Pricing Mortgage Stress. Lessons from Hurricanes and the Credit Risk Transfers*

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Abstract

We study a unique, hand-collected database of Credit Risk Transfers (CRTs) linked to U.S. mortgages. Exploiting heterogeneous CRT exposure to hurricane default risk, we estimate how markets price default risk. Then we calibrate a model of credit supply to match those estimates. Fannie and Freddie give g-fee subsidies that prevent internalizing natural disaster risk. Market-implied mortgage rates in hurricane-prone counties would be 15% higher than inland. The subsidy provides countercyclical stabilization. For example, it lowered mortgage rates by 41% during the 2009 Crisis. This subsidy increases mortgage originations, housing prices, consumption and GDP.

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

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1 Introduction

In this paper we analyze a hand-collected database of the new market for U.S. mortgage Credit Risk Transfers (CRTs) to study two related questions: How would private mortgage markets price credit risk from natural disasters? What would happen to mortgage rates if they were priced based on the market? These questions are unexplored even though an increasingly large literature shows that climate risk is priced in housing markets.[1] U.S. mortgage markets are characterized by 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 (the 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, at the moment, most mortgage credit risk in the U.S. is directly or indirectly priced by the government. One of the few exceptions is the Credit Risk Transfers market that we study.

Potential underpricing of mortgage credit risk provides incentives for lenders to originate risky mortgages as Elenev, Landvoigt and Van Nieuwerburgh (2016) theorize. GSE subsidies 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 began issuing in 2013 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 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 that different CRT securities have heterogeneous exposure to a positive shock to default risk, caused by Hurricanes Harvey and Irma. The hurricanes were unforeseen events that suddenly generated

[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.

large expectations of local mortgage defaults.[4] Second, we analyze a model of credit supply calibrated to match our empirical estimates. We solve for mortgage rates and run simulations like Campbell and Cocco (2015). We also 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. According to our estimates it is small except for the Great Recession. Finally, in the spirit of Walentin (2014), we use a structural vector-autoregression (VAR) model to estimate the aggregate effects of the g-fee subsidy.

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 Thomson Reuters Eikon, data on delinquencies in each CRT reference pool from the GSEs, loan-level characteristics and credit performance data from Freddie Mac. To our knowledge, this is the most detailed database about CRTs. We also use data of hurricane occurrences from the Federal Emergency Management Agency (FEMA), historical mortgage delinquencies and macroeconomic variables from FRED.

CRTs have heterogeneous exposure to the hurricanes because CRTs differ 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. This is the first paper to show and exploit these heterogeneities. For example, even if 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 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. 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 CRTs, that is, junior tranches with high LTVs, the yield spread to Libor is 11% higher than average. Yield spreads for the mezzanine tranche with the highest priority, which is less exposed to risk, increase by 4% 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).

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 use the previous results to calibrate a model of mortgage credit supply. This provides a structural way to extrapolate from mortgage defaults into the market price of mortgage credit risk. Our calibration matches the estimates obtained from the CRT market. We do not use any information from administrative g-fees to calibrate the model. Our first simulation studies differences in the exposure to hurricanes among U.S. counties. Market-implied mortgage rates in counties that are hit almost every year by a tropical storm or hurricane would be 15% 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.

Our second type of simulations analyzes the stabilization role of the GSEs. Given historical default rates, we compute time series of market-implied mortgage rates and implied guarantee fees (g-fees). The differences are small most of the time except for the Great Recession. That is, most of the time, the GSEs are pricing credit risk exactly as markets would do. However, during the Great Recession mortgage rates would have increased by 1.79 percentage points above the pre-crisis level of 4.37%, that is a 41% increase, if these rates reflected market pricing of credit risk. Thus, during episodes of market stress, the GSEs imply a countercyclical policy with strong subsidies to mortgage rates.

The previous result complements Fieldhouse, Mertens and Ravn (2018), who show that the portfolio activity of the GSEs is an important macroeconomic policy. We instead show the importance of the g-fee policy. This result contributes to the current debate on the expected role of the federal government in the housing finance system. As discussed by Frame, Wall and White (2013) the expected role of the federal government in the broader housing finance system is in dispute. The expected role ranges from no role to insuring against only extreme or tail events to insuring against all losses. Our paper shows that absolutely no government intervention would exacerbate the effects from a financial crisis because in such crises stress in markets would translate into a mortgage credit crunch with negative effects for the housing market.

In the third part of the paper we study the macroeconomic effects of the model implied g-fee subsidy. We follow Walentin (2014) who analyzed the macro effects of mortgage spreads using a structural VAR estimation. Increases in the g-fee subsidy generate higher mortgage originations, house prices, aggregate consumption and GDP. These effects are consistent with the theory that mortgage rate subsidies are credit supply shocks. The effects of the g-fee subsidy are equivalent in magnitude to the effects of the portfolio activity of the GSEs studied by Fieldhouse, Mertens and Ravn (2018).

This paper contributes to several literatures. First, it contributes to the literature that studies financial consequences of natural disasters. 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), and on managers perception of disaster risk (Dessaint and Matray 2017). The climate finance literature has shown that geographical exposure to climate risk is priced in municipal bonds (Goldsmith-Pinkham et al. 2020), house prices (Bernstein, Gustafson and Lewis 2019), and long-term interest rates (Giglio et al. 2021). It also causes more delinquencies and foreclosures (Issler et al. 2019). Our contribution is to implement the first study of the effects of default risk due to hurricanes on mortgage pricing.

This paper also contributes to the housing finance literature. Papers 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 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. Our estimates contribute to the literature that studies the macroeconomic effects of the U.S. government housing policies (e.g. Fieldhouse, Mertens and Ravn 2018; Passmore and Sherlund 2018) by showing a new channel through the g-fee subsidy. Our estimates speak more broadly to the literature that studies the macroeconomic effects of mortgage rates (e.g. Kydland, Rupert and Šustek 2016; Walentin 2014), and credit risk (e.g. Campbell and Cocco 2015; Garriga and Hedlund 2020).

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 analyzes the calibrated model of credit supply. Section 6 estimates the macroeconomic effects of the g-fee subsidy. 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% and 97%, and the low LTV between 60% 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.

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 and those retained by the GSEs, 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 cross-validate these data with data on CRT secondary prices from TRACE. From TRACE we collect the daily transaction volume of CRTs in the secondary market. 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 simulations we use extra data sources that we discuss in those sections.

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.[5]

4.1 Identification strategy

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 to 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.

In addition to the geographical composition of their reference pool, CRTs are also heterogeneous in the LTV of the mortgages in the pool. Figure 4 shows that, following the hurricanes, CRTs whose underlying pools had higher LTV ratios (80-97%) suffered higher delinquencies than CRTs whose pools had low LTV ratios (60-80%).

Figure 5 plots the spreads of the junior CRTs, issued in 2017, 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.

[5] 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.

A third source of heterogeneous exposure to credit risk is tranching because losses are allocated inversely to the seniority of the tranche. Figure 6 shows spreads in the junior tranches. It shows that investors 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. Figure A1 in the Online Appendix shows that, while 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.[6]

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. 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 shown above finally did not translate into defaults and foreclosures. The federal government and the GSEs granted extraordinary and immediate 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. Nevertheless, even if the hurricanes did not cause major ex-post surge in defaults, ex-ante markets were stressed as we discussed in Figures 3, and 5 to 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 high and low LTV CRTs and for junior and mezzanine tranches. Thus, we compare different dimensions (ge-

[6] 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 A2 in the Online Appendix shows how the average spreads from Freddie's junior CRTs compare with Fannie's junior CRTs.

ographical exposure, LTV 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 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. 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 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. 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 3 to 7 weeks before and after the treatment date.

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 3 to 7 weeks. For example, the junior CRTs with high LTV increase their spreads by 0.44 percentage points (pp) five weeks after the landfall, compared to five weeks 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 0.047 pp in the five-week window.

It is important to note that after controlling for the CRT fixed effects the geographical exposure on its own is not a significant factor affecting the spreads. This is what we would expect, the geographical exposure to specific counties in Texas and Florida should become relevant only in the weeks that follow the landfall. Overall, the spreads of the junior CRT tranche with high LTV and the average exposure to hurricanes increase on average by 0.715

percentage points (pp) in the five-week window.[7]

Table 4 summarizes the key takeaways from the empirical exercise for junior tranches. The CRTs with high LTV increase the spreads on average by 0.704 pp, while the CRTs with low LTV increase the spreads on average by 0.596 pp.[8] To put these results into perspective, the increase in spreads is 10.51% of the initial level of spread before the hurricanes for high LTV, and 9.47% of the initial level of spread before the hurricanes for low LTV.

Concerning the mezzanine tranches, Tables A1 and A2 in the Online Appendix have the results from the diff-in-diff analysis. Table A1 focuses on tranche M1, which has the highest hierarchy from all the tranches sold to investors. Table A2 reports tranches M2 and M3, which are only protected by the junior tranches. As expected, the results are stronger for tranches M2 and M3. For the low-risk mezzanine tranche M1 the results are either not significant or weakly significant (p-value > 0.01). Table A3 in the Online Appendix recaps the key effects for the mezzanine tranches. The magnitudes are smaller than for the junior tranches. Spreads of the mezzanine tranche M1 with high LTV increased by 0.036 pp on average, which is 4.14% from the average level of spreads before the hurricanes. Spreads of the mezzanine tranches M2 and M3 increased by 0.159 pp and 0.164 pp on average for high and low LTV correspondingly. This is an increase of 6.6 to 6.9% from the pre-hurricane levels.

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 A3) shows higher trading volume during the months of the hurricanes, July and August 2017. That is, not only there was no sign of illiquidity at the time of the hurricanes, but in fact, trading volume increased.

Another concern might be that the risk premia increase not because of higher default risk but because of higher prepayment risk. For example, as insurance contracts pay out for damaged homes in the areas affected by a hurricane, households might use the insurance payment to prepay their mortgages. If the CRT market was pricing prepayment risk, we would expect the risk premium to increase over time, as insurance pays out. 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

[7] $(0.047 \text{ (fromTable 3)} \times 5.855 \text{ (fromTable 2)}) + 0.44 \text{ (fromTable 3)} = 0.715\ pp.$

[8] These estimations assume the average geographical exposure in the data: 5.855% for high LTV and 4.986% for low LTV, from Table 2.

spreads are due to increased credit risk and not due to increased prepayment risk.

Finally, the results are robust to non-symmetric intervals and different controls. We get similar results when using a fixed interval before the hurricanes (e.g. five weeks before) and varying the interval after the hurricanes. The results do not change when we remove from the sample the days between the two landfalls. Also, the results are robust to using an alternative control for liquidity, the number of transactions of each individual CRT.

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 build on those estimations to compute mortgage rates implied by the CRT market. To do so, first we set up a model of credit supply that we calibrate to be consistent with the previous section. Since the CRT market only contains information on the supply of credit, our modeling approach focuses on the lenders. Then we analyze two types of credit risk shocks. First, we look at cross-sectional differences in the exposure to hurricane risk. Second, we study shocks that increase default risk like the Covid-19 pandemic or the 2008 Global Financial Crisis. For these shocks we focus on the time-series dimension. We measure the difference between how the GSEs price credit-risk and how markets would do it. The gap is small most of the time, except for the Great Recession.

5.1 Setup

We model mortgages as long-term loans with real payments, that is, we abstract from the inflation channels studied in Garriga, Kydland and Šustek (2017). 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,

$$M_t = \lambda M_{t-1}. \tag{2}$$

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,

$$x_t = (1 - \lambda + r_t^m)M_{t-1}. \tag{3}$$

We assume that 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,

$$V_t = (1 - \pi_t)(x_t + \frac{1}{1 + r_t^d} V_{t+1}) + \pi_t \min \left(\gamma_t P_h H_t, x_t + \frac{1}{1 + r_t^d} V_{t+1} \right), \tag{4}$$

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.

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

$$V_t = (1 + r_t^d + r_t^w)M_{t-1} \tag{5}$$

Or, in words, 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 (r_t^g) as the excess of the mortgage rate over the cost of funds and operating cost of the lender. That is,

$$r_t^g = r_t^m - r_t^d - r_t^w. \tag{6}$$

In other words, the guarantee 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.

5.2 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 5 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 (4) 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 82.3%, which is the average 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 4 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 with high LTV to be π_{-1} =1.78% ($\frac{0.0178\%}{1\%}$). According to Figure 4 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 $r^m_{-1} = 7.214\%$, the average spread of high LTV junior CRTs right before the first landfall.

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

$$\gamma_t = 1 - a\pi_t^b. \tag{7}$$

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 4. The estimates show an average increase in the mortgage rate of $r^m_0 - r^m_{-1} = 0.704$ 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 (7) , that is

$$\frac{d\gamma_t}{d\pi_t} = -ab\pi_t^{b-1}, \tag{8}$$

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

5.3 Pricing hurricane risk across U.S. counties

To price the credit risk caused by hurricanes, first we measure the frequency of occurrence of hurricanes and tropical storms in each U.S. county. We obtain the data from 2000 to 2019 from FEMA. Then we merge those data with loan-level characteristics and credit performance data from Freddie Mac. The goal is to estimate the probability of mortgage delinquency and defaults due to hurricane risk for each county. Finally, we input such probabilities into the credit supply model of Sections 5.1 and 5.2. We compute 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. Our sample contains one million single-family mortgage loans originated from 2000 to 2019 (random sample of 50,000 mortgages per year), covering all the U.S.

Figure A4 in the Online Appendix shows the average number of hurricanes and tropical storms that hit each county. These storms are especially frequent in Florida, Louisiana and North Carolina, where storms hit with probability 50% to 95% 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. The rest of the U.S. counties did not experience any hurricane.

Based on the hurricane frequency and an extensive list of mortgage characteristics, we estimate a logit model of the probability of mortgage delinquencies:

$$\ln\left(\frac{P_m}{1-P_m}\right) = \beta_0 + \beta_1 F_m + C_m + u_m, \tag{9}$$

where P_m is the probability that a mortgage becomes delinquent for 120 days or more. 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), 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, whether the property consists of 1, 2, 3 or 4 units, whether there is one or multiple borrowers, and origination year fixed effects. Table A4 shows the result of estimating (9). We find that one more hurricane every year increases the probability of delinquency by 57%.[10]

Figure 8 shows market-implied mortgage rates for each county while keeping the CD rate constant at 0.91% as in July 2017. Counties that are on the path of a tropical storm or hurricane every one to two years have market-implied mortgage rates of 1.76%. Rates for most other counties fluctuate around 1.53%. That is, the market-implied mortgage rate of the most exposed counties is 15% higher than the counties less exposed to hurricanes. However, as discussed by Hurst et al. (2016), effective mortgage rates across counties do not show much heterogeneity. Thus, Figure 8 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.

[10] That is, $\frac{e^{0.283}}{1+e^{0.283}}$.

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, Figure 8 shows 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. Thus, by preventing markets from pricing mortgage credit risk heterogeneously across U.S. counties, the GSEs reduce the internalization of the risk of natural disasters.

5.4 Estimating the GSE g-fee subsidy

We simulate mortgage credit risk in the U.S. in the last thirty years. As a proxy for credit risk we use the mortgage delinquency rate that Figure A5 reports. From the early 1990s to the end of 2006 delinquency rates were slightly decreasing from 3.3% to 1.9%. Then at the beginning of 2010 delinquencies jumped to 11.5%. Delinquencies remained at levels close to 10.3% up to mid-2012. Then they started decreasing, and at the beginning of 2020 they reached their lowest level since the Great Recession at 3.4%.

As before we input such probabilities into the credit supply model and compute time series of market-implied mortgage rates. Our calibration matches the estimates obtained from the CRT market in the empirical section, we do not calibrate using any information from administrative g-fees.

Figure 9 plots the market-implied g-fees derived from our model and the actual administrative g-fees over the last 30 years. Both are annual and reflect the credit risk of the respective year. Most of the time the difference between those series is small. That is, except for the Great Recession, the GSEs are pricing credit risk exactly as markets would do. During the period from 2008 to 2012 the market-implied g-fees were about five times higher than the actual ones. That is, the increase in credit risk during the Great Recession was not covered by the g-fees that the GSEs charge to the lenders to guarantee mortgage payments, even if the GSEs increased a bit their administrative g-fees in 2012. Market implied g-fees and administrative g-fees became again aligned between 2017 and early 2020 once credit risk receded.

Table 6 looks in detail at the Great Recession period.[11] It compares July 2007 and 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 0.074% operating cost). We use the time series of the single-family guarantee fees from 1991 to 2019 from the GSEs Financial Reports, and the historical delinquency rates from 1991 to 2021 for single-family residential mortgages from FRED. We also collect the time series

[11] Appendix B describes another simulation exercise that concerns the increase in credit defaults due to the Covid pandemic, using a different data source for delinquency rates.

of the average 5-year certificate of deposits (CD) rates from 1991 to 2021 from Bankrate[12], and origination costs at specific dates from the FHFA Monthly Interest rate Survey (FHFA 2020). Table 6 shows that if the rates reflected market pricing of risk, the jump in delinquencies and default rates would have caused an increase in mortgage rates of 1.79 percentage points from the initial level of 4.37%. This is an increase of 41%. Another way to see this result is in terms of the g-fees. The initial level of the g-fees was 0.36% in July 2007.[13] Market-implied g-fee would have been five times larger in July 2011. Thus, the GSEs, by preventing such market jumps are operating as stabilization policy.

Based on the previous results, we can compute the g-fee subsidy that the GSEs apply relative to markets as

$$subsidy = r_t^g - r_t^{adm}, \tag{10}$$

where r_t^g is the market-implied g-fee estimated from equation (6), and r_t^{adm} is the effective (or administrative) g-fee set by the GSEs. That is, the g-fee subsidy is the difference between the rate reflecting the market pricing of risk as estimated by our model, and the administrative g-fee rate. Figure 10 plots the time series of the g-fee subsidies. Most of the time the subsidy is close to zero, however, the subsidy was very high during the Great Recession confirming the stabilization policy role played by the GSEs during this period.

The previous results are important for the current debate on housing finance reform in the U.S. As discussed by Frame, Wall and White (2013), the expected role of the federal government in the broader housing finance system is in dispute. The expected role ranges from no role to insuring against only extreme or tail events to insuring against all losses. Figure 10 shows that absolutely no government intervention would exacerbate the effects from a financial crisis. Such a crisis would lead to a credit crunch in mortgage markets and translate into housing markets.

5.4.1 G-fee subsidy versus monetary policy

To gauge the importance of g-fees versus monetary policy in driving mortgage rates, Figure 11 plots the market-implied mortgage rates keeping the funding costs constant (as in Figure 9), the market-implied rates allowing the funding cost to vary over time with the 5-year CD rate, and the 5-year average CD rate. As before, we used the calibrated credit supply model with the data on delinquency and default probabilities.

Figure 11 reveals two interesting dynamics. First, the market-implied mortgage rates, when

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

[13] 4.37% mortgage rate - 3.94% CD rate - 0.074% operating cost.

allowing for changes in funding cost, closely follow the CD rates, from 1991 up to 2007. That is, monetary policy, which is likely the force behind the dynamics of the CD rate, has been the main reason why mortgage rates have been going down. As the model predicts, lenders passed lower funding costs into lower mortgage rates.

Figure 11 also shows that, during the Great Recession, the market-implied mortgage rates allowing for changes in funding cost diverge from the CD rates, why? Because this is a period of extreme mortgage credit risk, which is priced in our model (and thus in the market-implied rates) but not in the CD rates. We can see this because in this period the market-implied mortgage rates, keeping the funding costs constant, spike. That spike is accounted for by the higher defaults and credit risk. Interestingly, comparing with Figure 10 this is the period when the GSE subsidies to g-fees were the largest. Thus, we can conclude that over the Great Recession the GSEs prevented mortgage rates from deviating even more from CD rates. Such effect of the GSEs through the g-fee subsidy was quantitatively large, similar to the first order effect on mortgage rates of monetary policy.

6 Aggregate Effects of the G-fee Subsidy

Fieldhouse, Mertens and Ravn (2018) show that the portfolio activity of the GSEs have significant macro effects. In this section we want to study if the g-fee subsidy discussed above also has relevant macro effects. We follow the structural VAR approach with recursive identification of Walentin (2014) who analyzed the macro effects of mortgage spreads. Walentin (2014) defines mortgage spreads as the difference between mortgage rates and bond rates. Our model allows to decompose such mortgage spread as

$$r_t^{effective} - r_t^d = r_t^w + r_t^g - subsidy. \tag{11}$$

The left-hand side of (11) is the definition of the mortgage spread as the effective or observed mortgage rate $\left(r_t^{effective}\right)$ minus the CD rate $\left(r_t^d\right)$.[14] The right-hand side of (11) shows that such spread is the operating costs for mortgage lenders (r_t^w) plus the market-implied g-fees (r_t^g) minus the g-fee subsidy. Thus, (11) shows that the results from Walentin (2014) are potentially driven by changes in those three possible factors. In our analysis in this section we will look at what is coming from the subsidy. We estimate the vector autoregressions with the following variables, in this order: aggregate consumption, mortgage originations (total value), GDP, the g-fee subsidy, the personal consumption expenditures price index (PCE), the nominal policy

[14] The CD rate matches closely the government bond rate for the same maturity.

interest rate and house prices. That is, we estimate

$$Y_t = B(L)Y_{t-1} + u_t, \tag{12}$$

where $B(L)$ is the lag operator with four lags, that is, $B(L) \equiv B_1 + B_2L + B_3L^2 + B_4L^3$, and

$$Y_t \equiv \begin{bmatrix} \log C_t \text{ (aggregate consumption)} \\ \log M_t \text{ (mortgage originations)} \\ \log GDP_t \text{ (GDP)} \\ r^{subsidy} \text{ (g-fee subsidy)} \\ \log PCE_t \text{ (PCE price index)} \\ FFR_t \text{ (fed funds rate)} \\ \log P_t \text{ (house prices)} \end{bmatrix}.$$

We estimate the VAR in levels, for quarterly data frequency. The summary statistics of these variables are in Table 7. Consumption, mortgage originations, GDP and house prices are adjusted for PCE inflation and expressed in natural logs. The identifying restriction is that shocks to the g-fee subsidy are only allowed to contemporaneously (within the quarter) affect consumer prices, the policy rate and house prices. It is similar to the identification that Walentin (2014) uses to identify shocks to mortgage spreads.

Figure 12 shows the impulse response functions for a positive g-fee subsidy shock. The figure reports the mean response, the 68% (one standard deviation) and 90% probability intervals. The g-fee subsidy shock increases mortgage originations and house prices. It also yields a gradual expansion of aggregate consumption and GDP. In terms of magnitudes, an increase of one standard deviation (0.07 pp) to the g-fee subsidy, causes a rise in mortgage originations of 4.67%, in consumption of 0.16%, in GDP of 0.14% and in house prices of 0.43%. The largest effect on the aggregate quantities occurs after five quarters, while the mortgage originations and house prices react more quickly. Table 8 shows the peak responses for an one standard deviation increase in the g-fee subsidy and for a 0.1 pp increase.

Table 9 shows the fraction of the variance that is attributed to the g-fee subsidy shock. Between 86% (4 quarter horizon) and 43% (10 quarters horizon) of the variation in the g-fee subsidy is due to the subsidy shock itself. Thus, in the short-term it is very exogenous. On this short-term horizon, house prices and mortgage originations react the most to the subsidy shock. Then the effects propagate to consumption and GDP. The g-fee subsidy shock is two thirds as important for house prices and consumption, and less important for GDP, compared to the mortgage spread shock documented in Walentin (2014).

The previous results suggest that the g-fee subsidies are credit supply shocks. The GSEs subsidize credit risk, households access cheaper mortgages and thus mortgage originations increase. More credit into housing markets translate into higher housing prices. Then, the wealth and collateral effects studied in the housing literature translate into positive effects for consumption and for output.

Relative to the existing literature, the results are similar to the findings of Fieldhouse, Mertens and Ravn (2018) for bulk asset purchases. Thus, the g-fee channel is a relevant alternative mechanism for the GSEs to have macroeconomic effects. Our findings are also similar to Walentin (2014). This suggests that the changes in credit risk are the main driver of the mortgage spreads.[15]

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 11% 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 how mortgage rates would behave if these rates were purely priced by the markets without government intervention through the GSEs. We obtain two sets of interesting results: 1) in the cross-sectional dimension the GSEs are mispricing hurricane risk. Market pricing would make mortgage rates 15% more expensive in the U.S. counties most exposed to hurricanes. Thus, the GSEs are preventing the internalization of climate risks. 2) On a time series dimension, most of the time, the GSEs are pricing credit risk exactly as markets would do so. The differences are small most of the time except for the Great Recession. That is, only in a major financial crisis the GSEs provide a significant subsidy to credit risk. In this case, the GSEs are doing stabilization policy with positive macro effects.

Our results inform the literature that studies credit risk in private markets, as well as the debate about housing finance reform. Our results suggest that reforms may want to allow more market pricing of risk across geographical locations but keep some form of government intervention for financial crises.

[15] Figure A7 replicates the analysis of Walentin (2014), but instead of mortgage spreads the shock happens to the g-fee subsidy.

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Figures

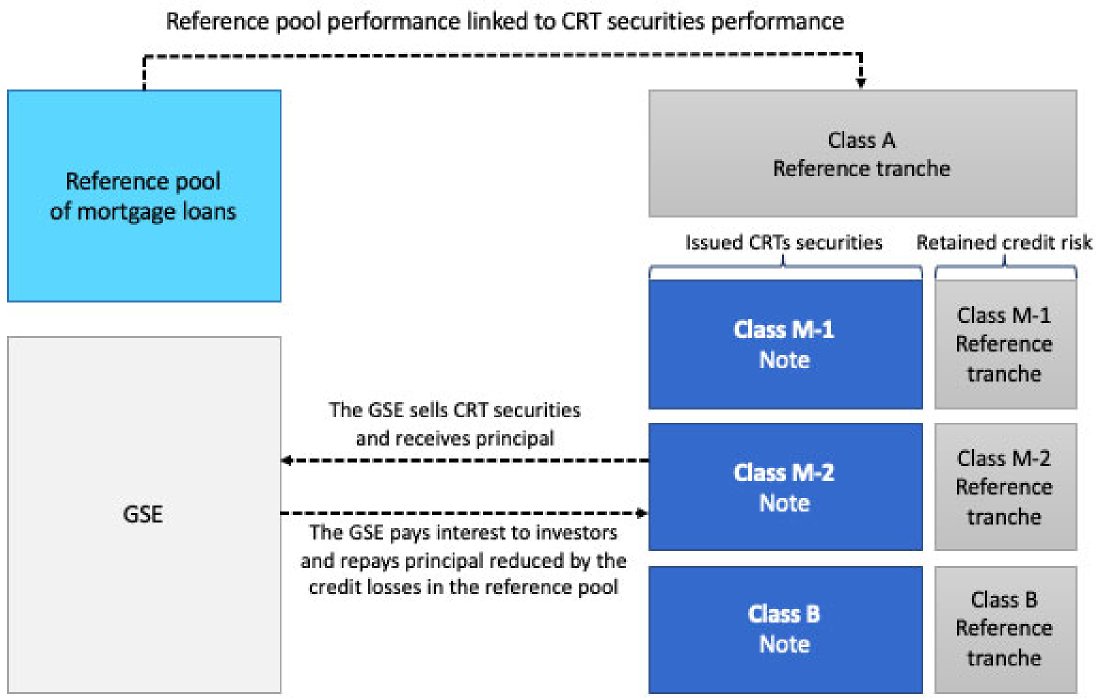

Figure 1. Example Credit Risk Transfer transaction. The figure shows an example of CRT transaction linked to a reference pool of loans. Credit losses on the reference pool reduce the obligation of the GSE to pay interest and repay principal on the CRT securities. This example contains a junior tranche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

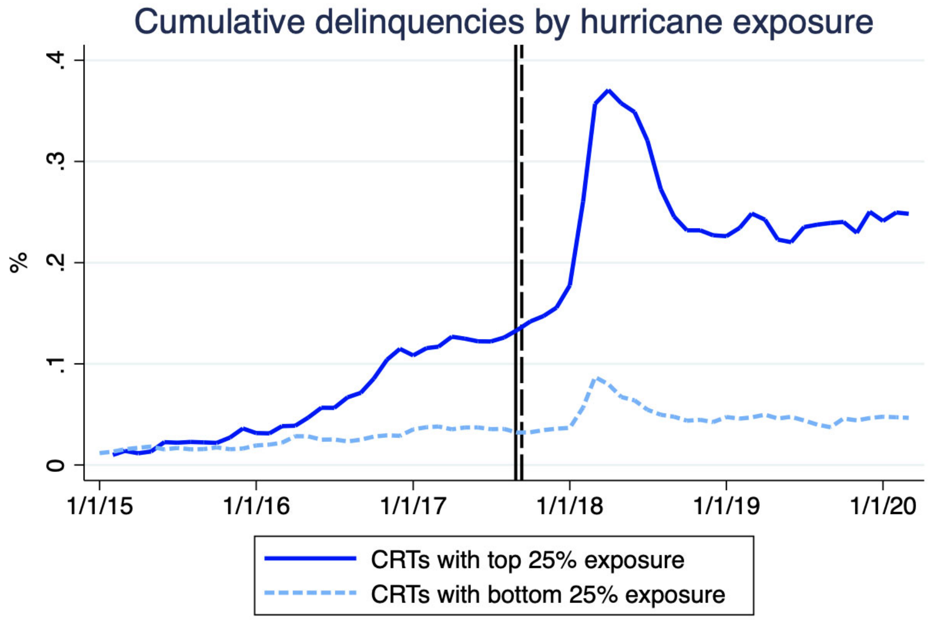

Figure 2. Cumulative delinquencies in pools of mortgages for CRTs with different geographical exposure to Harvey and Irma. The figure plots the average share of unpaid principal balance (delinquent for more than 120 days) for CRT mortgage pools that had the highest and lowest geographical exposures to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

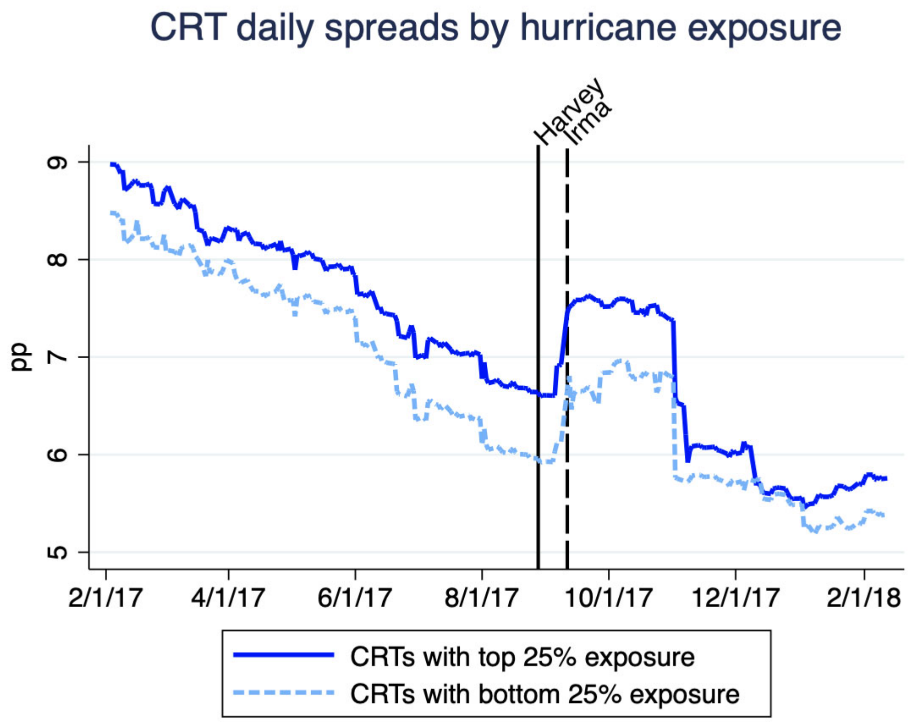

Figure 3. Spreads for CRTs by hurricane exposure. The figure plots the average daily spread (yield to maturity minus one month U.S. Dollar Libor) in the secondary market of Freddie Mac's junior CRT tranches, with mortgage pools that have the top 25% and the bottom 25% geographical exposure to the hurricanes.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

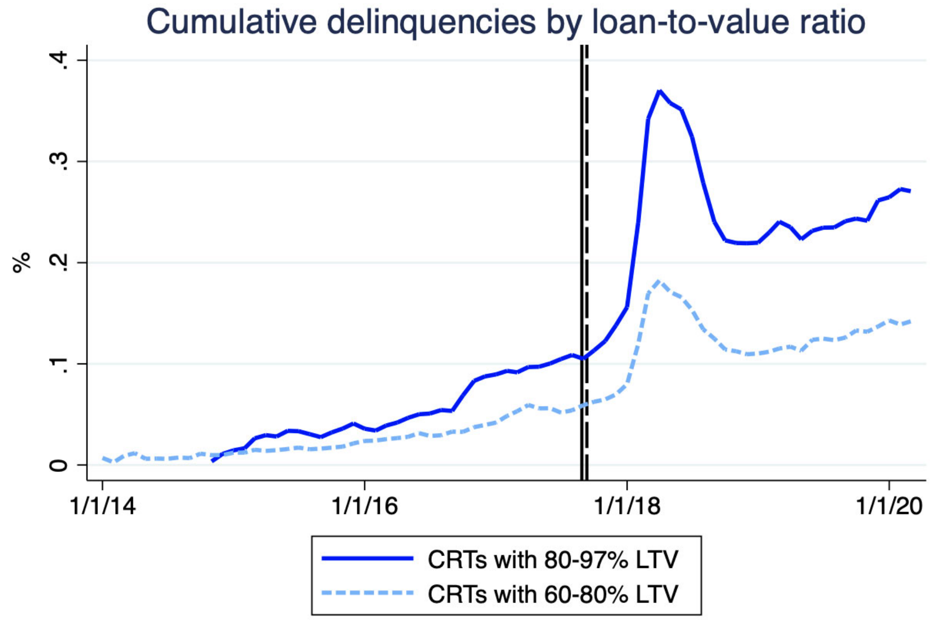

Figure 4. Cumulative delinquencies in pools of mortgages for CRTs with different loan-to-value. The figure plots the average share of unpaid principal balance (delinquent for more than 120 days) for CRT mortgage pools with different LTVs. The solid vertical line indicates August 28, 2017, which is the 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.

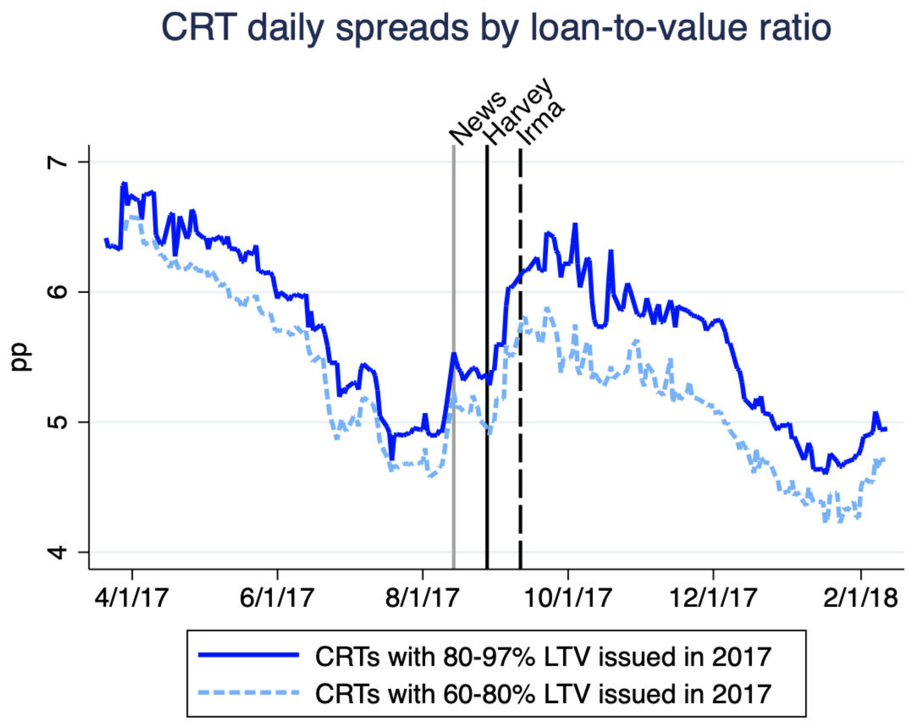

Figure 5. Spreads for CRTs by loan-to-value ratios. The figure plots the average daily spread (yield to maturity minus one month U.S. Dollar Libor) in the secondary market for Freddie Mac's junior CRT tranches issued in 2017 before Hurricanes Harvey and Irma, with high and low loan-to-value ratios. The 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.

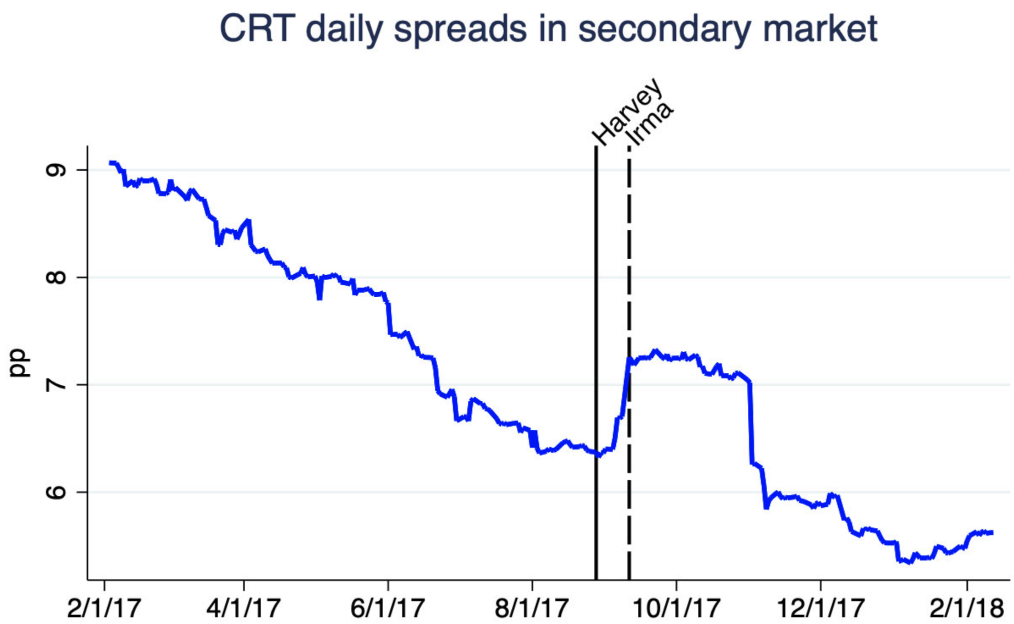

Figure 6. Spread of CRTs during Hurricanes Harvey and Irma. The figure plots the average daily spreads (yield to maturity minus one month U.S. Dollar Libor) in the secondary market of Freddie Mac's junior CRT tranches. The solid vertical line indicates August 28, 2017, which is the first trading day after Harvey's landfall, and the dashed vertical line is September 11, 2017, which is the first trading day after Irma's landfall.

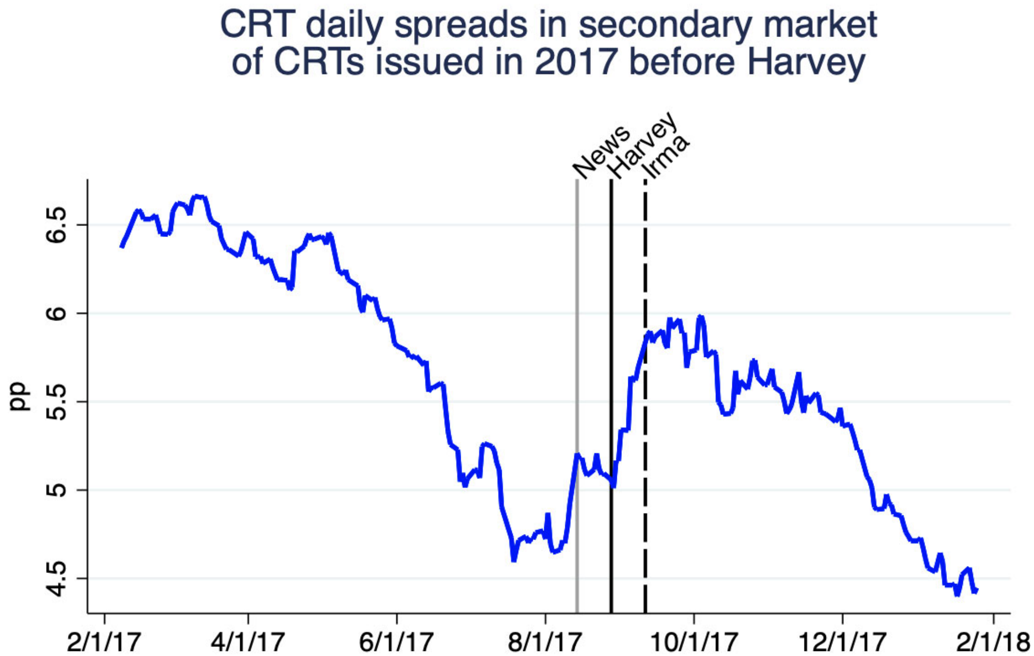

Figure 7. Spread of CRTs during Hurricanes Harvey and Irma. The top figure plots the average daily spreads (yield to maturity minus one month U.S. Dollar Libor) in the secondary market of Freddie Mac's junior CRT tranches issued between January and July 2017. The first solid vertical line indicates August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

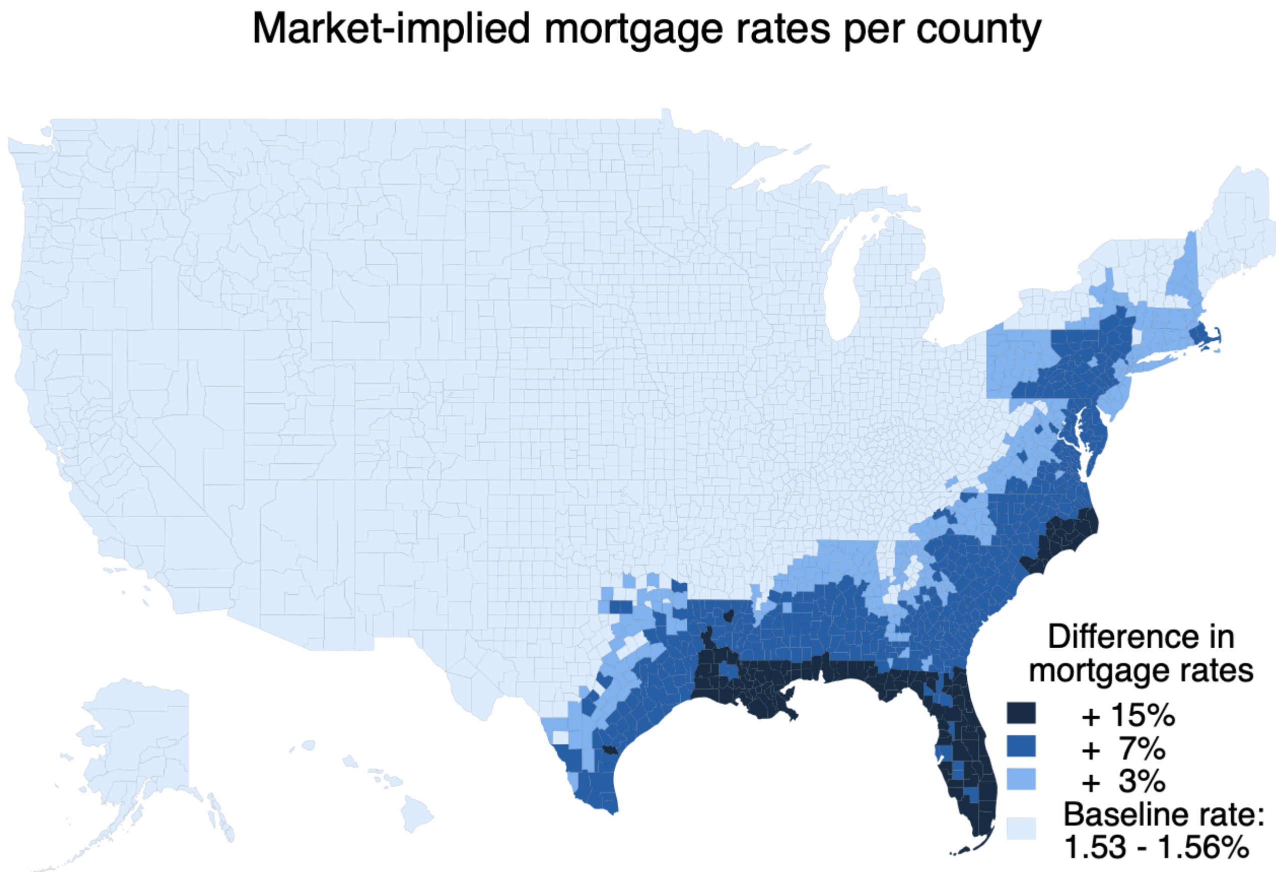

Figure 8. Market-implied mortgage rates. The map shows the county-wide average market-implied mortgage rates based on our model and the historical hurricane frequency between 2000 and 2019.

Figure 9. 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) rate. The dashed line plots the actual average g-fees of mortgages guaranteed by the GSEs.

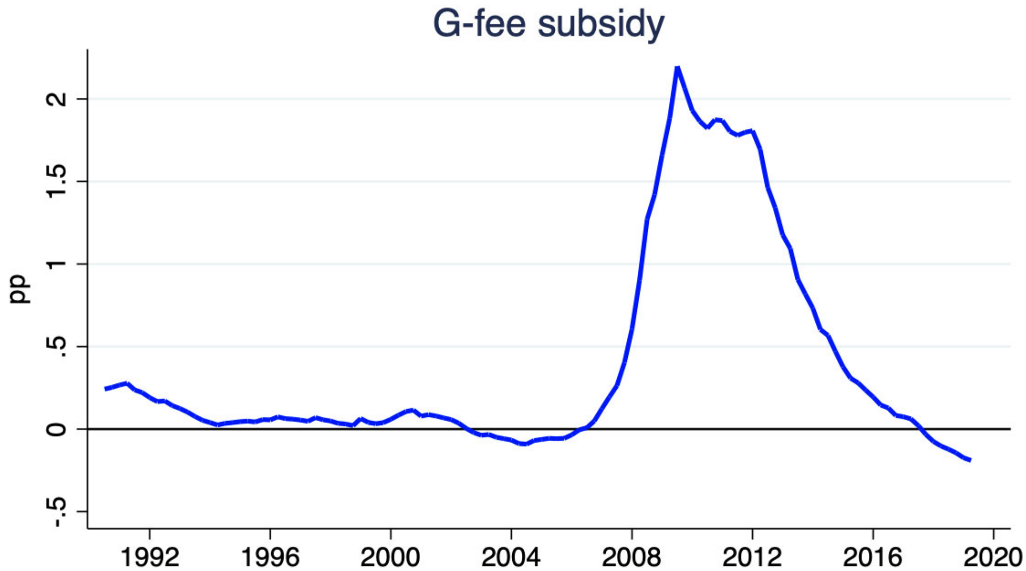

Figure 10. G-fee subsidy from GSEs. The figure plots the gap between the market-implied g-fees, estimated by our model, and the actual administrative g-fees set by the GSEs. Data are quarterly, from 1991Q1 to 2019Q4.

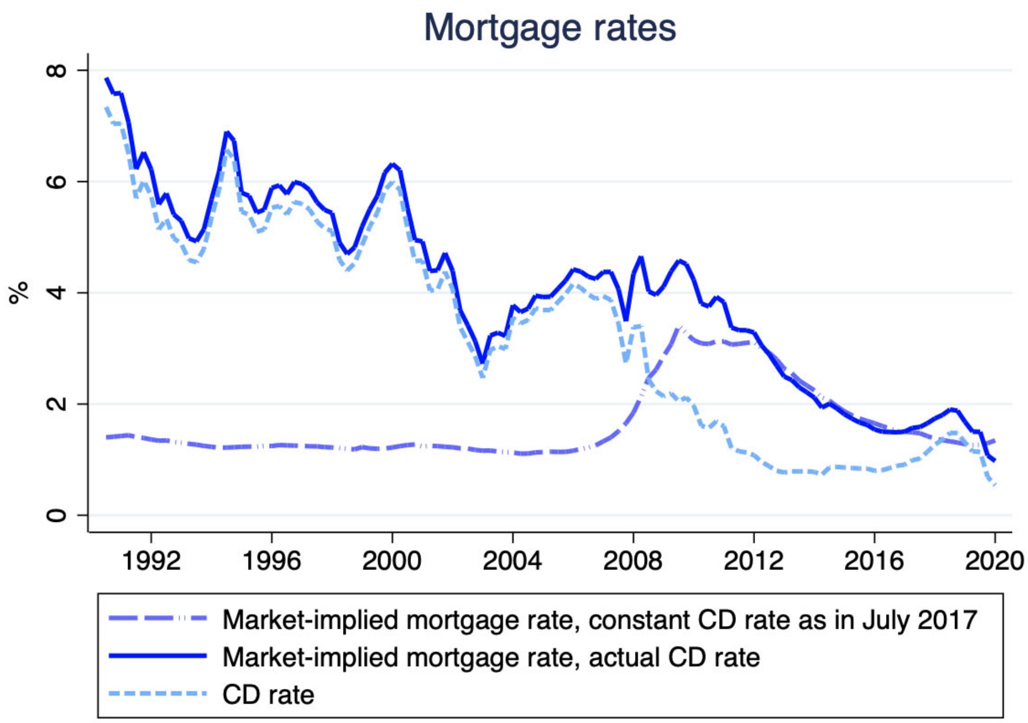

Figure 11. Market implied mortgage rates for GSE mortgages. The figure plots the estimated market implied mortgage rates based on our model, using (a) constant 5-year average CD rate equal to the value in July 2017 and (b) the actual 5-year average CD rate. The figure also plots the 5-year average CD rate.

Figure 12. Impulse response functions to a positive g-fee subsidy shock. The figure plots the estimated impulse responses to a shock of the gap between the market-implied mortgage rate and the effective mortgage rate. The data are quarterly, from 1991Q1 to 2019Q4. Units are in percent deviation. The confidence intervals are one standard deviation, that is, 68% (dark blue) and 90% (light blue).

Tables

Table 1. Summary statistics: CRT securities in the sample

		Number of securities		
		Fannie Mae	Freddie Mac	All
Loan-to-Value (LTV) Ratio	80-97%	27	45	72
	60-80%	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

	Obs.	Mean	SD	Min	Max
LTV 80-97%					
Spread daily (pp)	796	7.011	1.066	4.568	9.004
Geographical exposure (%)	796	5.855	2.902	1.960	9.300
Trading volume daily ($ million)	796	11.911	15.134	0	82.250
LTV 60-80%					
Spread daily (pp)	940	6.550	1.074	4.521	8.486
Geographical exposure (%)	940	4.986	2.736	1.920	9.600
Trading volume daily ($ million)	940	12.912	16.709	0	79.699
Hurricane landfall dummy	940	0.522	0.500	0	1
House prices ($ thousand)	940	203.981	0.818	202.552	205.332
Ten year treasury rate (%)	940	2.229	0.083	2.050	2.370
Two year treasury rate (%)	940	1.392	0.080	1.270	1.540

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 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 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 5 weeks before and 5 weeks after the treatment date, that is, from August 7 to October 16, 2017.

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

	Spread				
Window (weeks)	±3	±4	±5	±6	±7
LTV 80-97%					
Landfall × exposure	0.067***	0.055***	0.047***	0.038***	0.028***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Hurricane landfall	0.291***	0.348***	0.440***	0.513***	0.553***
	(0.047)	(0.044)	(0.045)	(0.044)	(0.043)
Exposure	-0.105	-0.107	-0.124	-0.098	-0.087
	(0.103)	(0.095)	(0.094)	(0.092)	(0.090)
Observations	486	641	796	951	1,106
R-squared	0.964	0.959	0.953	0.947	0.942
LTV 60-80%					
Landfall × exposure	0.063***	0.061***	0.062***	0.061***	0.057***
	(0.006)	(0.005)	(0.005)	(0.004)	(0.004)
Hurricane landfall	0.292***	0.267***	0.289***	0.304***	0.314***
	(0.037)	(0.034)	(0.032)	(0.030)	(0.031)
Hurricane exposure	-0.024	-0.060	-0.079	-0.091*	-0.086*
	(0.066)	(0.059)	(0.055)	(0.052)	(0.052)
Observations	580	760	940	1,120	1,300
R-squared	0.971	0.969	0.968	0.966	0.961

Standard errors are in parentheses. The spread is measured in percentage points. 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 onwards, and 0 otherwise. Geographical exposure is the exposure to the areas affected by Hurricane Harvey and Irma. Controls are the CRT security fixed effects, daily transaction volume, the 10-year and 2-year treasury rates. The sample and all variables are as defined in Table 2. *** p<0.01; * p<0.10.

Table 4. Impact of hurricanes on CRT spreads: Junior tranches

Window (weeks)	±3	±4	±5	±6	±7	Average
			LTV 80-97%			
Spread increase (pp)	0.683	0.670	0.715	0.735	0.717	0.704
Initial level of spread (pp)						6.697
Percentage increase (%)						10.51%
			LTV 60-80%			
Spread increase (pp)	0.606	0.571	0.598	0.608	0.598	0.596
Initial level of spread (pp)						6.294
Percentage increase (%)						9.47%

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 Table 3. For example, for a 5-week window the junior tranche with high LTV had an increase in spread equal to $(0.047 \times 5.855) + 0.440 = 0.715$ *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 spreads between three and seven weeks before the landfall.

Table 5. Calibration strategy

Parameter	Value	Description
		Exogenous parameters
l	1.215	Inverse of a 82.3% 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}	7.214%	Avg mortgage rate 2 weeks before landfall
		Endogenous parameters
a	0.932	Value of a in equation (7)
b	0.427	Value of b in equation (7)
		Targets
$r^m_0 - r^m_{-1}$	0.704 pp	Mortgage rate change estimated in Table 4
$\frac{d\gamma_t}{d\pi_t}\|_{t=0}$	-4	Avg slope of equation (7)

This table lists the parameters (exogenous and endogenous) and targets used in Section 5. The equation (7) is the relation between the market expectation of the recovery rate γ and the default probability π.

Table 6. Market-implied mortgage rates during the Great Recession

	Initial level	Level increase	Percentage increase
Default rate:	1.35%	3.80 pp	281%
Mortgage rate:	4.37%	1.79 pp	41%
G-fee rate:	0.36%	1.79 pp	497%

This table simulates the model of Section 5 to calculate how much the mortgage rates would change from Q3 2007 to Q3 2011 if they reflected market pricing of risk. The model matches the empirical estimates of Section 4.

Table 7. Summary statistics: G-fee subsidy and aggregate variables

	Mean	Standard deviation	Corr with g-fee subsidy
G-fee subsidy (pp)	0.389	0.639	1.000
Log consumption	9.146	0.231	0.283
Log mortgage originations	6.103	0.450	-0.101
Log GDP	9.552	0.211	0.266
Log PCE price index	4.458	0.158	0.380
Federal funds rate (%)	2.717	2.199	-0.598
Log house prices	5.000	0.199	-0.023

The table presents the summary statistics of the variables in the structural VAR model. Consumption, mortgage originations, GDP and house prices are in real terms, adjusted for PCE inflation.

Table 8. Peak effects of g-fee subsidy shock

	Max response (% increase) to g-fee subsidy shock	
Increase in g-fee subsidy	1 S.D. (0.07 pp)	0.1 pp
Consumption	0.16	0.24
Mortgage originations	4.67	6.72
GDP	0.14	0.20
House prices	0.43	0.61

The table shows the responses of the aggregate variables to a positive shock to the g-fee subsidy, estimated by the structural VAR model in Section 6. Consumption, mortgage originations, GDP and house prices are in real terms, adjusted for PCE inflation.

Table 9. Variance decomposition

	Fraction of variance explained by g-fee subsidy shock (%)			
Horizon (quarter)	4	6	8	10
Consumption	1.2	4.2	5.6	5.8
Mortgage originations	2.5	4.2	4.9	4.8
GDP	0.4	1.7	2.3	2.2
G-fee subsidy	86.2	69.7	53.4	43.3
House prices	5.5	5.8	5.3	4.3

The table presents the variance decomposition of the key variables for different horizons. That is, it shows the fraction of the variance that is attributed to the shock to the g-fee subsidy, based on structural VAR estimation in Section 6.

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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.[16] 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 A5 shows the process of merging the above datasets. For the simulations we put together the following data:

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

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

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 2000 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 50,000 mortgage loans originated per year, for the years 2000 to 2019. That is, a total of one million 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 zipcode 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.

4. We use the time series of the single-family guarantee fees from 1991 to 2019 from the GSEs Financial Reports. Figure A6 shows the g-fees reported by the GSEs. The historical data concern the effective g-fee rates, calculated by the g-fee income on the full mortgage portfolio. In the last decade the GSEs switched to reporting the actual g-fees they charged to newly acquired loans. When the data is available we use the charged fees, otherwise we use the effective fees.

B Model Simulation for Covid-19 Crisis

This simulation exercise concerns the increase in credit defaults due to the Covid-19 pandemic. The pandemic has caused a new increasing trend in mortgage delinquencies after the first quarter of 2020. The Mortgage Bankers Association estimated that the average mortgage delinquency rates for the GSE-guaranteed mortgages increased from 2.30% in the first quarter to 4.30% in the third quarter of 2020 (Mortgage Bankers Association 2020). That is, default rates increased from 1.15% to 2.15%. For this exercise we keep the funding costs constant at the January 2020 level (1.14% 5-year CD rate and 0.074% operating cost).

Table A6 shows the results of this simulation. Our credit supply model shows that this increase in default rates would have caused an increase in mortgage rates of 26% if rates reflected market pricing of risk. The market-implied g-fee increases by 0.38 pp, from 0.28% to 0.66%.

C 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

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

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FIGURES FOR THE ONLINE APPENDIX

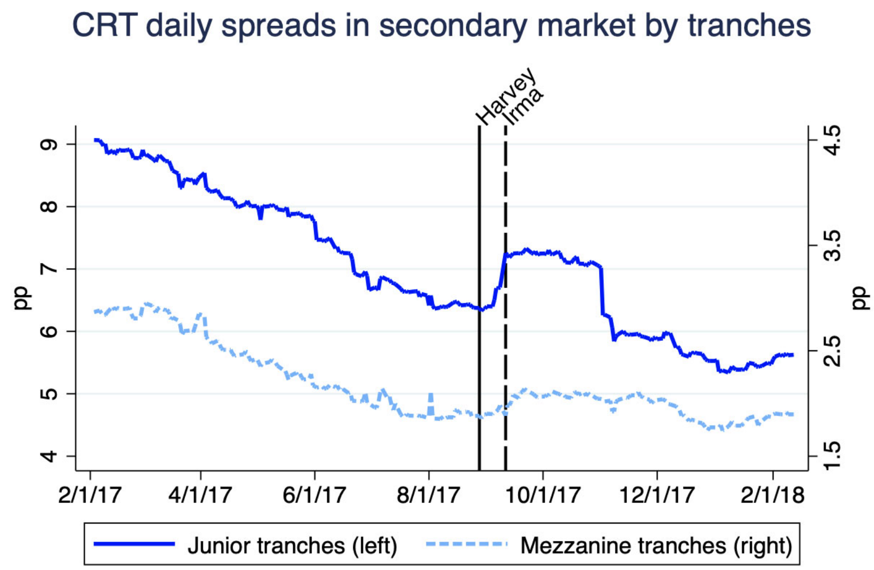

Figure A1. Spreads for CRTs by tranches. The figure plots the average daily spread (yield to maturity minus one month U.S. Dollar Libor) in the secondary market of the junior and mezzanine tranches of Freddie Mac's CRTs. The solid vertical line indicates August 28, 2017, which is the trading day after Harvey's landfall, and the dashed vertical line is September 11, 2017, which is the first trading day after Irma's landfall.

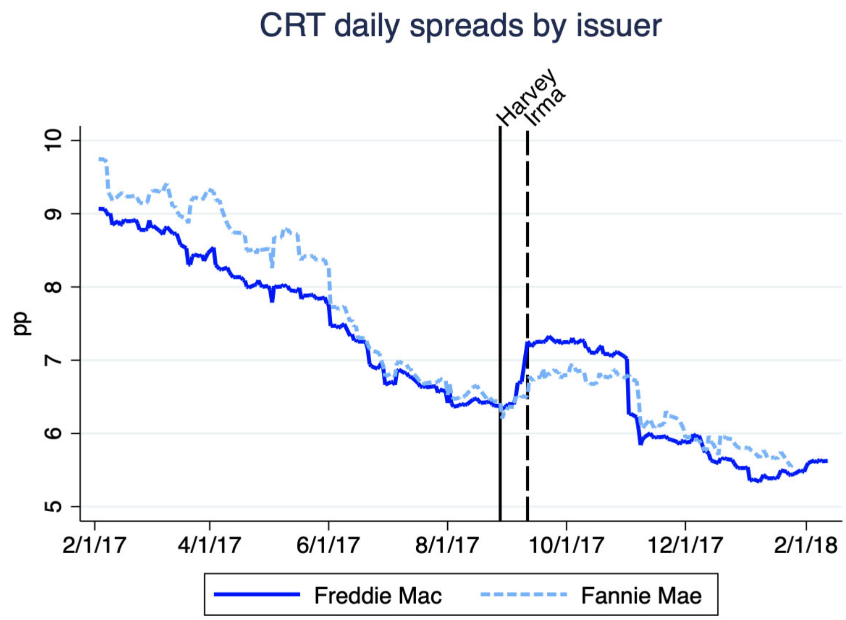

Figure A2. Spreads for CRTs by issuer. The figure plots the average daily spread (yield to maturity minus one month U.S. Dollar Libor) in the secondary market of all CRT risky tranches by the GSE issuer. The hurricane exposure of Freddie Mac's CRTs is between 3.60 and 9.60 percent, whereas the hurricane 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.

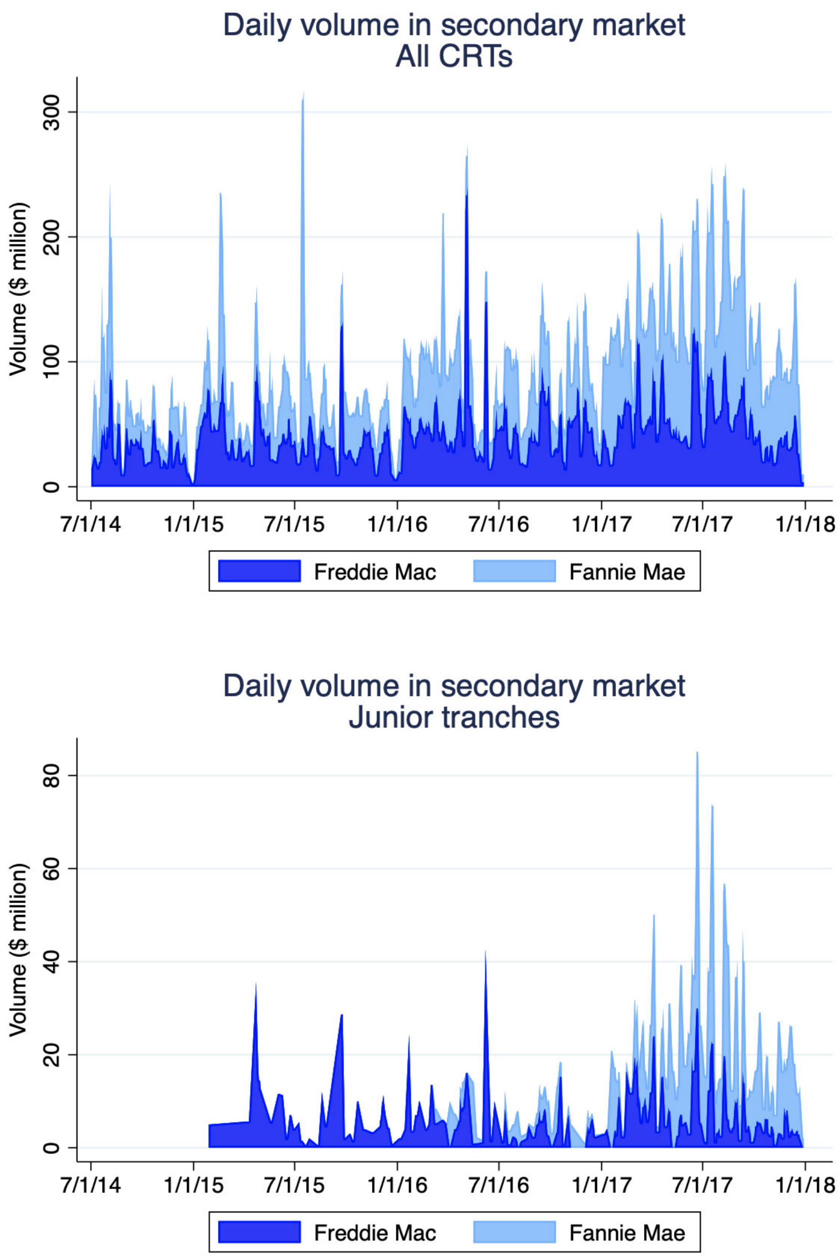

Figure A3. Trading volume of CRTs. The figures plot the time series of the total daily volume (7 days moving average) of the transactions in the secondary market of all CRTs, and only the junior tranches, from Fannie Mae and Freddie Mac. The reported trade size per transaction is capped at $5 million. Source: TRACE.

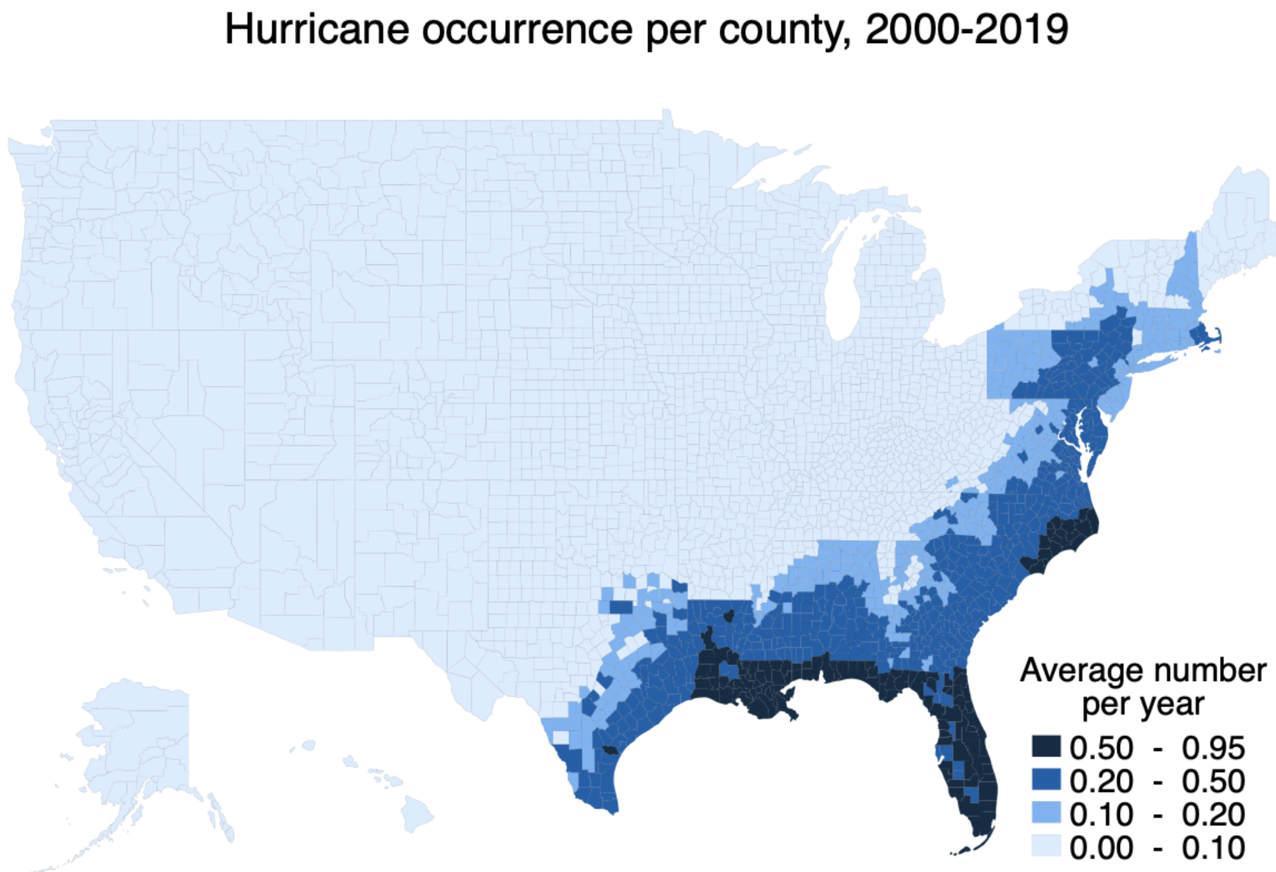

Figure A4. Occurrence of hurricane events per county. The map shows the frequency of disasters caused by hurricanes or tropical cyclones during the years 2000 to 2019 in the U.S. counties.

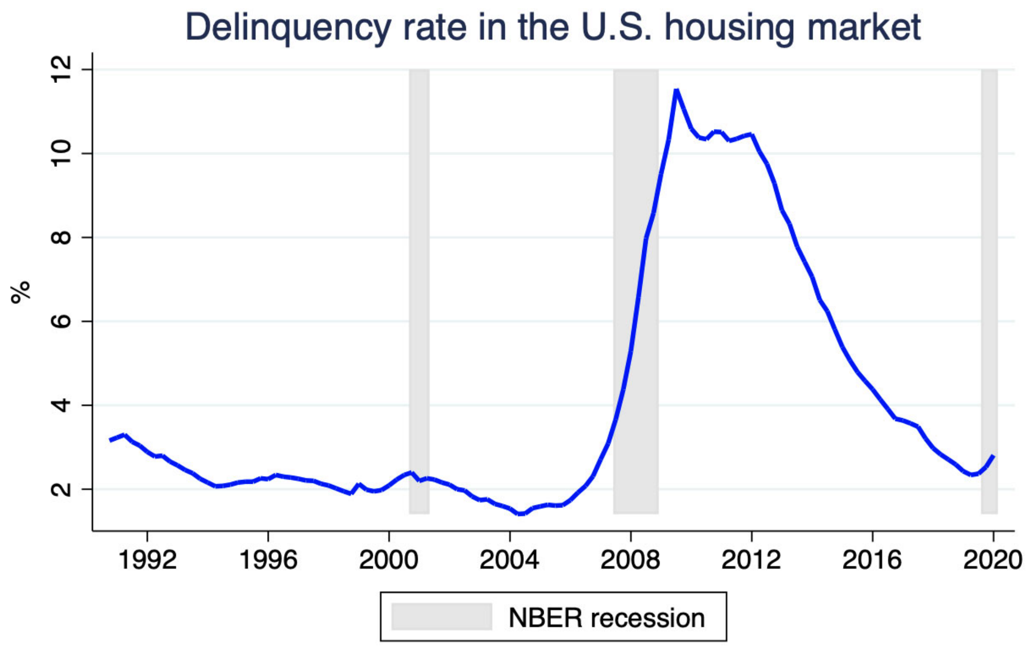

Figure A5. Delinquency rate in the U.S. housing market. The figure plots the delinquency rate on single-family residential mortgages in the U.S. from 1992 to 2020. The data are quarterly. Source: FRED.

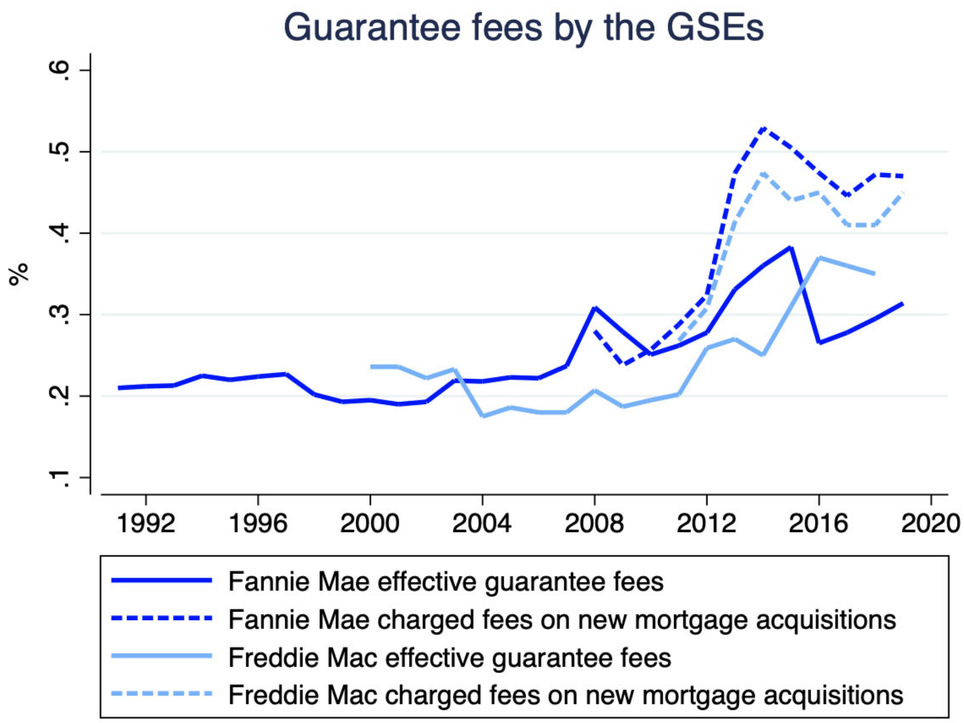

Figure A6. Guarantee fees by the GSEs. The figure plots guarantee fees by Fannie and Freddie as reported in Annual Reports on Form 10-K. Effective guarantee fees are calculated as the single-family guarantee fee income divided by the value of the single-family guarantee portfolio of each year. The charged fees are the average guarantee fees that Fannie and Freddie were actually charging for the single-family mortgages they acquired in each year. All fees exclude the increase of 10 basis points that was implemented in 2012 and onwards due to the Temporary Payroll Tax Cut Continuation Act of 2011 (TCCA).

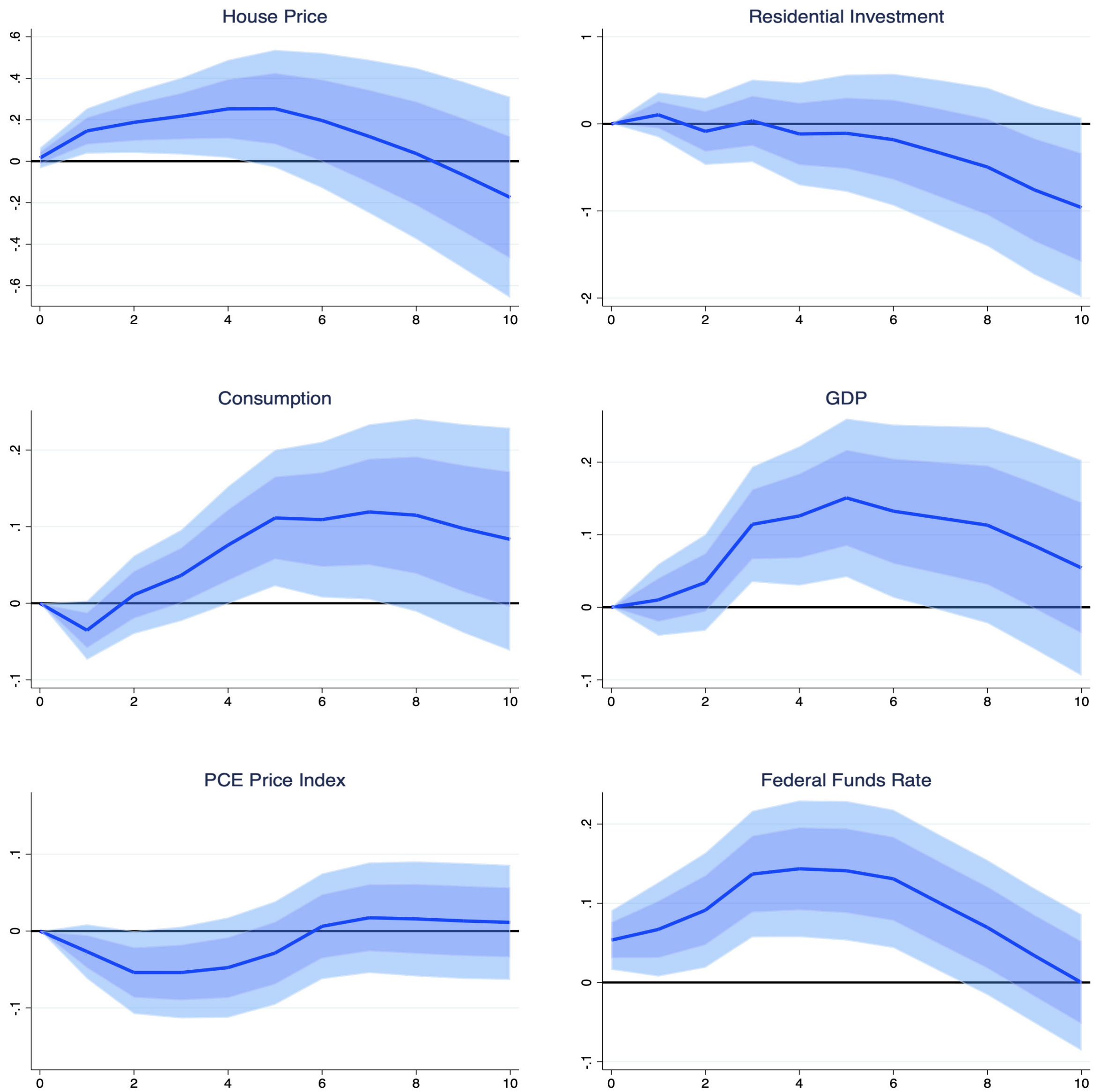

Figure A7. Impulse response functions to positive GSE subsidy shock. The figure plots the estimated impulse responses to a shock of the gap between the market-implied mortgage rate and the effective mortgage rate. The data are quarterly, from 1991Q1 to 2019Q4. Units are in percent deviation, except for the mortgage rate and federal funds rate, which are in terms of annual percentage rate (APR). The confidence intervals are one standard deviation, that is, 68% (dark blue) and 90% (light blue).

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TABLES FOR THE ONLINE APPENDIX

Table A1. Spreads after hurricanes by geographical exposure: Safest mezzanine tranche (M1)

	Spread				
Window (weeks)	±3	±4	±5	±6	±7
LTV 80-97%					
Landfall × exposure	-0.0002	-0.0004	-0.002	-0.004**	-0.006***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Hurricane landfall	0.037***	0.020*	0.036***	0.058***	0.089***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Exposure	0.018	0.031	0.036	0.036	0.039*
	(0.021)	(0.023)	(0.023)	(0.023)	(0.022)
Observations	397	522	647	772	897
R-squared	0.900	0.843	0.814	0.788	0.789
LTV 60-80%					
Landfall × exposure	0.0003	0.003	0.002	0.003	0.003
	(0.002)	(0.004)	(0.003)	(0.003)	(0.003)
Hurricane landfall	0.028**	0.018	0.024	0.020	0.038***
	(0.012)	(0.020)	(0.017)	(0.015)	(0.014)
Exposure	-0.072***	-0.070*	-0.066**	-0.065**	-0.62**
	(0.023)	(0.038)	(0.032)	(0.029)	(0.026)
Observations	614	805	995	1,185	1,375
R-squared	0.902	0.722	0.750	0.755	0.768

Standard errors are in parentheses. The spread is measured in percentage points. 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 onwards, and 0 otherwise. Geographical exposure is the exposure to the areas affected by Hurricane Harvey and Irma. Controls are the CRT security fixed effects, daily transaction volume, and the 10-year and 2-year treasury rates. The sample and all variables are as defined in Table 2. *** p<0.01, ** p<0.05, * p<0.1.

Table A2. Spreads after hurricanes by geographical exposure: Mezzanine tranches M2 & M3

	Spread				
Window (weeks)	±3	±4	±5	±6	±7
LTV 80-97%					
Landfall × exposure	-0.011*	-0.011**	-0.011**	-0.011**	-0.011**
	(0.006)	(0.005)	(0.005)	(0.005)	(0.004)
Hurricane landfall	0.196***	0.182***	0.228***	0.244***	0.262***
	(0.021)	(0.018)	(0.017)	(0.016)	(0.014)
Exposure	-0.063	-0.040	-0.031	-0.031	-0.033
	(0.066)	(0.058)	(0.053)	(0.050)	(0.046)
Observations	1,295	1,709	2,124	2,539	2,954
R-squared	0.977	0.976	0.975	0.973	0.973
LTV 60-80%					
Landfall × exposure	0.0001	-0.0001	-0.002	-0.003	-0.002
	(0.005)	(0.004)	(0.004)	(0.004)	(0.003)
Hurricane landfall	0.138***	0.137***	0.179***	0.197***	0.206***
	(0.017)	(0.016)	(0.015)	(0.014)	(0.013)
Exposure	-0.153**	-0.142***	-0.159***	-0.192***	-0.228***
	(0.064)	(0.055)	(0.050)	(0.046)	(0.041)
Observations	1,397	1,845	2,300	2,755	3,213
R-squared	0.978	0.976	0.973	0.971	0.972

Standard errors are in parentheses. The spread is measured in percentage points. 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 onwards, and 0 otherwise. Geographical exposure is the exposure to the areas affected by Hurricane Harvey and Irma. Controls are the CRT security fixed effects, daily transaction volume, and the 10-year and 2-year treasury rates. The sample and all variables are as defined in Table 2. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A3. Impact of hurricanes on CRT spreads: Mezzanine tranches

	Safest mezzanine tranche (M1)	Mezzanine tranches M2 & M3
LTV 80-97%		
Spread increase (pp)	0.036	0.159
Initial level of spread (pp)	0.859	2.422
Percentage increase (%)	4.14	6.56
LTV 60-80%		
Spread increase (pp)	not significant	0.164
Initial level of spread (pp)		2.377
Percentage increase (%)		6.90

This table shows the marginal change in CRT spreads after the landfall, for the average geographical exposure of the CRT pools. The figures shown in the table are calculated by taking the average of the estimation windows from three to seven weeks. The average exposure of the safest mezzanine tranche (M1) of high LTV is 4.942%. The average exposure of the mezzanine tranches M2 & M3 of high LTV is 5.798% and of low LTV is 5.074%. The calculations use the coefficients from Tables A1 and A2. For example, for a 5-week window the mezzanine tranches M2 & M3 with high LTV had an increase in spread equal to $(-0.011 \times 5.798) + 0.228 = 0.164\ pp$. The percentage increase in the spread is calculated as the average increase in spreads divided by the average level of the CRT spreads between three and seven weeks before the landfall.

Table A4. Logistic regression

	Probability of delinquency
Annual hurricane frequency	0.283***
	(0.018)
Observations	977,425

This table shows the results of the logistic regression for the probability a mortgage loan becomes delinquent for more than 120 days 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), 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, 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 mortgages issued between January 2000 and December 2019: 50 thousand randomly selected mortgages per year covering geographically all the United States.

Table A5. 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 Thomson Reuters 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.

Table A6. Market-implied mortgage rates during the Covid Crisis

	Initial level	Level increase	Percentage increase
Default rate:	1.15%	1.00 pp	87%
Mortgage rate:	1.49%	0.38 pp	26%
G-fee rate:	0.28%	0.38 pp	138%

This table simulates the model of Section 5 to calculate how much the mortgage rates would change from Q1 2020 to Q3 2020 if they reflected market pricing of risk and the model matches the empirical estimates of Section 4.