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

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Goals:

1. How would markets price credit risk from natural disasters?

2. What would happen to mortgage rates in the U.S. if they were priced based on the market?

3. What are the macroeconomic effects of the GSEs' mortgage rate subsidy?

Strategy, Step 1:

- Hand-collected a unique database of a new financial product in the U.S.:

  Credit Risk Transfers (CRTs)

- Diff-in-diff analysis: exploit heterogeneity in CRT exposure to unpredictable exogenous local shock that alters credit risk
  - Hurricanes Harvey and Irma in 2017 are such shock

Strategy, Step 2:

- Calibrate model of credit supply to match estimates from Step 1
- Run simulations and predict market-implied mortgage rates:
  - Cross-sectional dimension: climate risk
  - Time series dimension: estimate GSE implicit mortgage rate subsidy

Strategy, Step 3:

- Estimate the aggregate effects of the GSE mortgage rate subsidy
  - Use the previous estimates of the market-implied mortgage rates versus the effective rates to calculate the subsidy
  - Estimate a structural VAR model
  - Infer the magnitude of effects of GSEs as stabilization policy

Preview of Results

- Without GSEs, hurricane risk makes mortgage rates 15% more expensive in riskiest counties, e.g. Miami-Dade
- Mortgage rates without monetary policy interventions would have increased by 41% during the Global Financial Crisis if they were priced by the market

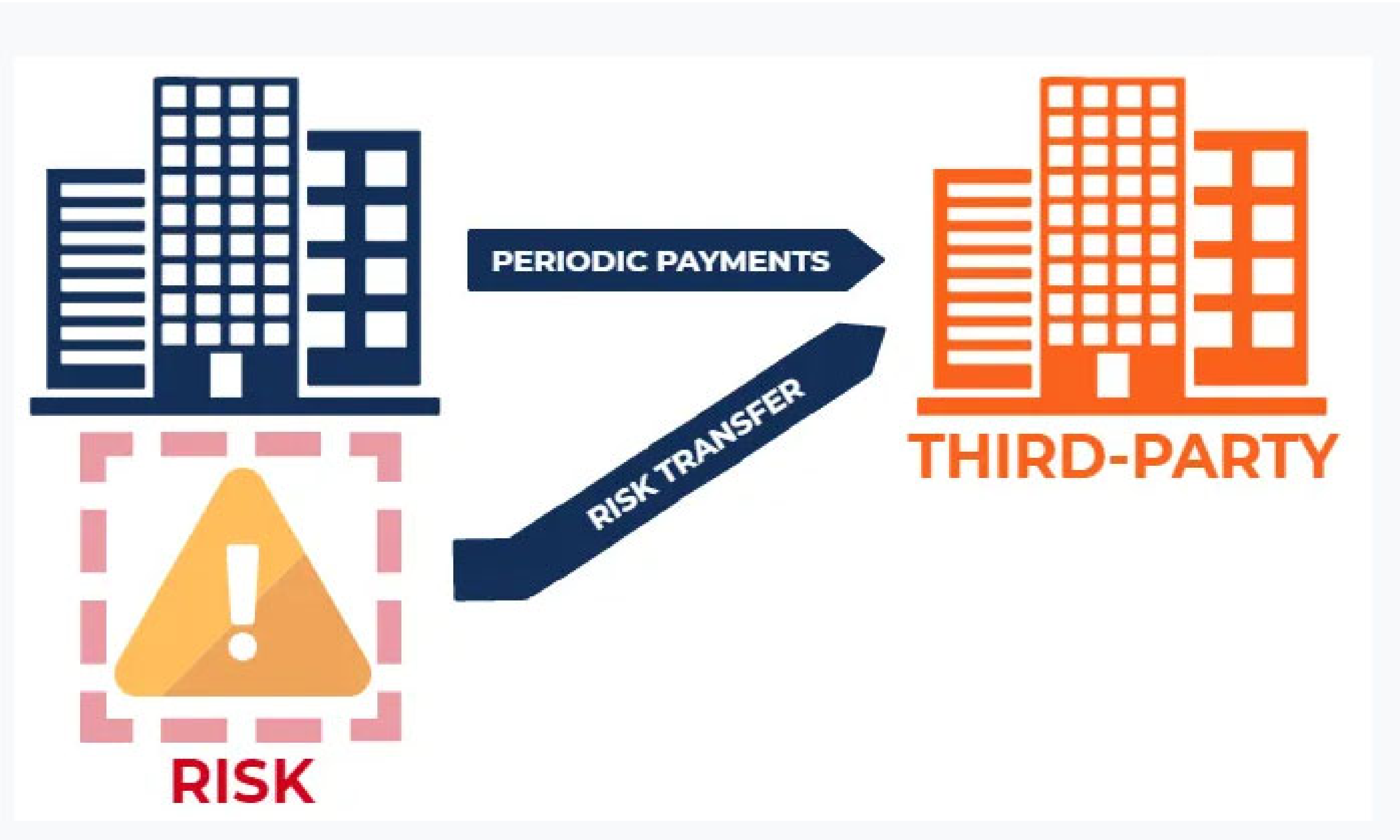
Preview of Results (cont.)

- The GSE subsidy increases house prices, mortgage originations, consumption and GDP
- GSE policy through the g-fees similar to policy through MBS purchases (Fieldhouse, Mertens and Ravn 2018)

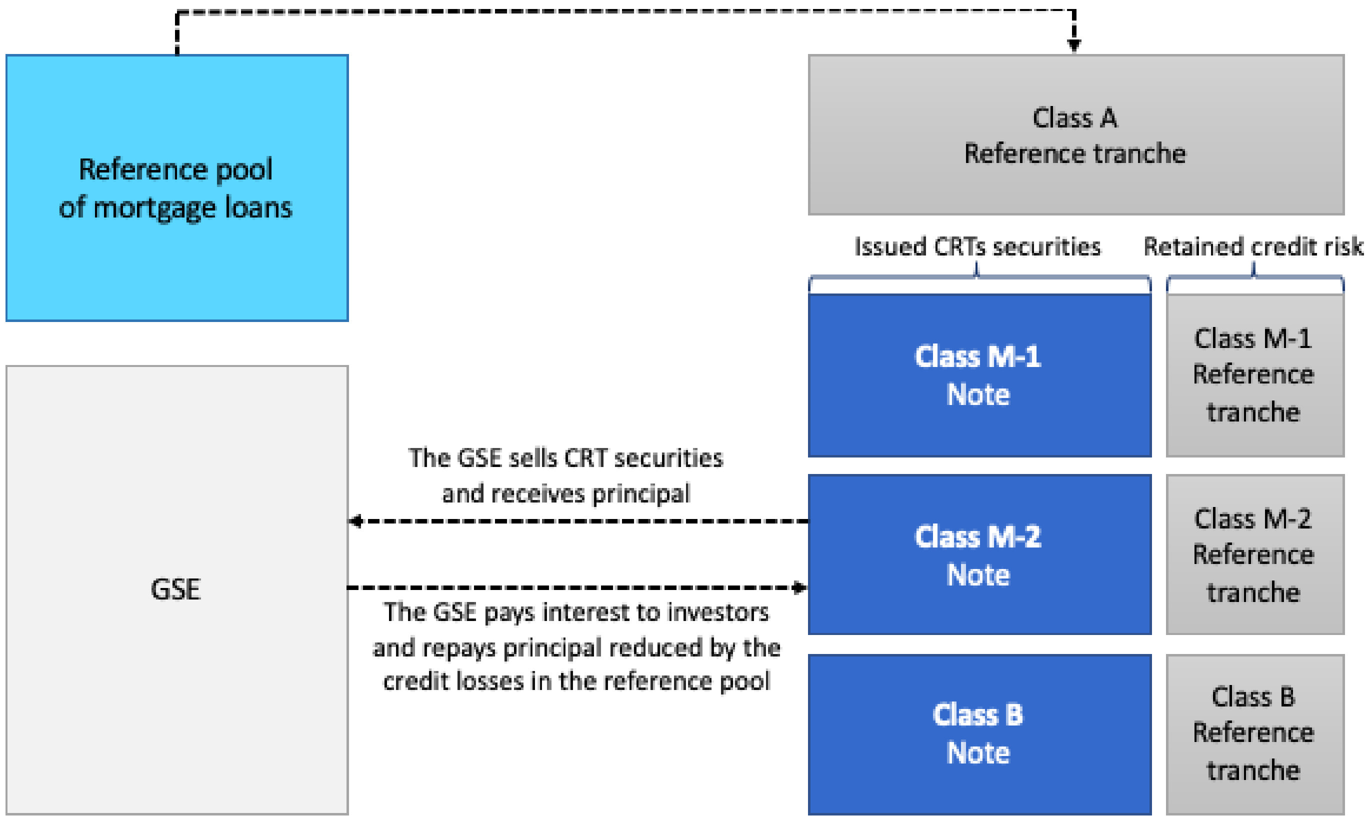
Credit Risk Transfers (CRTs)

- Pioneered by Freddie in 2013, CRTs structure mortgage credit risk into securities (Vickery et al. 2018)
- Purpose to transfer credit risk exposure from U.S. taxpayers to private capital

Credit Risk Transfers (CRTs)



CRT Structure



- From July 2013 to June 2017, the GSEs using CRTs transferred risk on $1.3 trillion of mortgage loans

Empirical Analysis

Data

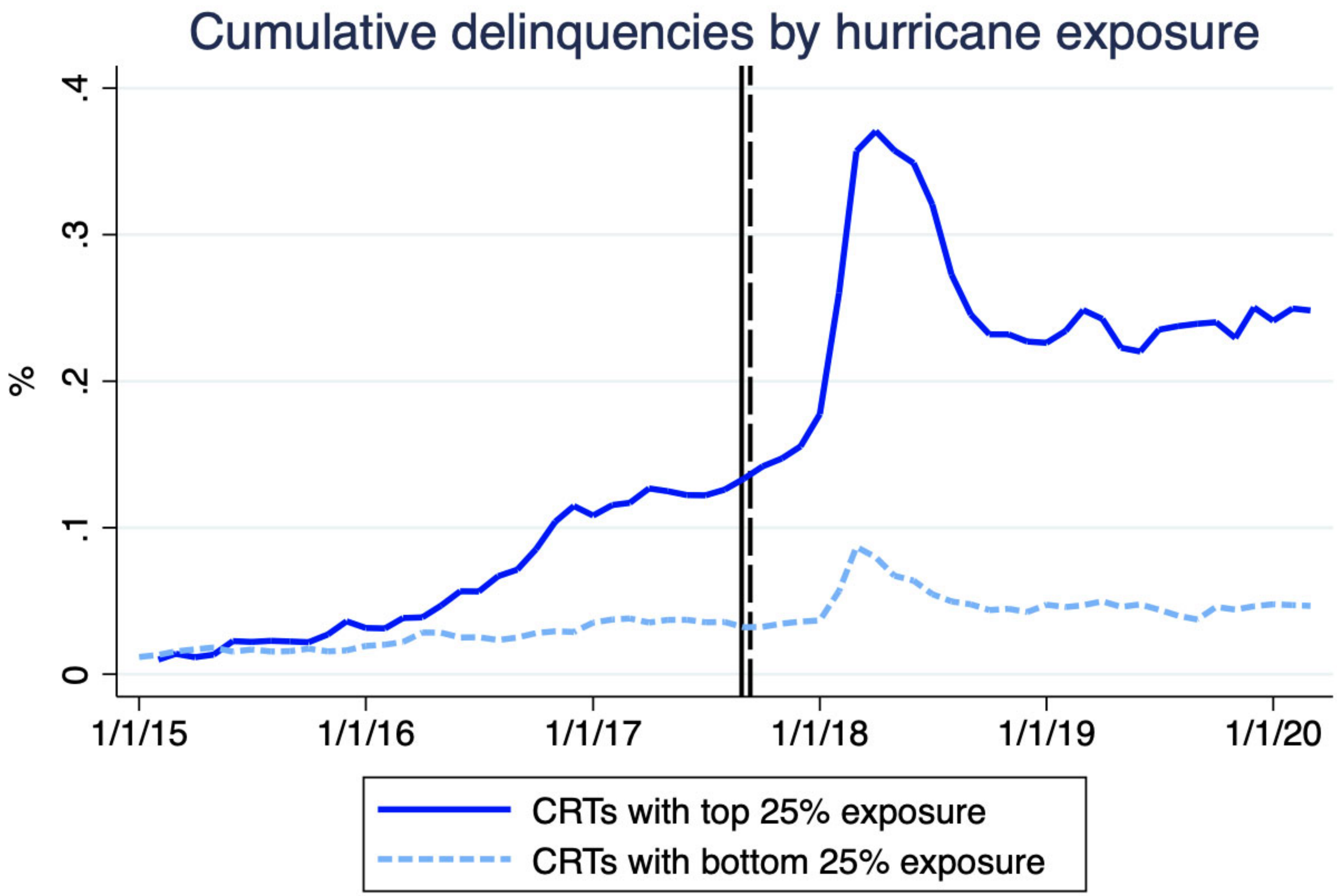
Unique database combining information from different sources:

- Time series of daily yields in the secondary market of CRTs and U.S. Dollar Libor benchmark from Refinitiv Eikon
- All CRT issuances: issuance date, original principal balance, floater spread, seniority tranches from Bloomberg
- Mortgages' features and performance: (1) CRT reference pools, from the GSEs: LTV, geographical composition, delinquencies, etc. (2) sample of 1 million mortgages purchased or guaranteed by Freddie since 2000
- Delinquency rates and guarantee-fees (g-fees) since 1991

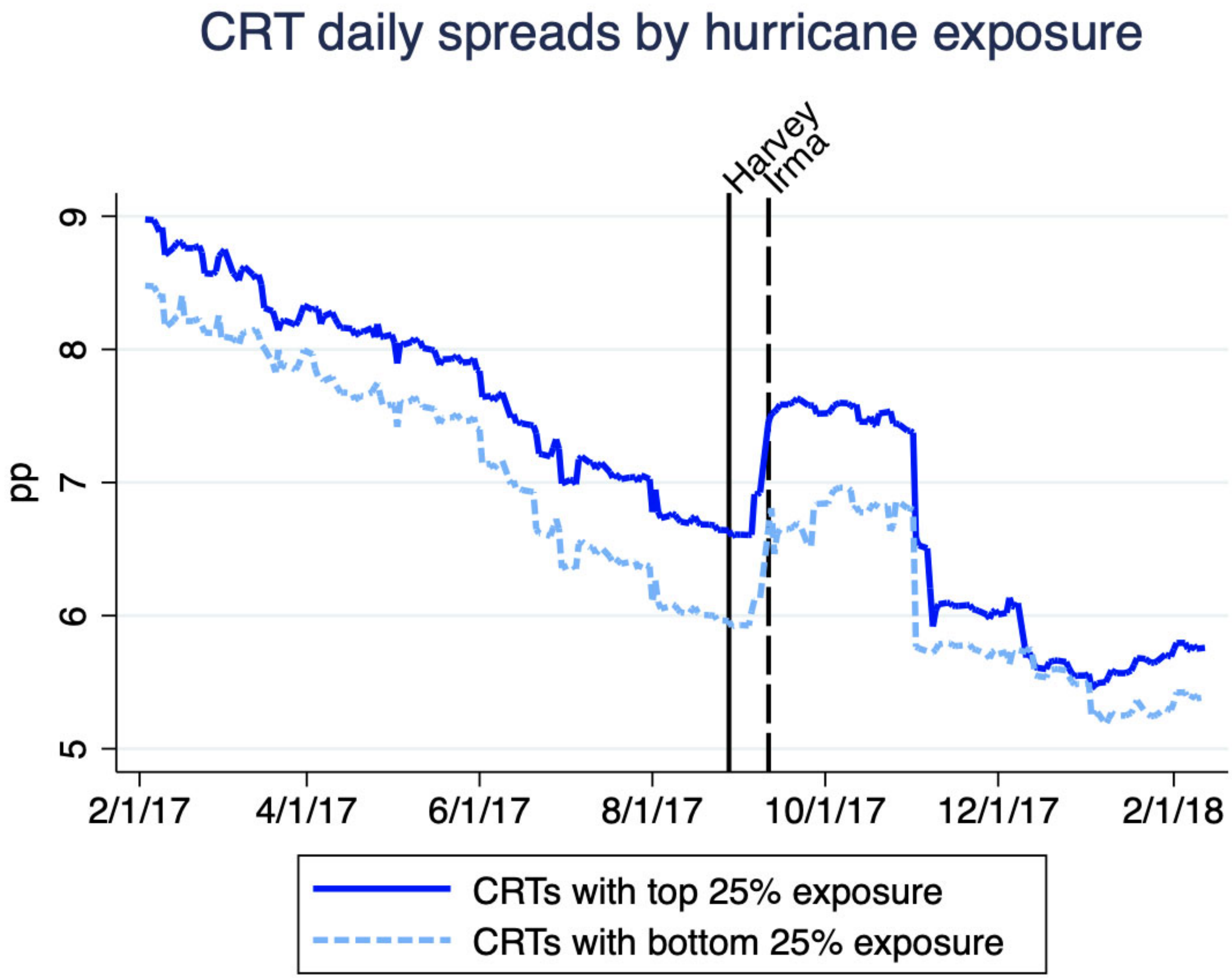
Diff-in-Diff

- CRTs differ in
  - seniority of tranches
  - loan-to-value ratio (LTV)
  - geographical composition of reference pool
  - time to maturity
- Study effects of hurricanes in spreads of CRTs in secondary market
  - Control for liquidity, CRT features and economic factors

CRTs heterogeneous in geographical exposure

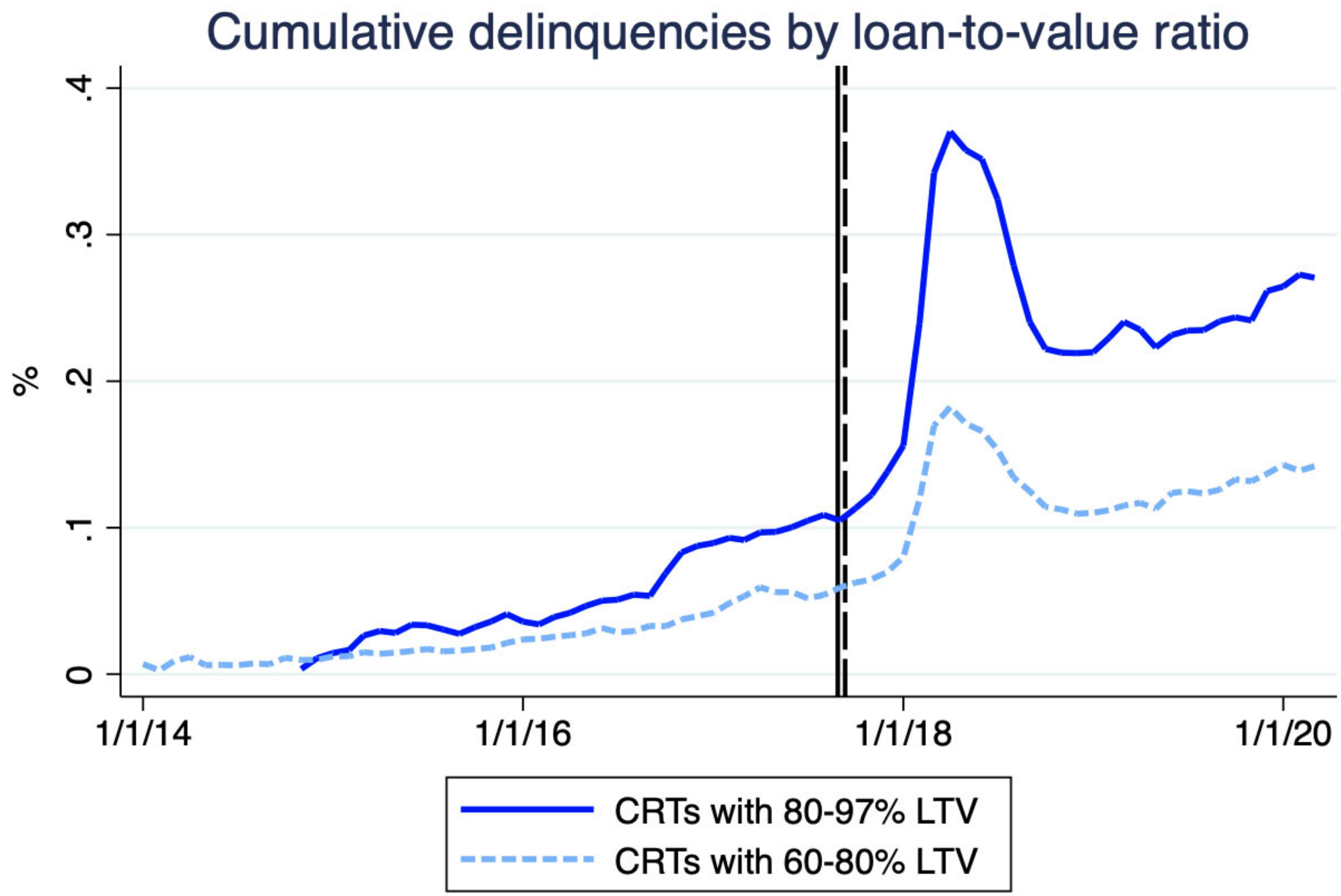


Average share of unpaid principal balance delinquent for more than 120 days. Vertical lines show the landfalls of Harvey and Irma.



Daily spread (yield to maturity - Libor) in the secondary market of CRTs.

CRTs heterogeneous in LTV



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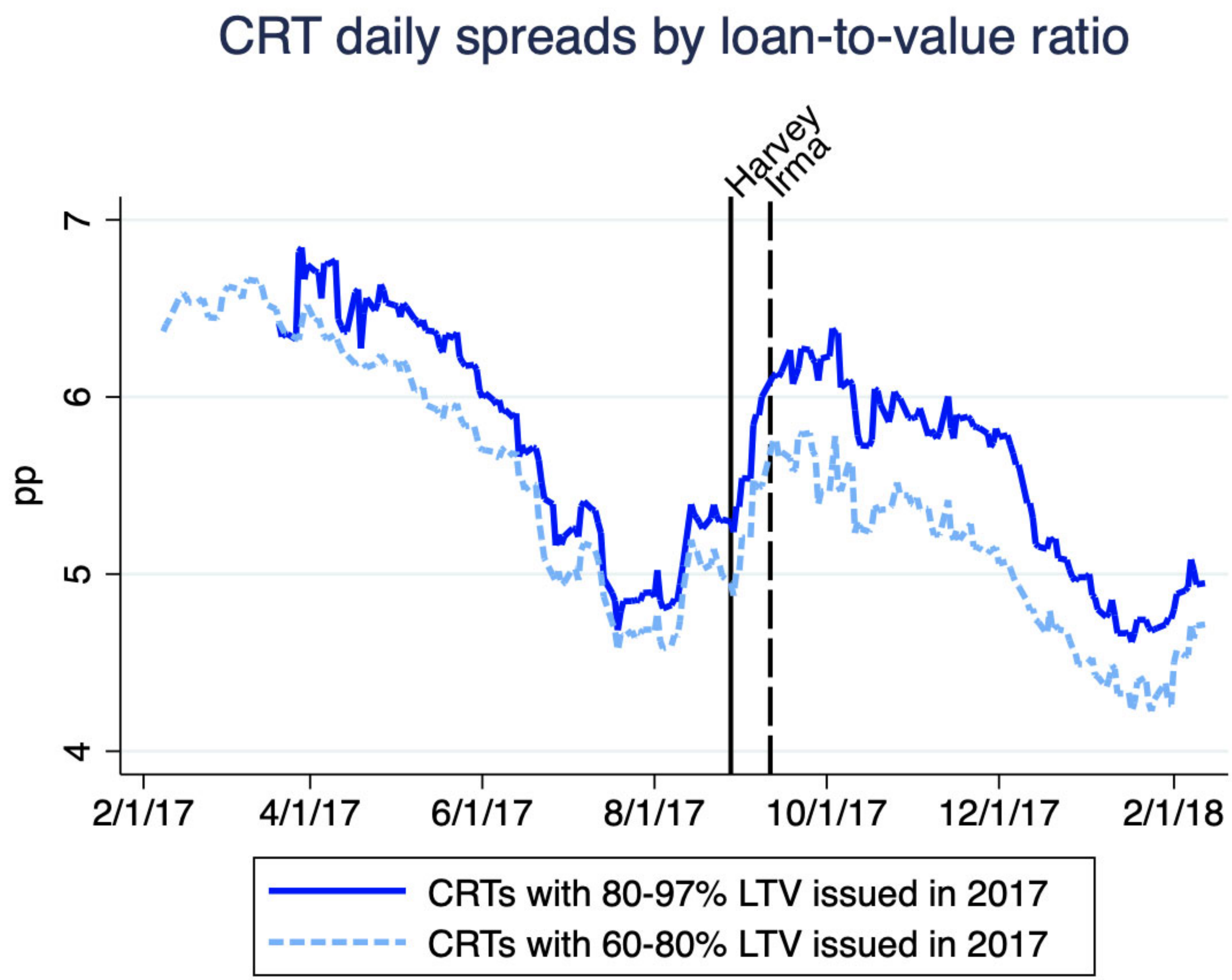


Daily spread (yield to maturity - Libor) in the secondary market of CRTs.

Specification Diff-in-Diff

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

- $S_{i,t}$: spread over one month U.S. Dollar Libor of CRT security i at day t
- T_t : 1 for t on and after the first trading day after the landfall in the U.S. coast of Hurricane Irma on September 11th 2017, zero otherwise
- E_i : geographical exposure to default: share of CRT unpaid principal balance of mortgages in the counties hit by Harvey and Irma
- C_i : CRT security fixed effects; $V_{i,t}$: trading volume; D_t : 10-year and 2-year treasury rates
- Separate estimations for junior versus mezzanine tranches, and for LTV ratios below versus above 80%

Junior Tranches React to Hurricanes

	Spread for Junior CRTs with LTV 80.01-97%			
Window (weeks)	± 3	± 4	± 5	± 6
Landfall $\times$ exposure	0.067***	0.055***	0.047***	0.038***
	(0.006)	(0.006)	(0.006)	(0.006)
Hurricane landfall	0.291***	0.348***	0.440***	0.513***
	(0.047)	(0.044)	(0.045)	(0.044)
Observations	486	641	796	951
R-squared	0.96	0.96	0.95	0.95

Standard errors clustered by security in parentheses. ***sig. at 1%.

Controls: Security FE, trading volume, 10-year and 2-year treasury rates.

	Spread for Junior CRTs with LTV 60.01-80%			
Window (weeks)	± 3	± 4	± 5	± 6
Landfall $\times$ exposure	0.063***	0.061***	0.062***	0.061***
	(0.006)	(0.005)	(0.005)	(0.004)
Hurricane landfall	0.292***	0.267***	0.289***	0.304***
	(0.037)	(0.034)	(0.032)	(0.030)
Observations	580	760	940	1,120
R-squared	0.97	0.97	0.97	0.97

Standard errors clustered by security in parentheses. ***sig. at 1%.
Controls: Security FE, trading volume, 10-year and 2-year treasury rates.

Takeaway: Impact of Hurricanes on CRT Spreads

	Spread of Junior CRTs			
Window (weeks)	±3	±4	±5	±6
LTV 80.01-97%				
Change in spread (pp)	0.683	0.670	0.715	0.735
LTV 60.01-80%				
Change in spread (pp)	0.606	0.571	0.598	0.608

- CRT spreads increase by 0.70 pp on average five weeks after the landfall, compared to five weeks before
- Equivalent to 11% of the average level of spreads before the landfall

Model

Credit Supply Model

- Mortgages are long-term
- Lenders are risk neutral and compete loan by loan
- Input: Exogenous probability of default
- Output: Mortgage rate
- Calibrate to match previous estimates from diff-in-diff

- The outstanding principal M_t decays geometrically at rate λ, $0 < \lambda < 1$

$$M_t = \lambda M_{t-1}$$

- The mortgage payment x_t covers the part of the mortgage repaid plus interest on the outstanding mortgage, at the mortgage rate r_t^m

$$x_{t+1} = (1 - \lambda + r_t^m) M_t$$

- 2 states of nature: default or not
- Value of a mortgage:

$$
\begin{aligned}
V_t &= (1-\pi_t)\left(x_t + \frac{1}{1+r^d} V_{t+1}\right) + \\
&\quad \pi_t \min\left(\gamma_t P_h H_t,\ x_t + \frac{1}{1+r^d} V_{t+1}\right)
\end{aligned}
$$

- r^d = lenders' cost of funds (e.g. deposits or warehouse funding)
- V_t = loan value; $P_h H_t$ = house value
- π_t = default probability
- γ_t = recovery rate of collateral

- Perfect competition between lenders
- Mortgage rates adjust so expected revenue from lending covers costs to the lenders of keeping a deposit of M_{t-1}

$$V_t = (1 + r^d + r^w) M_{t-1}$$

- r^w = operating costs (e.g. origination and servicing costs)

- r^g is the market-implied guarantee fee

$$r^g = r^m - r^d - r^w$$

Decompose mortgage rates (r^m) into:

- compensation for credit risk (r^g)
- cost of funds (r^d)
- operating costs (r^w)

Calibration

- $t = 0$ hurricane hits; $t = -1$ pre-hurricane

Exogenous parameters		
Parameter	Value	Description
l	1.215	Inverse of a 82.3% loan-to-value ratio
λ	0.950	Mortgage amortization parameter
r^d	0.910%	Lenders' cost of funds: 5y CD rate, July 2017
r^w	0.074%	Lenders' operating cost
r^m_{-1}	7.214%	Avg mortgage rate before landfall
π_{-1}	1.780%	Avg default probability before landfall
$\pi_0 - \pi_{-1}$	1.462 pp	Change in default probability due to landfall

$t = -1$ (pre-shock)

- Mortgage rate r^m_{-1}=7.214% (credit spread before the landfall)
- Probability of default = 50% of delinquencies of 120 days (historical average, prudent assumption)
- Probability of default in entire pool = 50%(0.0356%) = 0.0178%
- First losses in the most junior tranche are allocated in 1% of the mortgage pool
- Probability of default in junior tranche = π_{-1} = 0.0178%/1% = 1.78%

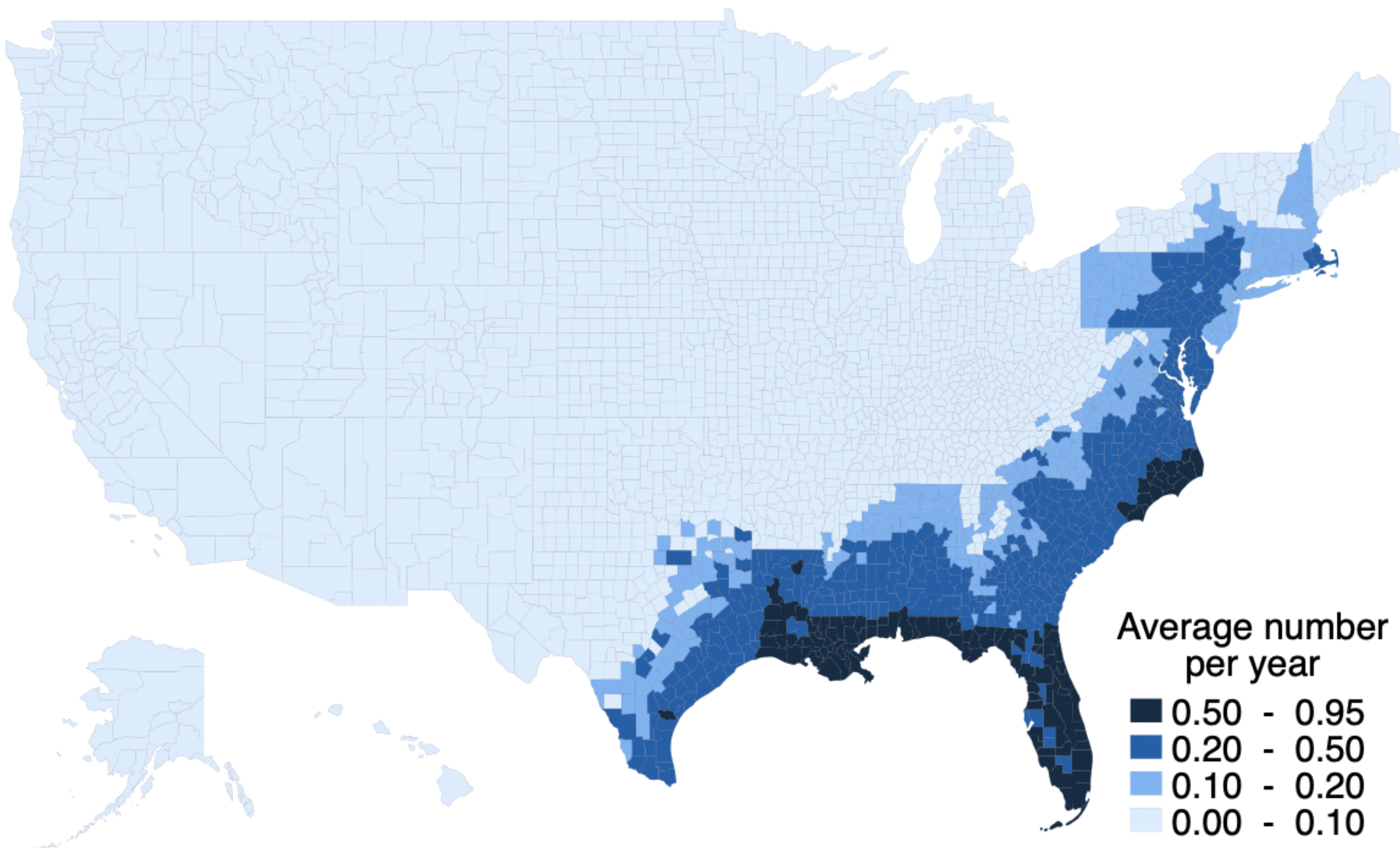
$t = 0$ (post-shock)

- Probability of default increase in entire pool $=$ 50%(0.0292 pp) $=$ 0.0146 pp
- Probability of default increase in junior tranche $=$ $\pi_0 - \pi_{-1} =$ 0.0146 pp$/$1% $=$ 1.46 pp

Targets		
$r_{m,0} - r_{m,-1}$	0.70 pp	Change in rates from diff-in-diff estimate
$\frac{d\gamma}{d\pi}\mid_{t=0}$	-4	Avg slope of $\gamma_t = f(\pi_t) = 1 - a\pi_t^{b-1}$
Endogenous parameters		
a	0.932	Value of a in $\gamma_t = 1 - a\pi_t^b$
b	0.427	Value of b in $\gamma_t = 1 - a\pi_t^b$

Cross-sectional Results

Hurricane occurrence per county, 2000-2019

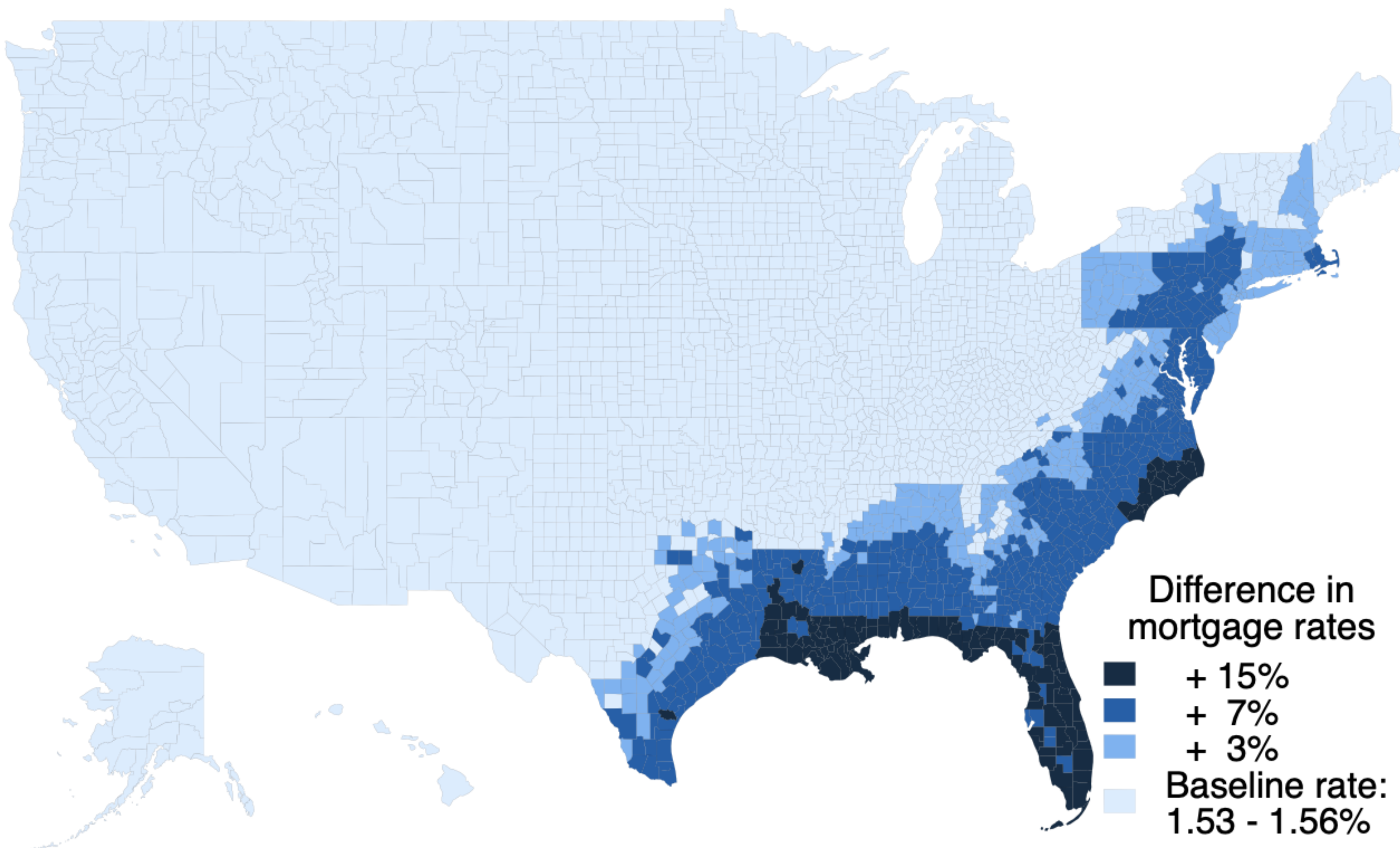


County-level data from FEMA about hurricanes and tropical storms.

- Based on default risk from hurricanes and CRT estimates, what would be the cross-sectional mortgage rates?
  - GSEs suppress cross-sectional differences in pricing of credit risk (Keys, Hurst, Seru and Vavra 2016)

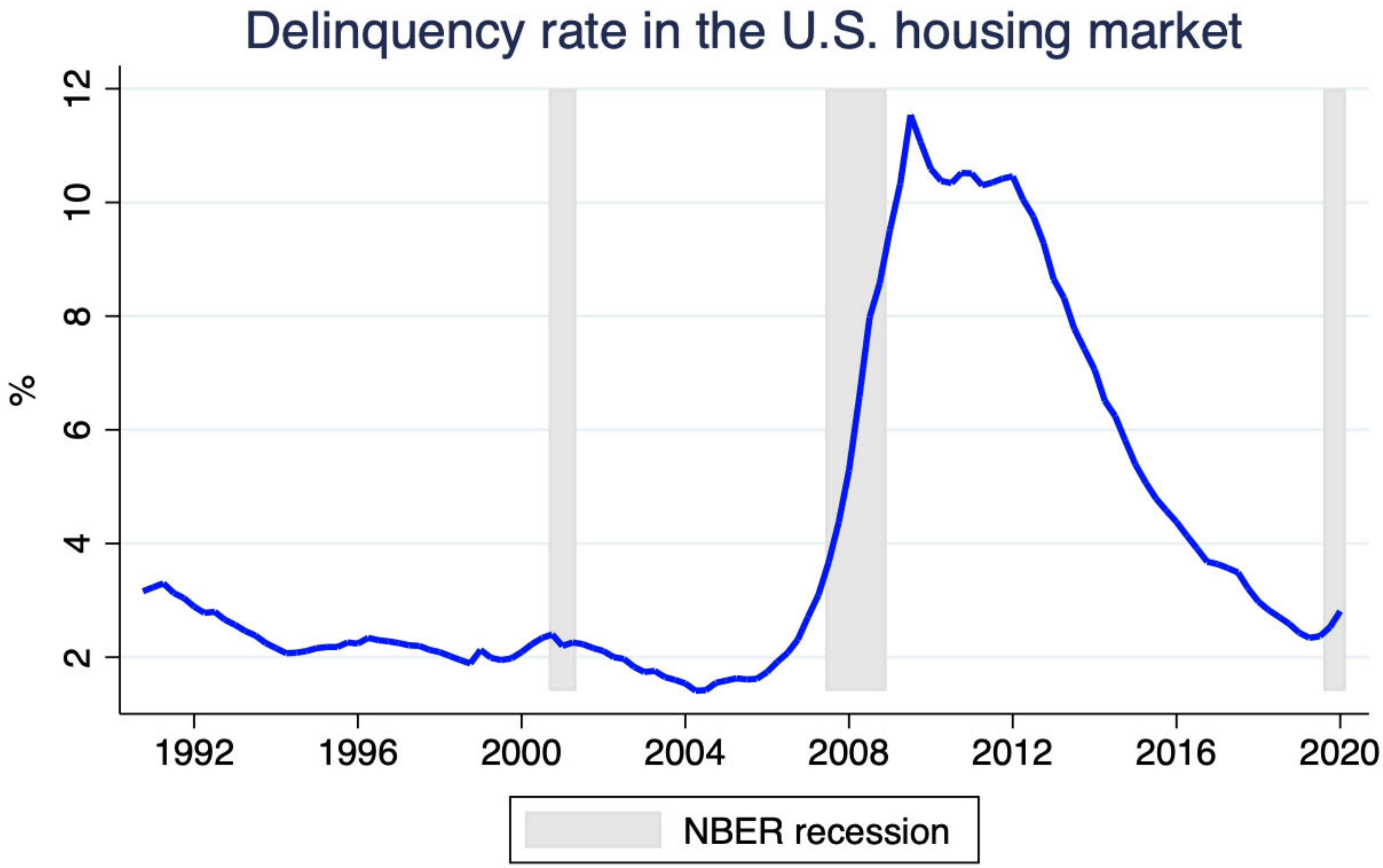
- Logistic regression: Probability of delinquency based on hurricane frequency, controlling for loan, property and borrower characteristics
  - Sample: 1 million loans from Freddie Mac, from 2000-2019
- Map delinquency probability on mortgage rates using our model

Market-implied mortgage rates per county



Time Series Results

Simulations: Stress is Exogenous Change In Default Risk

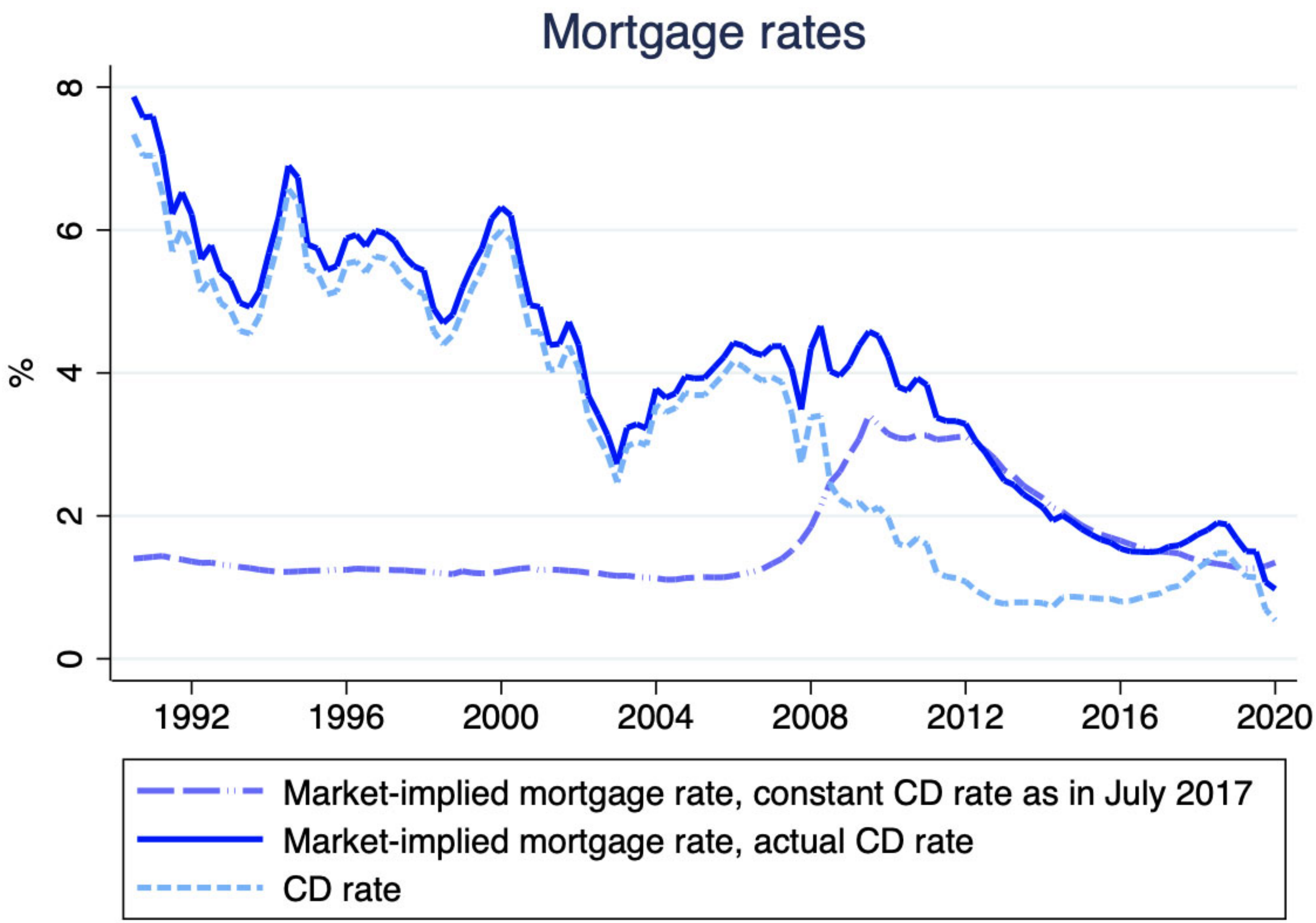


Data from FRED.

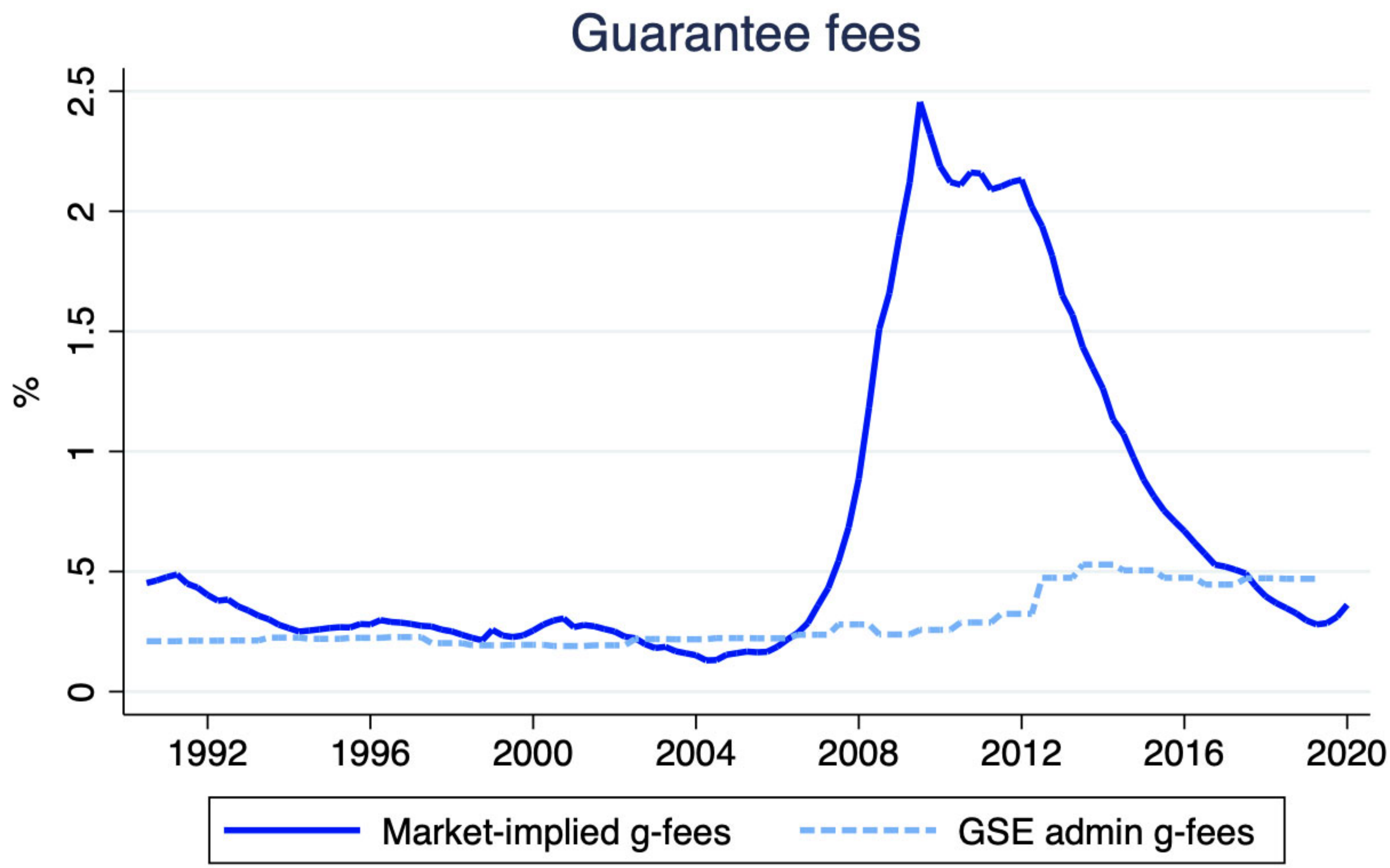
Mortgage Rates Under Stress Without Government Guarantees

	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%

Government Guarantees versus Monetary Policy



Pricing Credit Risk: Markets versus Government

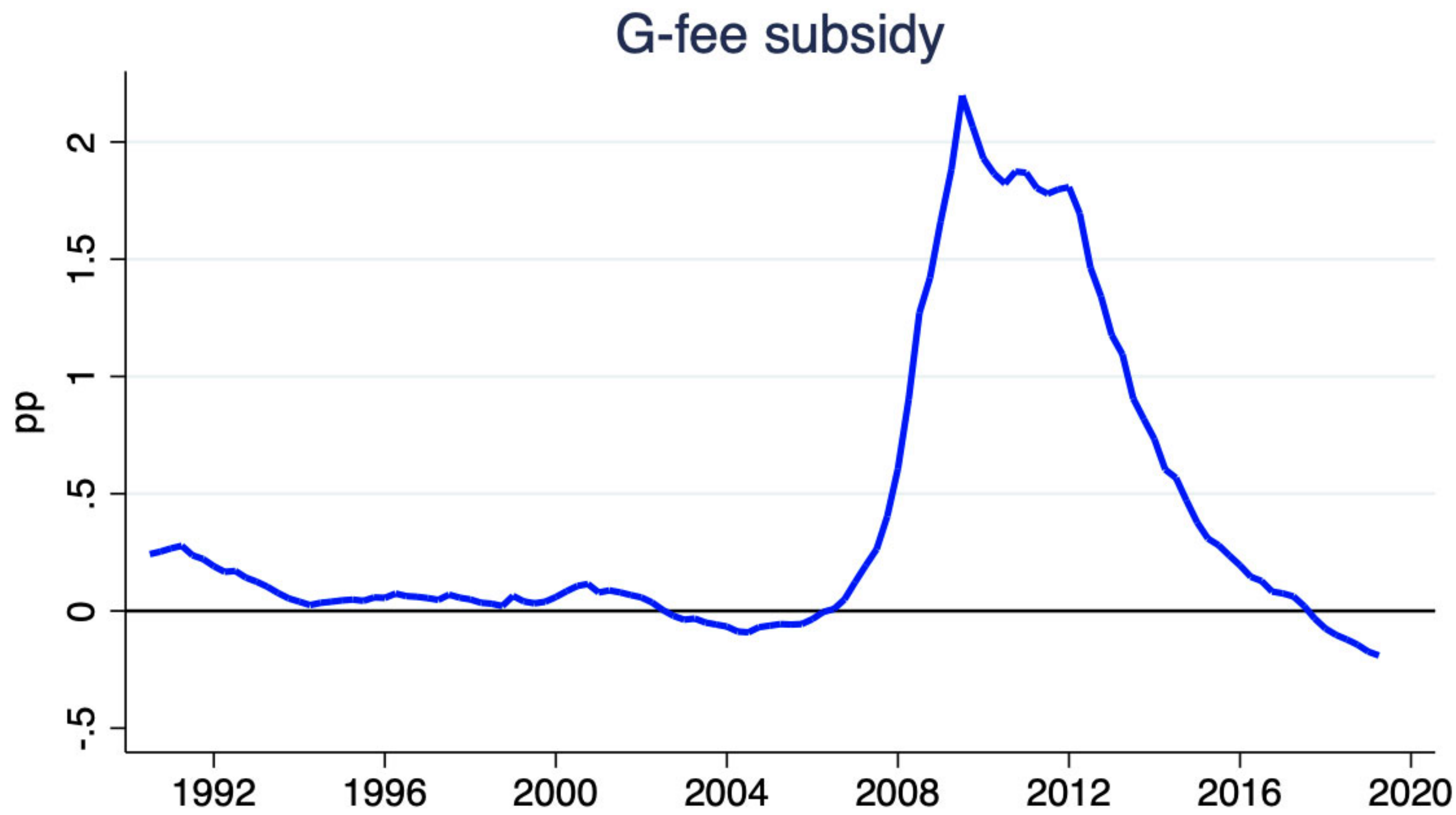


Aggregate Effects

$$r^{subsidy} = r^{g} - r^{adm}$$

- $r^{subsidy}$: GSE subsidy
- r^{g} : Market-implied g-fee
- r^{adm} : Effective (administrative) g-fee

GSE Subsidy


G-fee subsidy
pp
-.5
0
.5
1
1.5
2
1992
1996
2000
2004
2008
2012
2016
2020

Structural VAR

$$Y_t = B(L)Y_{t-1} + u_t$$

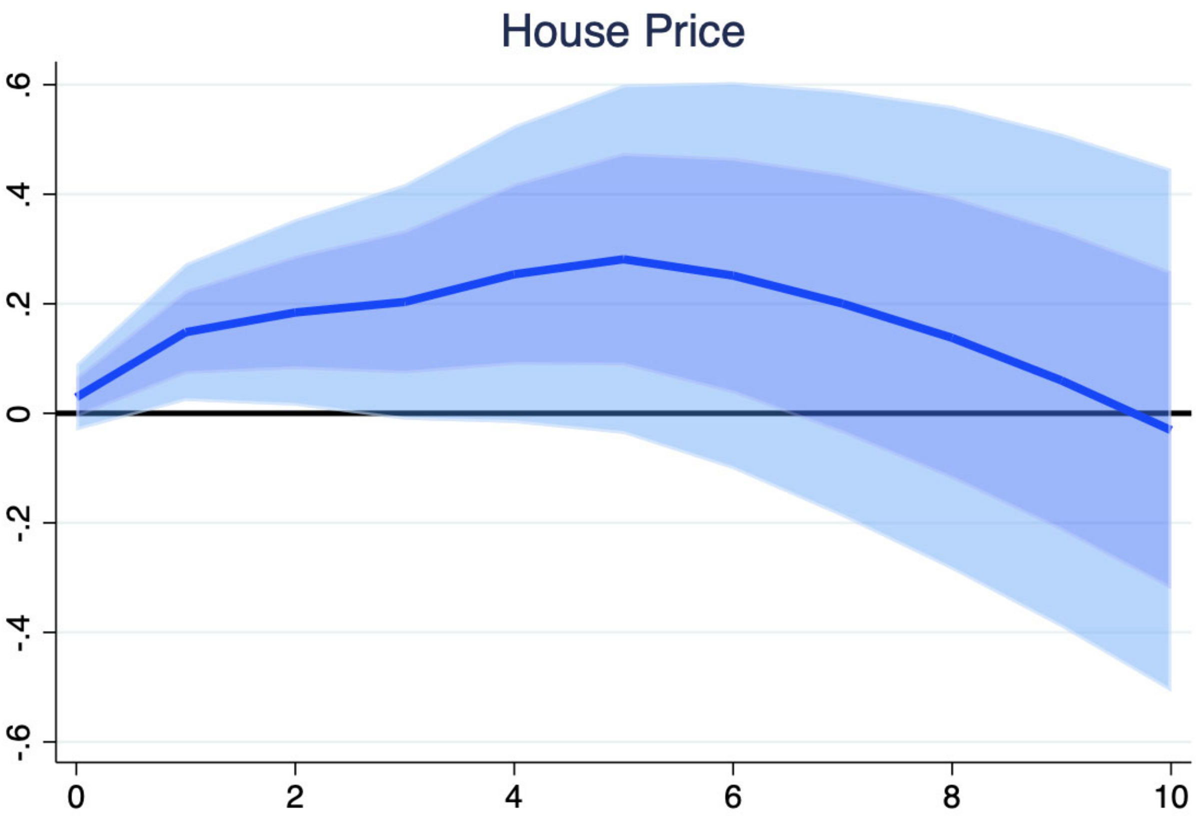
$$B(L) \equiv B_1 + B_2 L + B_3 L^2 + B_4 L^3$$

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

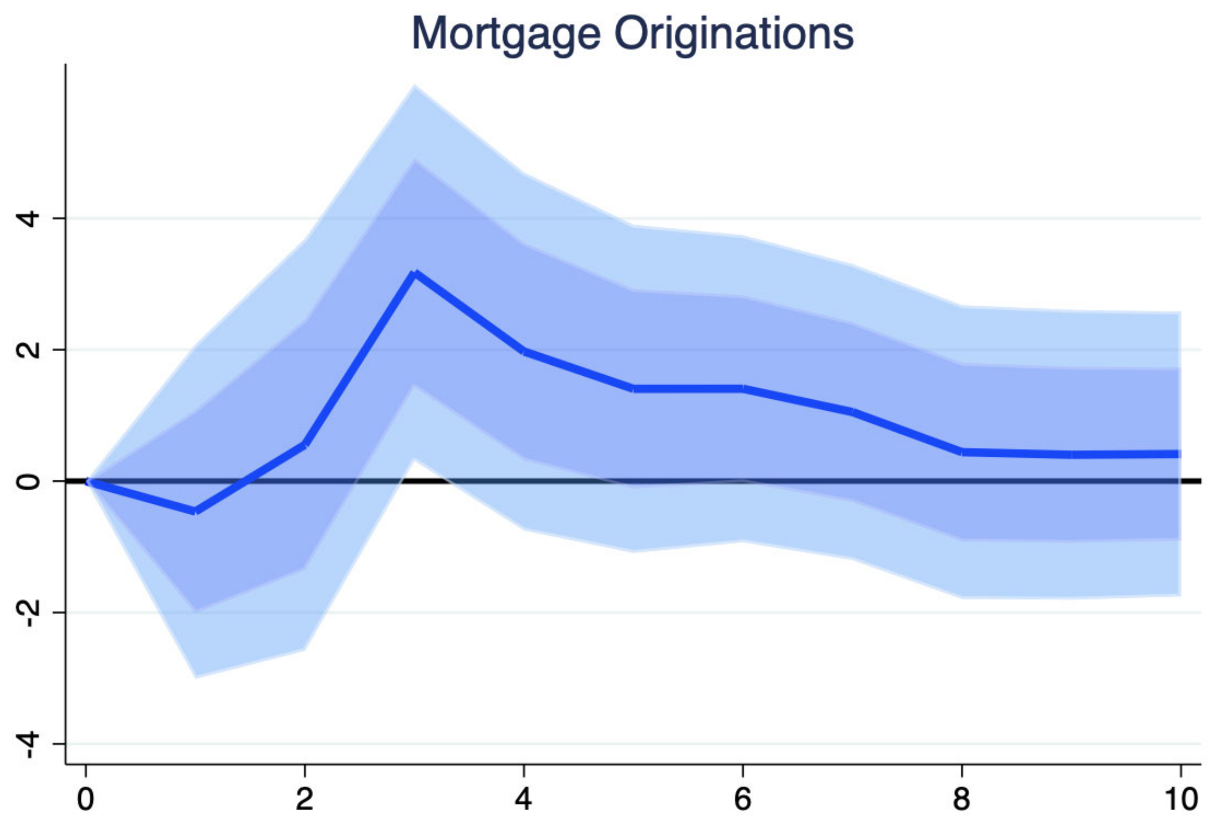
Identification Restrictions

- Shocks to $r^{subsidy}$ do not affect aggregate quantities or consumer prices on impact
- Shocks to $r^{subsidy}$ are allowed to contemporaneously (within the quarter) affect policy rate and house prices
- Similar to Walentin (2014)

Impulse Responses to Positive Subsidy Shock



Time in quarters. Confidence intervals of 68% and 90%.



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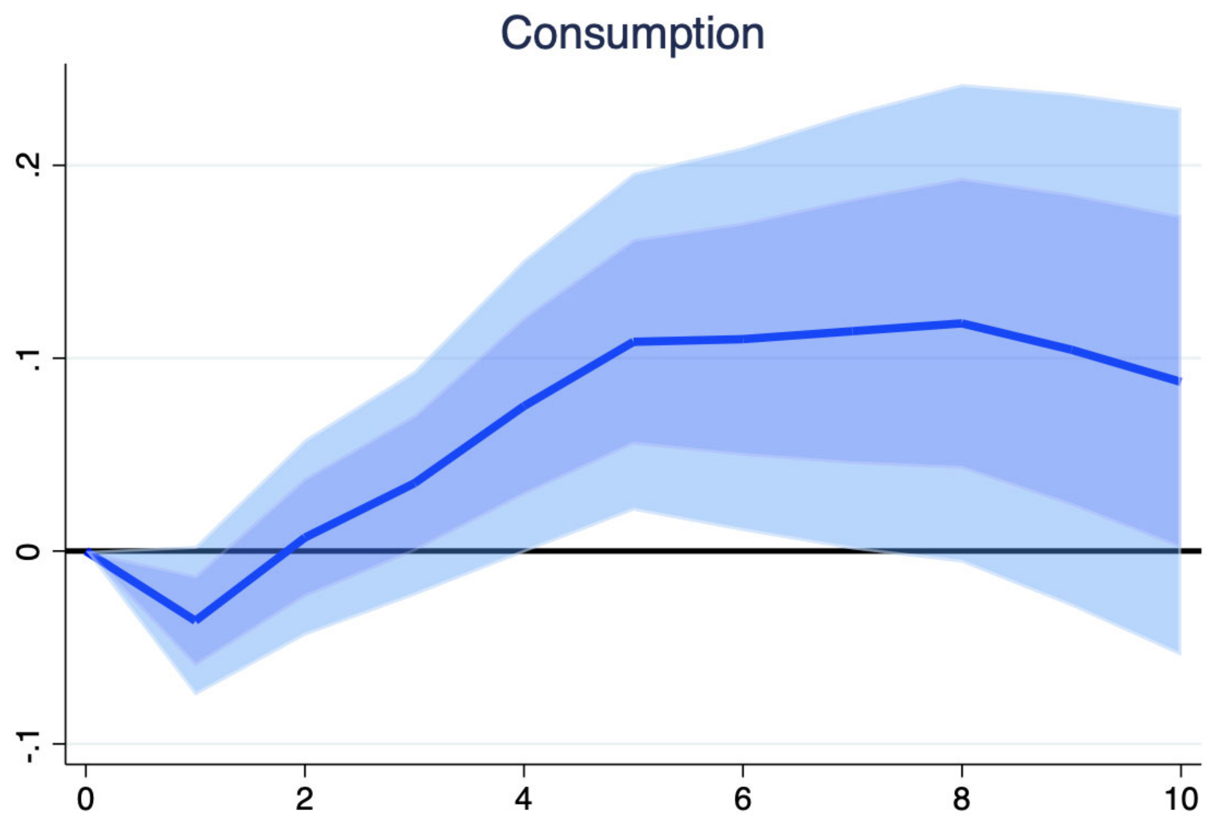

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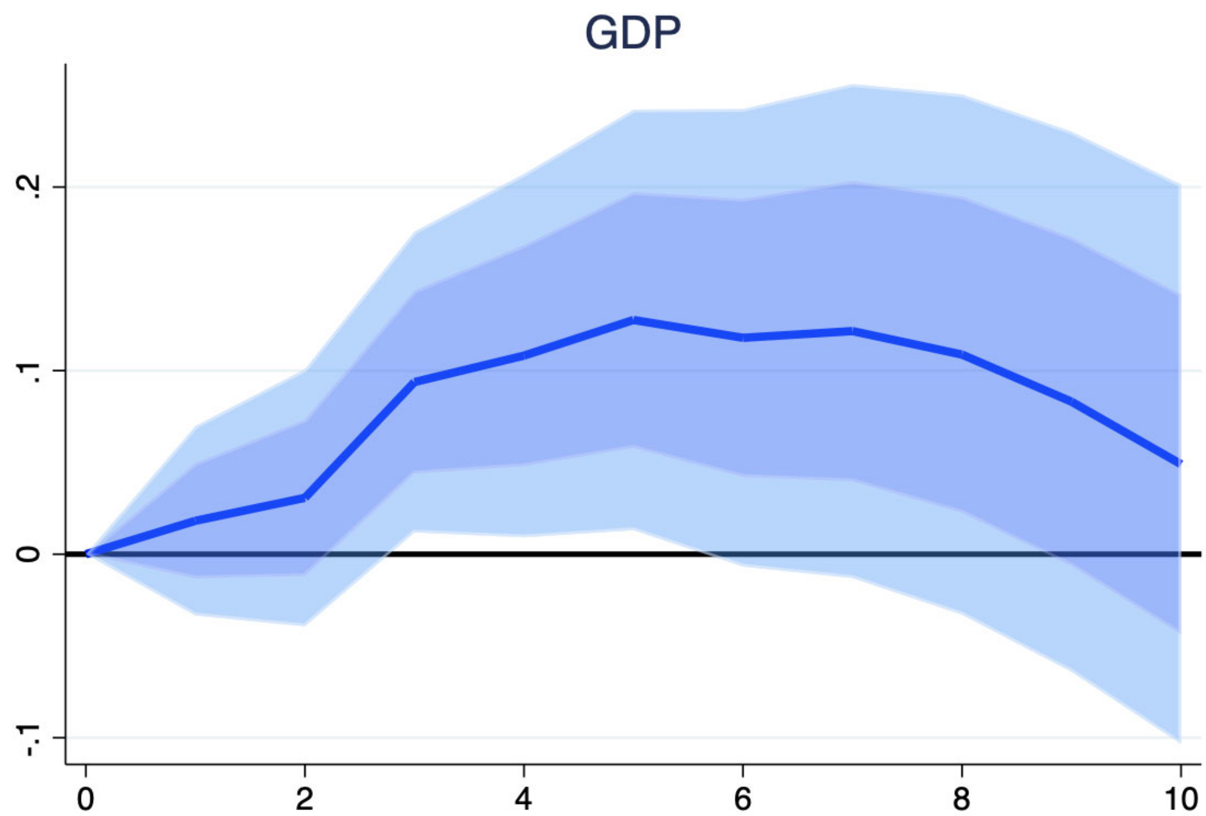

Time in quarters. Confidence intervals of 68% and 90%.

Significant Aggregate Effects

- One standard deviation (7 bps) increase to the mortgage subsidy results in:
  - 4.67% rise in mortgage originations
  - 0.16% rise in consumption
  - 0.14% rise in GDP
  - 0.43% rise in house prices

Conclusions

- Hurricanes significantly increased spreads for the riskiest CRTs by 11% of the average spreads before the landfall
- CRT investors are absorbing part of the risk of natural disasters due to climate change
- GSEs prevent internalizing risk of natural disasters

- GSEs imply countercyclical policy:
    - Strong subsidies to mortgage rates during mortgage stress episodes
    - Market-implied g-fees rise above actual levels in market stress scenarios
    - Rises in actual g-fees before Covid brought them above what market would price in good times
    - Stimulative effects from GSE subsidy