{L}. \tag{4}$$

We set the loan-to-value ratio to be 82.3%, which is the average ratio for GSE guaranteed mortgages in 2017.[8] Our goal is to match the average borrower with average leverage.[9]

We denote by $t = 0$ the time right before the hurricanes' landfall, and by $t = 1$ the time right after this shock. We assume that the funding and origination costs for the lender remain constant before and after the shock of the hurricanes. The hurricanes will impact default and

[8] The inverse of the loan-to-value ratio is $\frac{P_h}{L} = 1.215$.

[9] It is widely shown that the risk of default increases with leverage (see, for example, Schwartz and Torous 1993; Garriga and Schlagenhauf 2009; Mayer, Pence and Sherlund 2009; Corradin 2014; Corbae and Quintin 2015; Ganong and Noel 2017).

recovery rates and these will lead to mortgage rate changes. From equation (4), we get:

$$(1-\pi_0)(1+r_0^m)+\pi_0\gamma_0\frac{P_h}{L}=(1-\pi_1)(1+r_1^m)+\pi_1\gamma_1\frac{P_h}{L}. \tag{5}$$

Next, we discuss how we pick the targets for equation (5).

We set the value of the mortgage rate before the hurricanes to be consistent with the data. The expectations during the two weeks before the shock due to the hurricanes kept the average spreads of junior CRTs with high LTV at 7.21 percentage points. The one month U.S. Dollar Libor was 1.232% at the beginning of August 2017. Thus the pre-hurricane mortgage rate in our model is $r_0^m = 7.21 + 1.232 = 8.442\%$.

Also, we set the expectations of default to be consistent with the experience of CRTs with high LTV before the hurricanes. Since actual defaults take long to be realized and finalized in the available data, the CRT investors infer the risk from the reported delinquencies within the pool of mortgages that back up the CRTs. To convert delinquencies to defaults, we assume that the expected default rate is 50% of the delinquency rate, as this is a simple approximation to the true historical data (e.g. Guren and McQuade 2020).

The experience of CRTs with high LTV was that, on average, from July 2015 to July 2017 the delinquencies increased by 0.071 percentage points (the data are plotted in Figure 3). The average CRT was issued in July 2015, thus, right before the hurricanes the average remaining time to maturity was eight years. With a simple extrapolation, we set the expectations of investors for the remaining duration to be equal to a delinquency rate of 0.285% (0.071×4).[10] That is, the expected default rate is 0.143% (0.285%/2). This default rate is for the entire mortgage pool. The junior tranches on which we base the calibration, are the first to take the losses and they are allocated on average 1.5% of the mortgage pool. This means that the CRT investors of junior tranches with high LTV expect defaults of π_0 =9.51% (0.143%×100/1.5), when they buy a CRT right before the hurricanes.

We obtain the change in the default probability expectation from the actual delinquency experience due to the hurricanes. Like before, we assume that, at the time of the shock, the market expects the delinquencies that are realized in the following months. Figure 3 shows that for high-LTV CRTs, the share of unpaid principal due to delinquencies was 0.235% in July 2019, when the cumulative delinquencies went back to follow the pre-shock trend.[11] Based on

[10] A more complex calculation taking into account the reduction of the total mortgage pool each period does not change the results.

[11] We ignore the hump in delinquencies that followed immediately after the hurricane. A substantial number of delinquencies were reversed, likely due to the hurricane assistance measures.

the previous extrapolation, the delinquencies in July 2019 would have been 0.176% (0.105% in July 2017 + 0.071 pp two years later) in the absence of a shock. That is, the hurricanes caused expectations of delinquencies to increase by 0.0437 pp (0.235%-0.176%). An implicit assumption is that the hurricanes caused an one-time level increase in delinquencies and then delinquency rates followed the pre-hurricane trend, consistent with the data in Figure 3. The equivalent increase in the default rate in the mortgage pool is 0.0218 pp (0.0437/2), and the corresponding increase for the junior tranches is 1.46 pp (0.0218×100/1.5). That is, CRT investors of junior tranches with high LTV expect that the hurricanes would cause $\pi_1 - \pi_0 = 1.46$ pp increase in the default rate.

Our first calibration target is the change in the market implied mortgage rate, obtained from the change in the CRT yield in the private market due to the hurricanes. We model the payment of risky CRTs, consisting of the junior tranches of a mortgage pool, like a risky mortgage. Table 5 says that the increasing credit risk expectations caused by the hurricanes lead to an increase in the mortgage rate of $r_1^m - r_0^m = 0.728$ percentage points (that is, 0.729 change in spread -0.001 change in Libor). This increase shows how much additional compensation investors demand to take on the increased credit risk. That is, this is the rate change that investors demand to be compensated for the credit risk they are taking on.

The main object of the calibration strategy is to find the link between recovery values and default probabilities that match the estimates from Section 4. The GSEs use a simple step-function to describe the relationship between γ and π, for example as a feature of fixed-severity CRTs.[12] We approximate this step function with a continuous one by assuming:

$$\gamma_t = 1 - a\pi_t^b, \tag{6}$$

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

Since we are calibrating two parameters, a and b in (6), we need a second target. We calibrate to match the slope of (6) to be equal to the average slope at the probability of default π_0 before the hurricanes' landfall. The slope is:

$$\frac{d\gamma_t}{d\pi_t} = -ab\pi_t^{b-1}. \tag{7}$$

We target it to be -0.5 at $t = 0$.[13]

[12] See, e.g. http://www.freddiemac.com/creditriskofferings/docs/STACR_2015_HQA1_Investor_Presentation.pdf.

[13] Slope $= (\gamma_{02} - \gamma_{01})/(\pi_{02} - \pi_{01}) = (0.6 - 0.75)/(0.35 - 0.05) = -0.5$, where the values are consistent with Freddie Mac's step function that links severity to defaults

We solve equations (5) and (7) for a and b. Table 6 summarizes the model parameters and targets. To compute rates of change we only need the information discussed above because we are assuming constant costs of funding for the lenders. To compute levels of mortgage rates we set as exogenous parameters: r_0^d the average five-year CD rate in July 2017, which was 0.91%; and r_0^w the mortgage origination cost, which was 1.17% in July 2017.

5.3 Simulations

Our solution derives that the expectations of the recovery rate are linked to the expected default probabilities in the following way: $\gamma_t = 1 - 0.551\pi_t^{0.113}$. The values are consistent with the estimations of recovery rates by the GSEs at levels higher than the historical average, since in our model the recovery rate captures not only expectations of losses, but also risk preferences. For example 1% probability of default corresponds to a 67.2% recovery rate, whereas 10% probability of default corresponds to a 57.5% recovery rate.

Based on the model we simulate the mortgage credit risk in the U.S. in the last thirty years. As a proxy for mortgage credit risk we use the mortgage delinquency rate, as shown in Figure 7. From the early 1990s to the end of 2006 the delinquency rates were approximately constant and slightly decreasing from 3.3% to 1.9%. Then a big jump brought the delinquency rates to 11.5% at the beginning of 2010, and they remained at levels close to 10.5% up to mid-2012 before they started decreasing. The rates reached their lowest level after the Great Recession at 3.4% at the beginning of 2020. However, there are signs of increases in the second quarter to 2020 due to the financial crisis brought to by Covid. In our model we simulate probabilities of default that are 50% of the delinquency rates.

Table 7 shows the results of the simulation exercise for two notable periods of increasing credit risk. First, during the Great Recession, the default rates exploded from 1.35% in July 2007 to 5.24% in July 2011. For this exercise we hold constant the funding cost at the level it was in July 2007 (3.94% 5-year CD rate and 0.47% origination cost). The change in the default rates would have caused an increase in mortgage rates of 1.38 percentage points from the initial level of 4.74% (an increase by 29%) in the absence of government guarantees and monetary policy interventions.

Figure 8 plots the market-implied g-fees derived from our model and the actual administrative g-fees over the last 30 years. While our model predicts values of market-implied g-fees identical to the actual administrative g-fees charged in 2005, the market-implied g-fees are five

(http://www.freddiemac.com/creditriskofferings/docs/STACR_2015_HQA1_Investor_Presentation.pdf).

times higher than the actual ones during the period from 2008 to 2012. That is, the increase in credit risk during the Great Recession was not captured by the g-fees that the GSEs charge to the lenders to guarantee mortgage payments. An increase in the administrative g-fees by the FHFA from 2012 onwards was minimal compared to the pricing of credit risk by the market. However, the drop in credit risk after 2016 and until early 2020 resulted in the g-fees to be higher than the market pricing.

The second simulation exercise in Table 7 concerns the increase in credit defaults due to the Covid pandemic. For this exercise the funding costs stays constant at the January 2020 level (1.14% 5-year CD rate and 1.05% origination cost). The Mortgage Bankers Association estimated that the average mortgage default rates increased from 1.58% to 3.34% in the second quarter of 2020. This increase in default rates would have caused an increase in mortgage rates of 21% if the government guarantees and monetary policy interventions were not in place.

Figure $A3$ shows the market-implied mortgage rates derived by our model and the simulation exercise, first keeping the funding costs constant, and second varying the funding cost as the 5-year CD rate. The market-implied mortgage rates, when accounting for funding cost, follow the trend of the CD rates, from 1991 up to 2007. Then, the increased default probabilities force the market-implied mortgage rates to derail from the trend, as the market demands higher compensation for the increased credit risk.

6 Conclusions

This paper analyzed the market for Credit Risk Transfers (CRTs) and the Harvey and Irma Hurricanes that hit the U.S. in 2017. We showed that markets priced the credit risk generated by the hurricanes. We created a unique database of CRT securities. Then we exploited that CRTs are heterogenous in the geographical exposure of their underlying pools of mortgages to the hurricanes, in the LTVs of such pools, and in the subordination of their tranches. We found that for the riskiest CRTs the hurricanes increased spreads by 10% 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 estimate how changes in default probabilities change the cost of mortgage credit in absence of the government guarantees. For example, for the Global Financial Crisis mortgage rates would have increased by 29% absent government guarantees and monetary policy interventions. Our results can inform the quantitative literature that studies credit risk in private markets, as well as the debate about housing finance reform.

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Figures

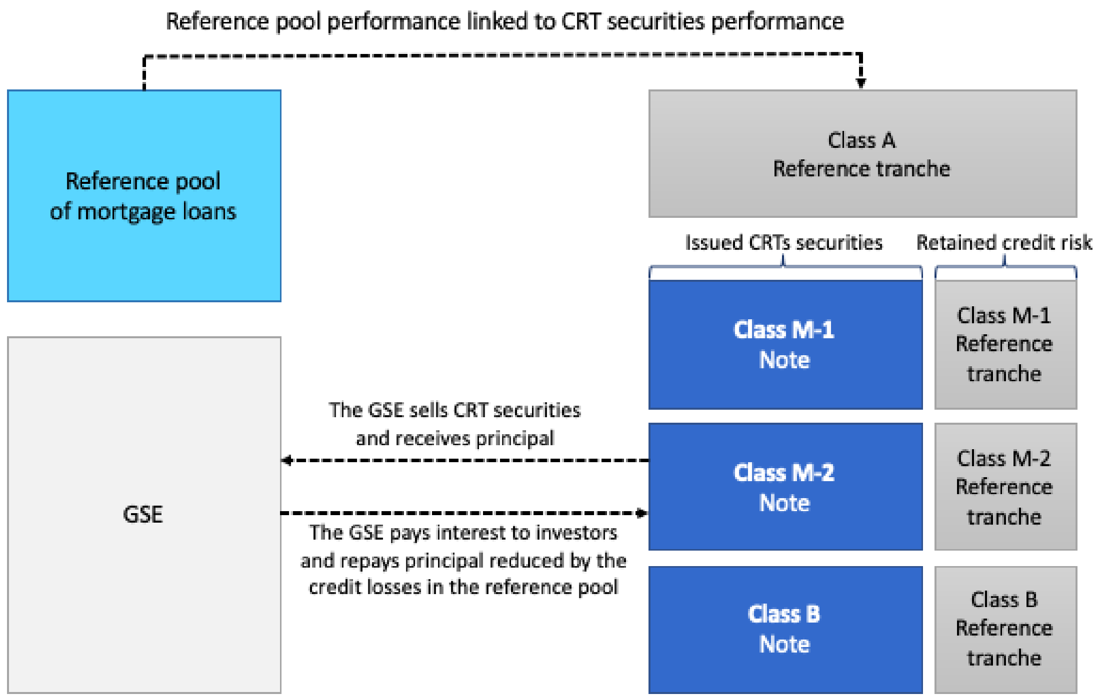


Figure 1. Example Credit Risk Transfer transaction. The figure shows an example of CRT transaction linked to a reference pool of loans. Credit losses on the reference pool reduce the obligation of the GSE to pay interest and repay principal on the CRT securities. This example contains a junior tranche (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. Source: GSEs.

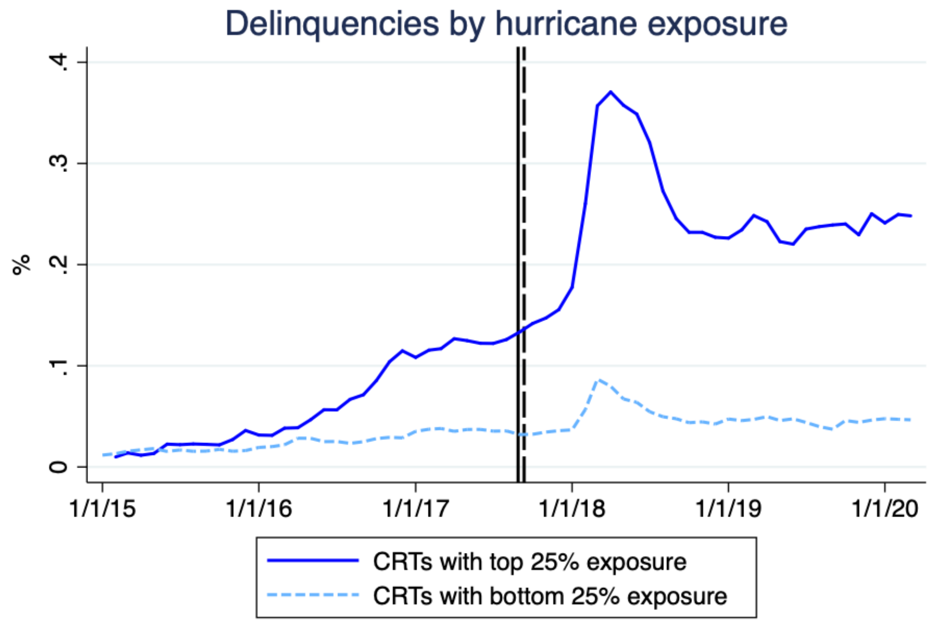


Figure 2. Delinquencies in pools of mortgages for CRTs with different geographical exposure to Hurricanes Harvey and Irma. The figure plots the average share of unpaid principal balance (delinquent for more than 120 days) for CRT mortgage pools that had the highest and lowest geographical exposures to the hurricane-hit areas. 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.

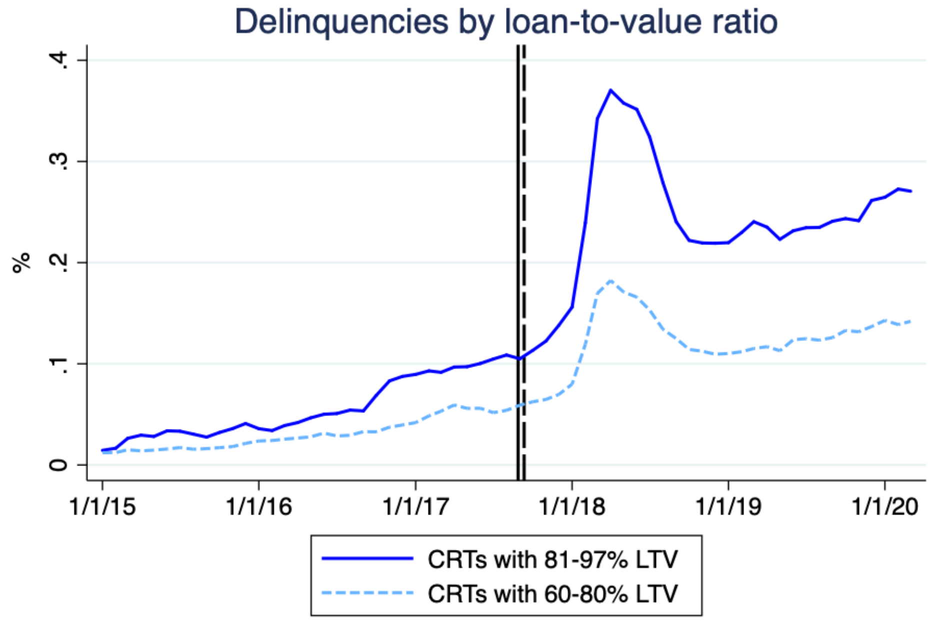
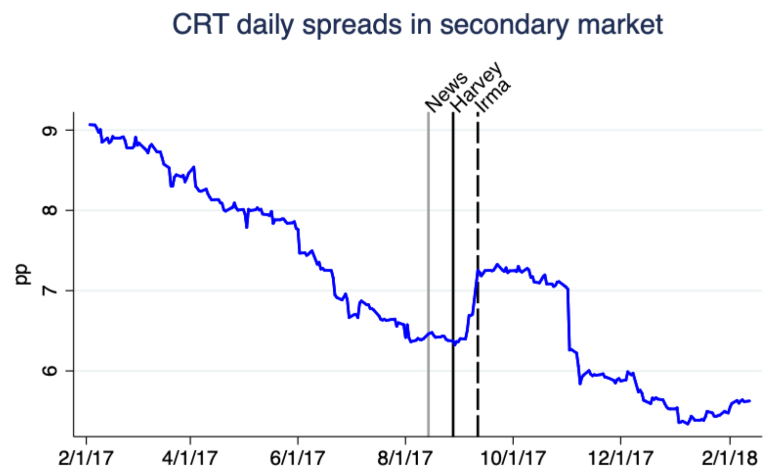


Figure 3. Delinquencies in pools of mortgages for CRTs with different loan-to-value. The figure plots the average share of unpaid principal balance (delinquent for more than 120 days) for CRT mortgage pools with different LTVs. The solid vertical line indicates August 28, 2017, which is the first trading 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.



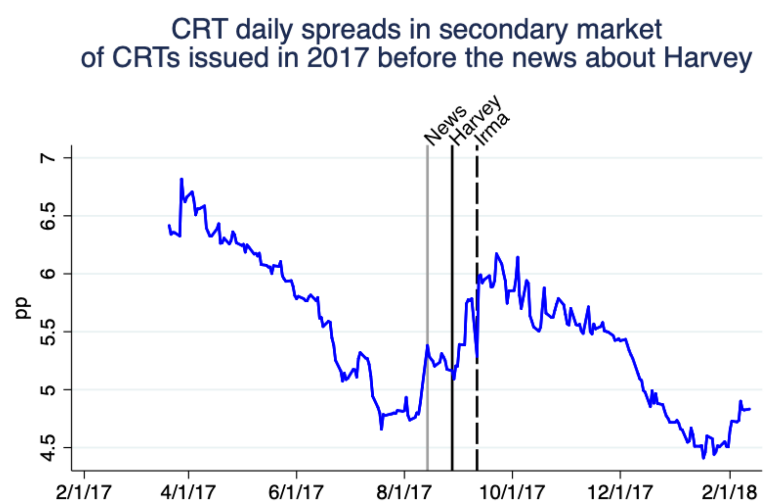


Figure 4. Spread of CRTs during Hurricanes Harvey and Irma. The top figure plots the average daily spreads (yield to maturity minus one month U.S. Dollar Libor) in the secondary market of the junior CRT tranches. The bottom figure restricts the sample to only the junior CRT tranches issued between January 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.

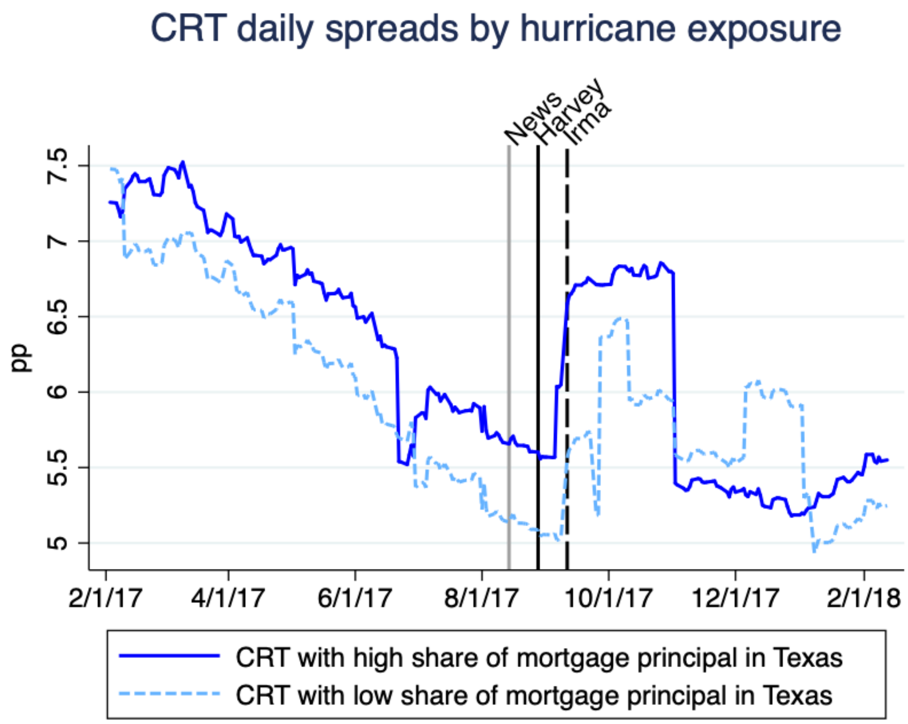


Figure 5. Spreads for CRTs by ex-ante hurricane exposure. The figure plots the daily spread (yield to maturity minus one month U.S. Dollar Libor) in the secondary market of two CRTs that only differ in their geographical concentration to Texas. One CRT's original principal balance was located 7.03% in Texas, and 5.48% in Florida, whereas the other CRT was 3.62% in Texas, and 2.78% in Florida. These CRTs from Freddie Mac were issued in the second quarter of 2015, they have the same original term to maturity, they are linked to the most junior tranche, and they have LTV average ratios of 76% and 74% respectively. 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.

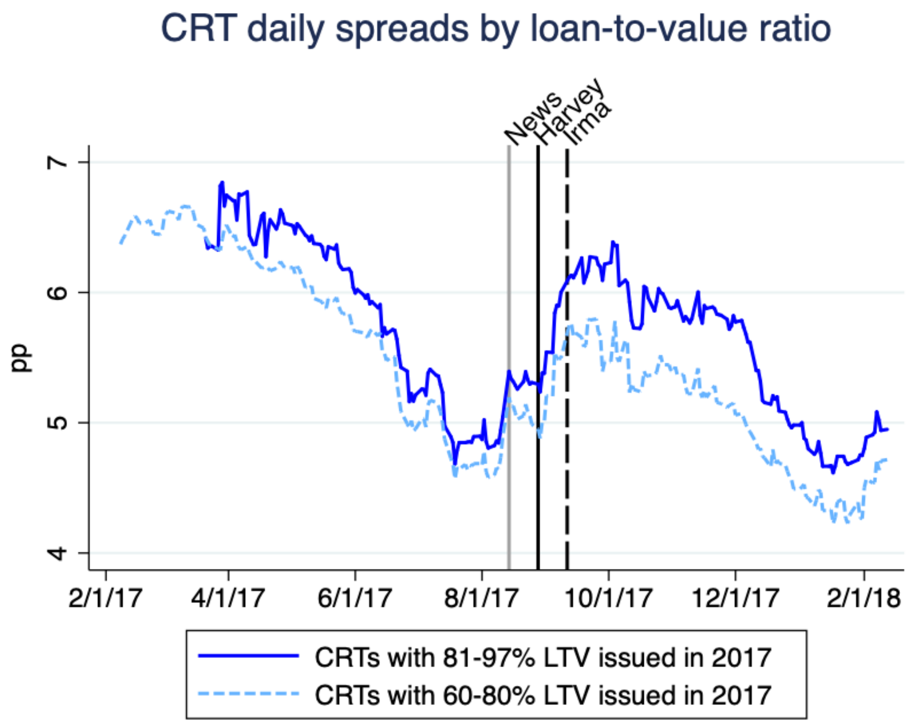


Figure 6. Spreads for CRTs by loan-to-value ratios. The figure plots the average daily spread (yield to maturity minus one month U.S. Dollar Libor) in the secondary market for junior tranches issued in 2017 before Hurricanes Harvey and Irma, with high and low loan-to-value ratios. The first solid vertical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

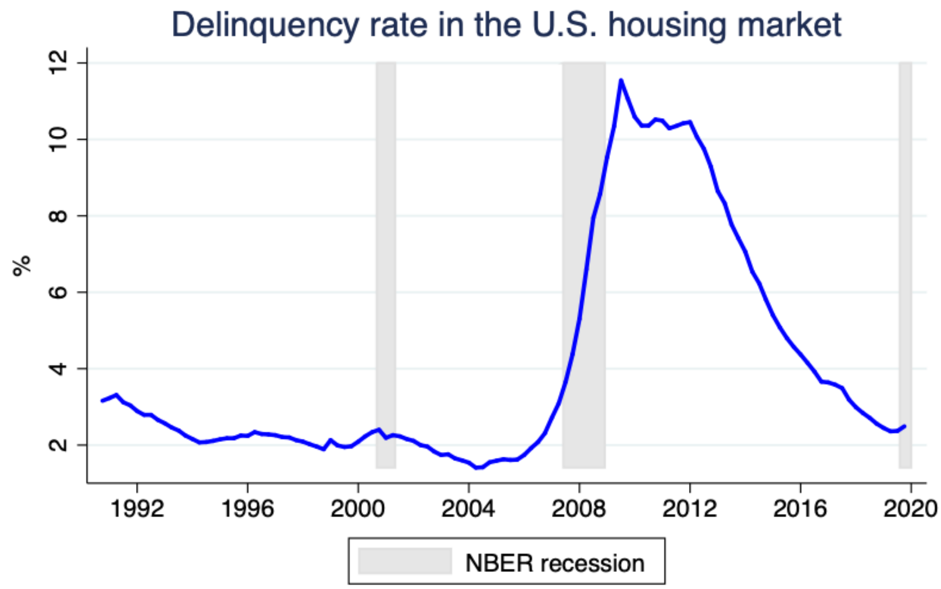


Figure 7. Delinquency rate in the U.S. housing market. The figure plots the delinquency rate on single-family residential mortgages in the U.S. from 1992 to 2020. The data are quarterly. Source: FRED.

Figure 8. Market implied and actual guarantee fees. The solid line plots time series of the simulated market implied g-fees using the model of Section 5, the actual delinquencies, and the actual 5-year average certificate of deposit (CD) rates. The dashed line plots the actual average g-fees of mortgages guaranteed by the GSEs.

Tables

Table 1. Summary statistics: Securities in the sample

		Number of securities		
		Fannie Mae	Freddie Mac	All
Loan-to-Value Ratio	81-97%	27	45	72
	61-80%	42	49	91
Tranches	Junior	15	23	38
	Mezzanine	54	71	125
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 for junior tranches

	Mean	SD	Min	Max
LTV 81-97%				
Spread daily (pp)	7.519	0.790	5.645	9.004
Hurricane landfall dummy	0.524	0.501	0	1
Geographical exposure (%)	6.475	2.777	2.160	9.300
Floater spread (pp)	10.273	1.552	7.950	12.750
Issue by Freddie dummy	0.727	0.446	0	1
LTV 61-80%				
Spread daily (pp)	7.020	0.882	5.020	8.486
Hurricane landfall dummy	0.522	0.500	0	1
Geographical exposure (%)	5.474	2.777	2.170	9.600
Floater spread (pp)	10.249	1.366	7.550	12.250
Issue by Freddie dummy	0.614	0.488	0	1
Ten year treasury rate (%)	2.170	0.066	2.050	2.280
Two year treasury rate (%)	1.358	0.056	1.270	1.460

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, as reported by Thomson Reuters Eikon. The landfall is a dummy that 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 Hurricane Harvey and Hurricane 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 number of observations (daily transactions) is 231 for LTV 81-97% and 272 for LTV 61-80%. The statistics are calculated for the window of 2 weeks before and after the treatment date, that is, from August 28 to September 25, 2017.

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

	Spread					
Window (weeks)	±2	±3	±4	±5	±6	±7
LTV 81-97%						
Landfall × exposure	0.106***	0.094***	0.081***	0.072***	0.061***	0.053***
	(0.015)	(0.014)	(0.012)	(0.011)	(0.010)	(0.010)
Hurricane landfall	0.043	0.066	0.137	0.203**	0.263***	0.296***
	(0.122)	(0.105)	(0.097)	(0.090)	(0.083)	(0.078)
Exposure	0.119***	0.125***	0.131***	0.134***	0.140***	0.150***
	(0.023)	(0.020)	(0.018)	(0.017)	(0.015)	(0.014)
Observations	231	341	451	561	671	781
R-squared	0.837	0.816	0.795	0.779	0.764	0.754
LTV 61-80%						
Landfall × exposure	0.072***	0.075***	0.072***	0.072***	0.072***	0.070***
	(0.012)	(0.010)	(0.009)	(0.008)	(0.007)	(0.007)
Hurricane landfall	0.234***	0.184***	0.173***	0.170***	0.164***	0.173***
	(0.086)	(0.070)	(0.063)	(0.057)	(0.052)	(0.049)
Exposure	0.083***	0.068***	0.055***	0.054***	0.054***	0.060***
	(0.015)	(0.012)	(0.011)	(0.009)	(0.009)	(0.008)
Observations	272	402	532	662	792	922
R-squared	0.904	0.899	0.895	0.895	0.891	0.881

Standard errors are in parentheses. The dependent variable (spread) is measured in percentage points. Controls are the "floater" spread at issuance, a dummy for Freddie, the 10-year and 2-year treasury rates, and dummies for the year of issuance of the CRT security. The sample and all variables are as defined in Table 2. *** $p<0.01$, ** $p<0.05$.

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

	Spread					
Window (weeks)	±2	±3	±4	±5	±6	±7
LTV 81-97%						
Landfall × exposure	-0.003	-0.006	-0.010	-0.014*	-0.017**	-0.019***
	(0.012)	(0.010)	(0.008)	(0.007)	(0.007)	(0.006)
Hurricane landfall	0.105	0.120*	0.140**	0.188***	0.218***	0.244***
	(0.085)	(0.068)	(0.061)	(0.055)	(0.050)	(0.046)
Exposure	-0.064***	-0.062***	-0.060***	-0.058***	-0.057***	-0.056***
	(0.018)	(0.015)	(0.013)	(0.012)	(0.010)	(0.010)
Observations	1,152	1,692	2,231	2,771	3,311	3,851
R-squared	0.692	0.691	0.690	0.689	0.690	0.691
LTV 61-80%						
Landfall × exposure	0.007	0.008	0.010	0.007	0.004	0.003
	(0.011)	(0.009)	(0.008)	(0.007)	(0.006)	(0.006)
Hurricane landfall	0.070	0.061	0.052	0.087*	0.109***	0.127***
	(0.067)	(0.054)	(0.049)	(0.045)	(0.040)	(0.038)
Exposure	0.092***	0.095***	0.096***	0.101***	0.104***	0.106***
	(0.014)	(0.011)	(0.010)	(0.009)	(0.008)	(0.007)
Observations	1,368	2,011	2,650	3,295	3,940	4,588
R-squared	0.756	0.751	0.744	0.740	0.739	0.737

Standard errors are in parentheses. The dependent variable (spread) is measured in percentage points. Controls are the “floater” spread at issuance, a dummy for Freddie, the 10-year and 2-year treasury rates, and dummies for the year of issuance of the CRT security. The sample and all variables are as defined in Table 2. *** p<0.01, ** p<0.05, * p<0.1.

Table 5. Impact of hurricanes on spread: Junior tranches

	Spread					
Window (weeks)	±2	±3	±4	±5	±6	±7
LTV 81-97%						
Change in CRT spread (pp)	0.729	0.677	0.663	0.666	0.660	0.639
LTV 61-80%						
Change in CRT spread (pp)	0.629	0.595	0.568	0.562	0.560	0.555
Change in one month Libor (pp)	0.001	0.012	0.012	0.012	0.140	0.140

This table shows the marginal change in the CRT spreads of junior tranches after the hurricanes' landfall, for different time windows before and after the landfall. The estimates use the coefficients from the diff-in-diff in Table 3 and the average geographical exposure from Table 2. For example, for a 2-week window the junior tranche with high LTV had an increase in spread equal to $(0.106 \times 6.47) + 0.043 = 0.729$ percentage points (pp). The one month U.S. Dollar Libor matches the data used in the diff-in-diff and it applies the corresponding monthly rate on the first day of the month to all days of the month.

Table 6. Calibration strategy

Parameter	Value	Description
Exogenous parameters		
$\frac{P_h}{L}$	1.215	Inverse of a 82.3% loan-to-value ratio
r_0^d	0.910%	Lender's cost of funds: 5y CD rate
r_0^w	1.170%	Lender's origination cost
r_0^m	8.442%	Avg mortgage rate 2 weeks before landfall
π_0	9.512%	Avg default probability 2 weeks before landfall
$\pi_1 - \pi_0$	1.456 pp	Change in default probability due to landfall
Targets		
$r_1^m - r_0^m$	0.728 pp	Mortgage rate change estimated in Section 4 (Table 5)
$\frac{d\gamma_t}{d\pi_t}\Big\|_{t=0}$	-0.500	Avg slope of equation (6)
Endogenous parameters		
a	0.551	Value of a in equation (6)
b	0.113	Value of b in equation (6)

This table lists the parameters (exogenous and endogenous) and targets used in Section 5. The equation (6) is the relation between the market expectation of the recovery rate γ and the default probability π.

Table 7. Mortgage rates under stress without government guarantees

Initial level of default rate	Change in default rates	Change in mortgage rates	Description
1.35%	3.89 pp or 288% increase	1.38 pp or 29% increase	During the Great Recession (2007-2011)
1.58%	1.76 pp or 114% increase	0.55 pp or 21% increase	During the Covid pandemic (second quarter 2020)

This table simulates the model of Section 5 to calculate how much the mortgage rates in periods of stress would change if there were no GSEs and the model matches the empirical estimates of Section 4.

Online Appendix (Not for Publication)

A1. Credit Risk Transfer Cashflows

In this section we describe the sequence of cashflows from CRT notes to investors. We consider a given time t, measured in months, during the life of the CRT note in which L_t is the outstanding principal of the CRT note at the beginning of the period. Then we can derive the following quantities for the CRT note at time t:

$$\begin{aligned}
&\text{Scheduled interest:} && I_t = (r_t^L + s)\ L_t, \\
&\text{Principal prepayment:} && PREP_t = p_t\ L_t, \\
&\text{Mortgage default:} && DEF_t = d_t\ L_t,
\end{aligned}$$

where r_t^L is the one month U.S. Dollar Libor, s is the floater spread, p_t is the share of outstanding principal that was prepaid between time $t-1$ and t, and d_t is the share of outstanding principal that defaulted between time $t-1$ and t.

Given the scheduled principal payments $SCHED_t$, prepayments and defaults, the outstanding principal of the CRT note for the following month $t+1$ is given by

$$L_{t+1} = L_t - SCHED_t - PREP_t - DEF_t,$$

or equivalently,

$$L_{t+1} = (1 - p_t - d_t)\ L_t - SCHED_t.$$

The new outstanding principal is equal to the previous month principal minus scheduled principal payments, prepayments and defaults. If, for example, 100% of the mortgages default between time $t-1$ and t, then $d_t = 1$ and $SCHED_t = 0$ and the outstanding principal at time $t+1$ is eliminated. Conversely, if nobody from the homeowners prepay their mortgages or default between time $t-1$ and t, then $p_t = d_t = 0$, and $L_{t+1} = L_t - SCHED_t$, that is the outstanding principal is reduced by the scheduled principal payments.

The scheduled principal payment, mortgage prepayment and interest rate sum up to the total cash flow of the CRT note at the given month

$$CF_t = SCHED_t + PREP_t + I_t.$$

Online Appendix: Figures

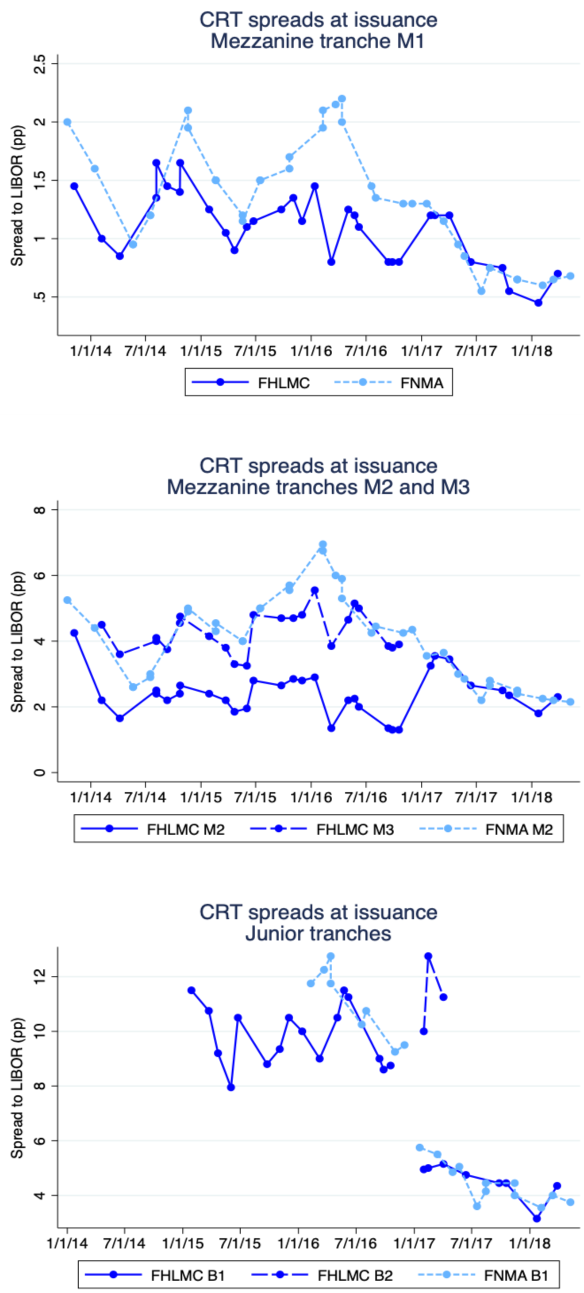


Figure A1. Spread of Credit Risk Transfers in the Primary Market. The figures plot the spreads at issuance in annualized percentage points, for different tranches of CRTs and by GSE issuer. The interest rate paid by the CRT is one month U.S. Dollar Libor plus this spread, applied on the principal outstanding of the CRT. Source: Bloomberg, GSEs.

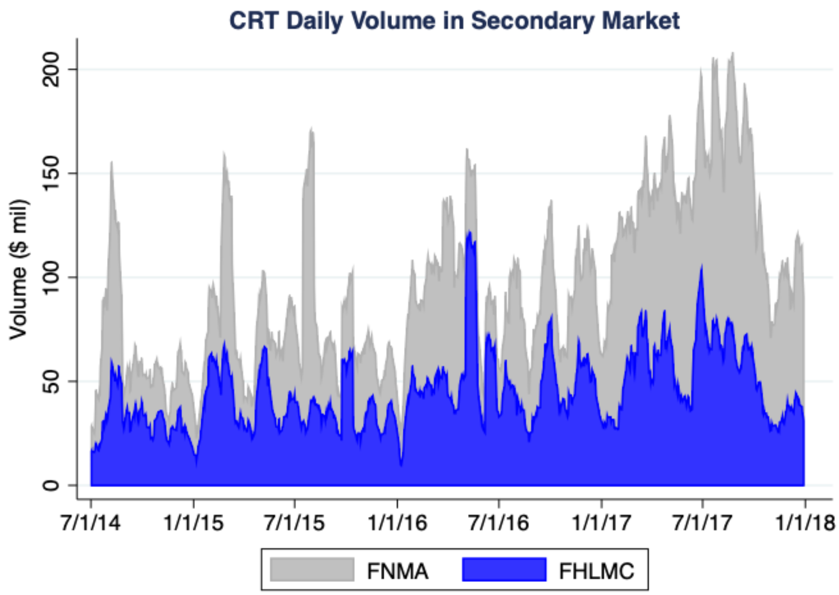


Figure A2. Historical Trading Volume of Credit Risk Transfers. The figure plots the time series of the total daily volume (20 days moving average) of the transactions in the secondary market of all CRTs from Fannie Mae (FNMA) and Freddie Mac (FHLMC). The trade size per transaction is capped to $5 million. Source: TRACE.

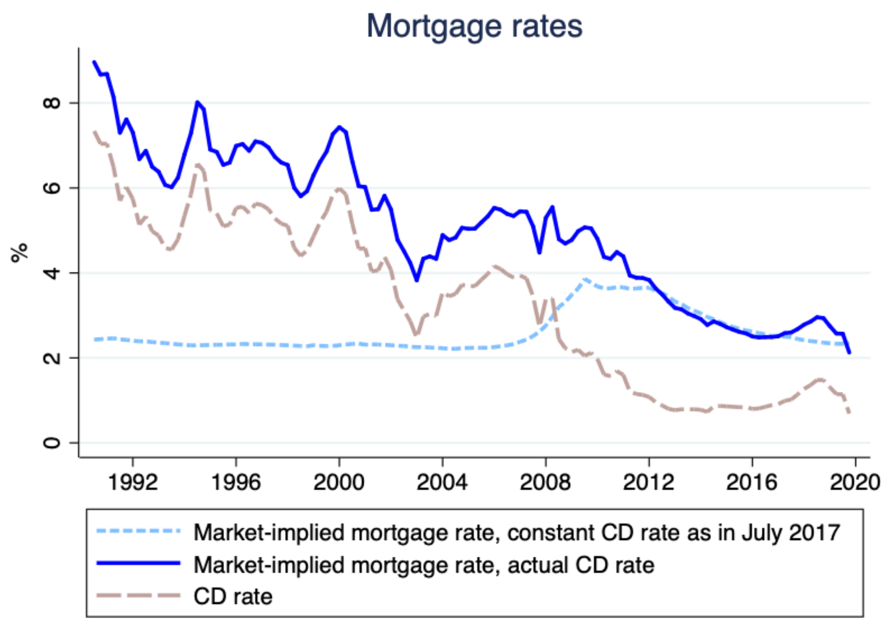


Figure A3. Market Implied Mortgage Rates for GSE Mortgages. The figure plots the estimated market implied mortgage rates based on our model, using (a) constant 5-year average CD rate equal to the value in July 2017 and (b) the actual 5-year average CD rate. The figure also plots the 5-year average CD rate.

Online Appendix: Tables

Table A1. Spreads of junior tranches controlling for liquidity

	Spread					
Window (weeks)	±2	±3	±4	±5	±6	±7
LTV 81-97%						
Landfall × exposure	0.103***	0.092***	0.081***	0.072***	0.061***	0.052***
	(0.015)	(0.013)	(0.012)	(0.011)	(0.010)	(0.010)
Hurricane landfall	0.050	0.078	0.139	0.202**	0.268***	0.302***
	(0.120)	(0.105)	(0.097)	(0.090)	(0.084)	(0.078)
Exposure	0.100***	0.114***	0.130***	0.134***	0.139***	0.149***
	(0.023)	(0.020)	(0.018)	(0.017)	(0.016)	(0.014)
Observations	231	341	451	561	671	781
R-squared	0.843	0.820	0.795	0.779	0.764	0.754
LTV 61-80%						
Landfall × exposure	0.071***	0.074***	0.071***	0.071***	0.072***	0.069***
	(0.012)	(0.010)	(0.009)	(0.008)	(0.007)	(0.007)
Hurricane landfall	0.247***	0.188***	0.175***	0.172***	0.168***	0.179***
	(0.088)	(0.071)	(0.063)	(0.057)	(0.052)	(0.050)
Exposure	0.083***	0.068***	0.055***	0.054***	0.054***	0.060***
	(0.015)	(0.012)	(0.011)	(0.009)	(0.009)	(0.008)
Observations	272	402	532	662	792	922
R-squared	0.904	0.899	0.895	0.895	0.891	0.881

Standard errors are in parentheses. The sample consists of all Fannie Mae's and Freddie Mac's CRTs from the junior tranches issued from July 23, 2013 to August 15, 2017. The daily spread is the yield to maturity minus the one month U.S. Dollar Libor, as reported by Thomson Reuters Eikon. The landfall is the first trading date after the first landfall in the U.S. coast of Hurricane Irma on September 11th, 2017. The exposure to Hurricane Harvey and Hurricane Irma is estimated by Fannie Mae and Freddie Mac as the percentage of unpaid principal balance in the reference pools of loans secured by houses in the counties affected by the hurricanes. We control for the "floater" spread at issuance, GSE issuer, 10-year and 2-year treasury rates, the year of issuance of the CRT security, and the daily transaction volume. *** p<0.01, ** p<0.05.