# Impacts of increasing flood losses on mortgage credit risk in the United States

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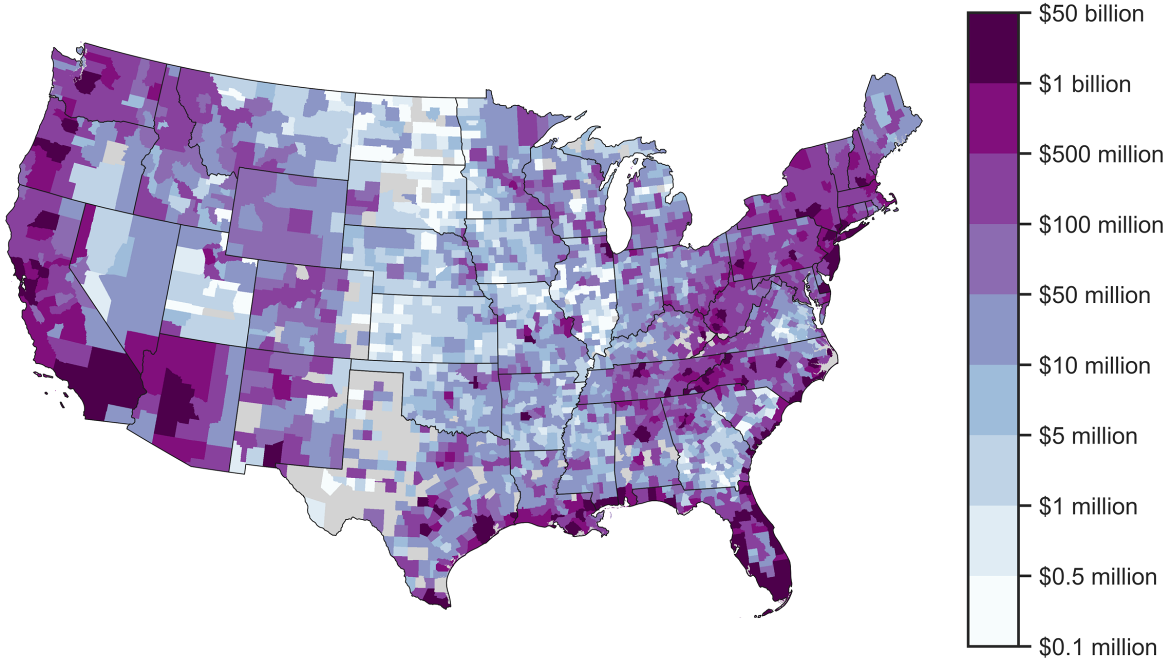
Carolyn Kousky (Environmental Defense Fund)
Jeremy Porter (First Street Technology)



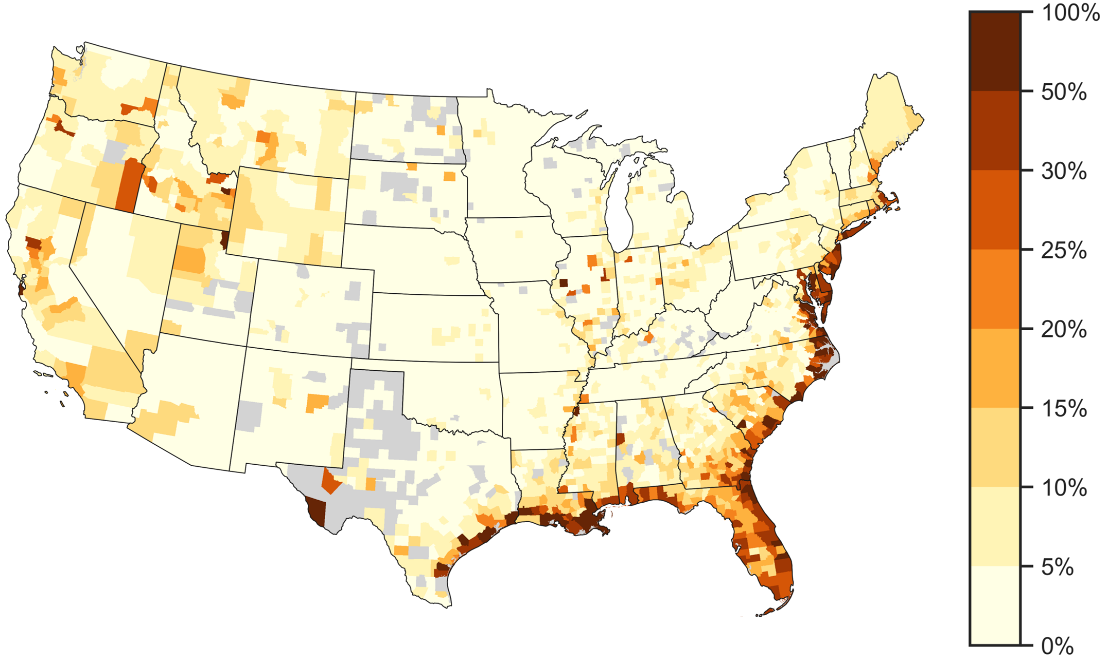
Environmental Defense Fund

# Costs associated with extreme flood events

In 30% of counties, damages to residential structures from a 100-year flood event are expected to exceed $100 million




By 2050 under RCP 4.5, damages from a 100-year flood event are expected to increase by over 10% in 17% of counties



# Background & motivation

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- Delinquencies and defaults can also create liquidity risks and potential losses for lenders, investors, and the federal government

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- Mortgage lenders are beginning to show signs of insulating themselves from credit risk associated with exposure to climate-related hazards

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- Delinquencies and defaults can have devastating impacts on households, leading to a drop in credit score, foreclosure, loss of equity, and an inability to access future credit
- Delinquencies and defaults can also create liquidity risks and potential losses for lenders, investors, and the federal government
- Mortgage lenders are beginning to show signs of insulating themselves from credit risk associated with exposure to climate-related hazards
- However, the potential magnitude and distribution of mortgage delinquencies and defaults associated with extreme events remains uncertain

# Research questions

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2) How do these effects vary, according to inundation depth, borrower characteristics, and insurance uptake?

3) How will increasing flood hazards under future climate change affect the magnitude and distribution of mortgage credit risk?

4) How can tightening lending standards, investments in flood risk reduction, and increased insurance uptake mitigate risk of mortgage defaults associated with flooding?

# Main contributions

**Several recent papers have estimated the effects of climate-related extreme events on mortgage performance outcomes:**
Billings et al. 2022, Biswas et al. 2023, Calabrese et al. 2024, del Valle et al. 2024, Gallagher and Hartley 2017, Issler et al. 2020, Kousky et al. 2020, Rossi 2021

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- ❖ Exploration of heterogeneity in treatment effects
  - ➢ *Improves understanding of distribution of credit risk among borrowers*
- ❖ Projecting mortgage default associated with 100 and 500-year flood events in the present and under future climate change
  - ➢ *Allows for exploration of alternative scenarios to mitigate risk*

# Key datasets

**Loan-level origination & performance data (FR Y-14M)**

- Loan origination and performance data available on a monthly timestep
- Federal Reserve began collecting data from 29 large US banks in June 2012
- Location of properties identified at address-level
- Borrower and loan characteristics similar to broader samples of loans (link)

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**Modeled inundation from historical flood events (First Street)**

- Estimates flood depth from historical events for individual properties
- Location of properties identified at address-level
- Includes information on properties' foundation height
- Modeled flood depths are well validated against observed flood extents (link)

# Estimation sample

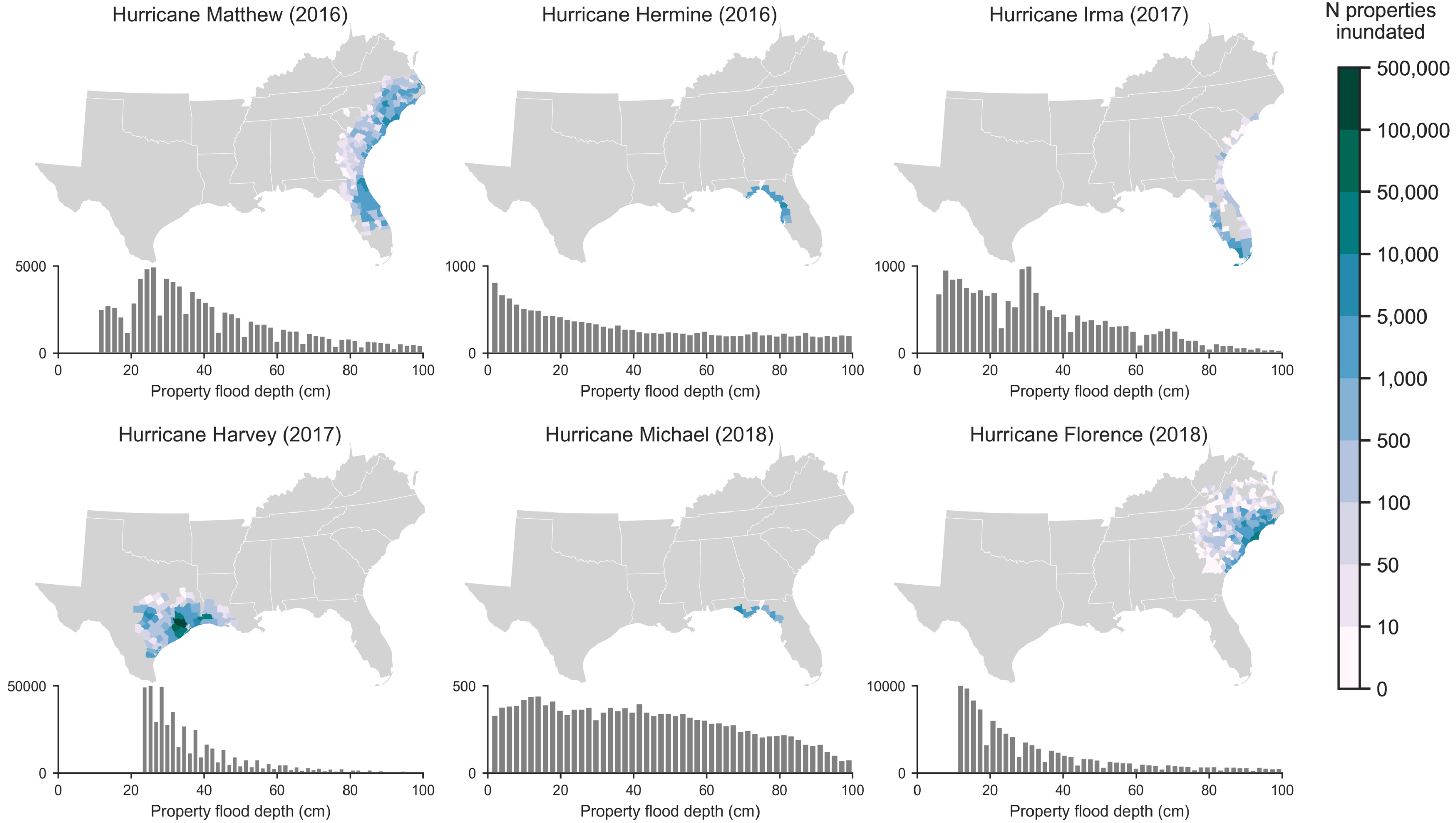
**Treated units (N = 643k)**

Loans for 1-4 unit residential properties that have been impacted by flooding during major hurricanes between 2016 and 2018

**Control units (N = 5.2 million)**

Loans for residential properties that have <u>not</u> been impacted by flooding during major hurricanes between 2016 and 2018, but are located in the same set of states as impacted loans

# Distributions of treated units



# Model specification: Two-Stage Diff-in-Diff

$$Y_{it} = \sum_{k=-12}^{k=36} \beta_k Flood_{it}^{k} + \lambda_i + \gamma_t + \epsilon_{it}$$

**Where:**

$Y_{it}$ is a binary variable equal to 1 if loan *i* is 90+ days delinquent or in foreclosure at time *t*

$\beta_k$ is the estimated ATT *k* months relative to the flood event

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$$Y_{it} = \lambda_i + \gamma_t + \epsilon_{it}$$

*Stage 2:* Regress adjusted outcomes on treatment dummy variables

$$Y_{it} - \widehat{\lambda_i} - \widehat{\gamma_t} = \sum_{k=-12}^{k=36} \beta_k Flood_{it}^{k} + \epsilon_{it}$$

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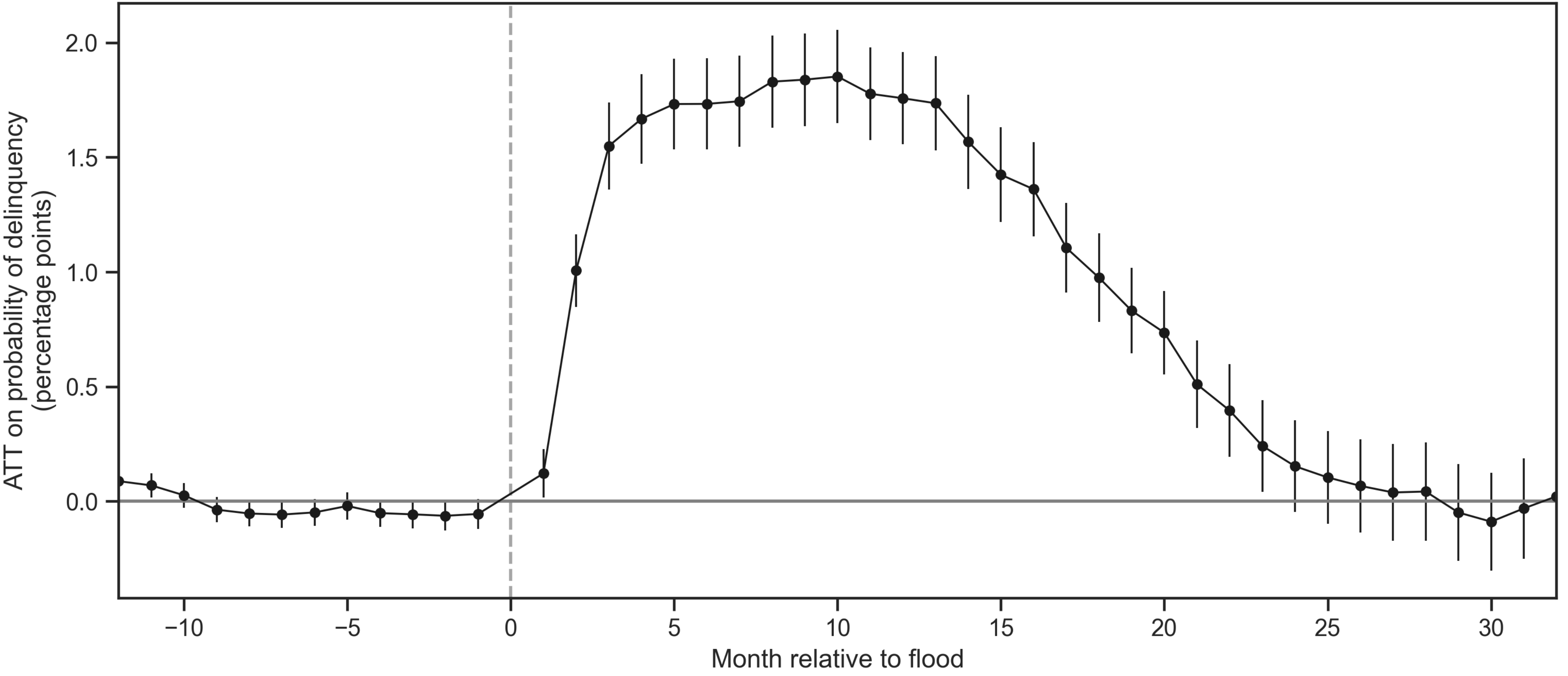
# Dynamic treatment effects



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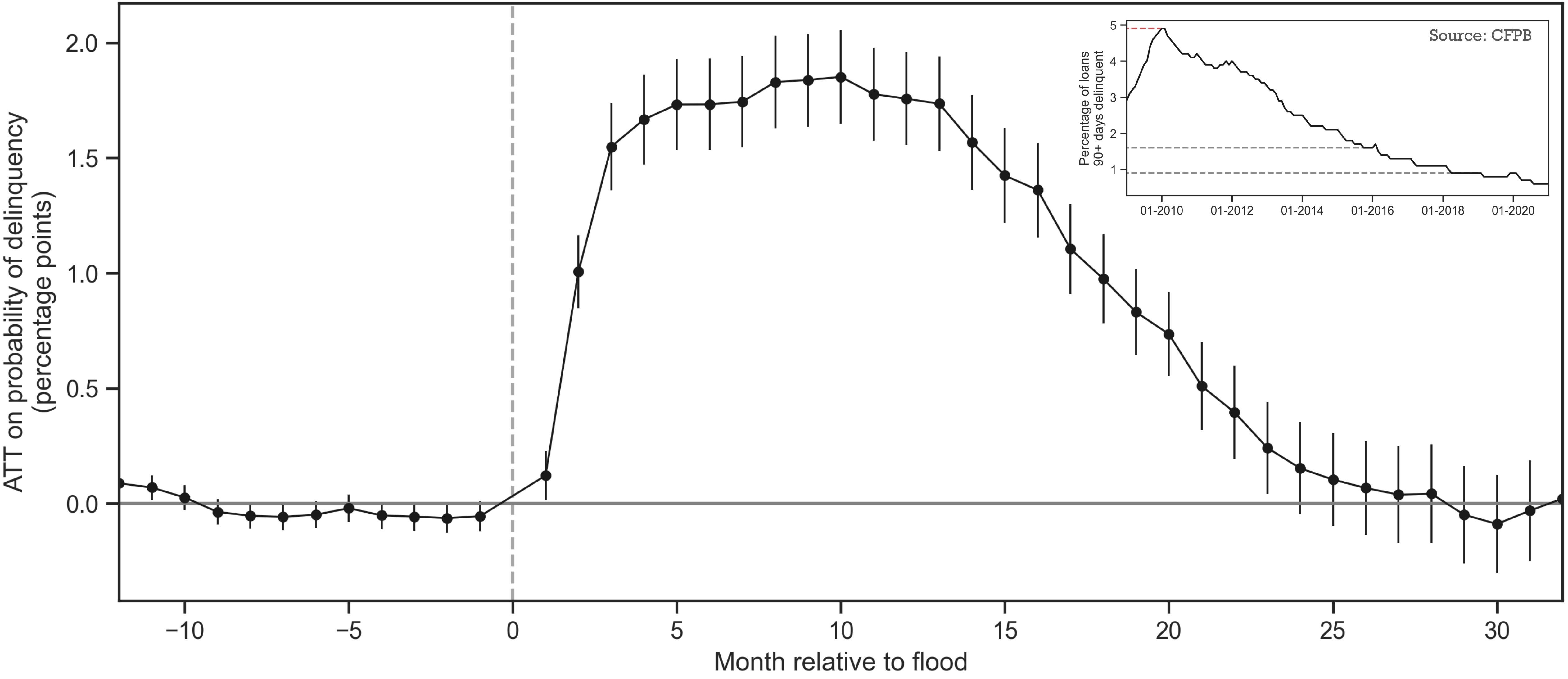

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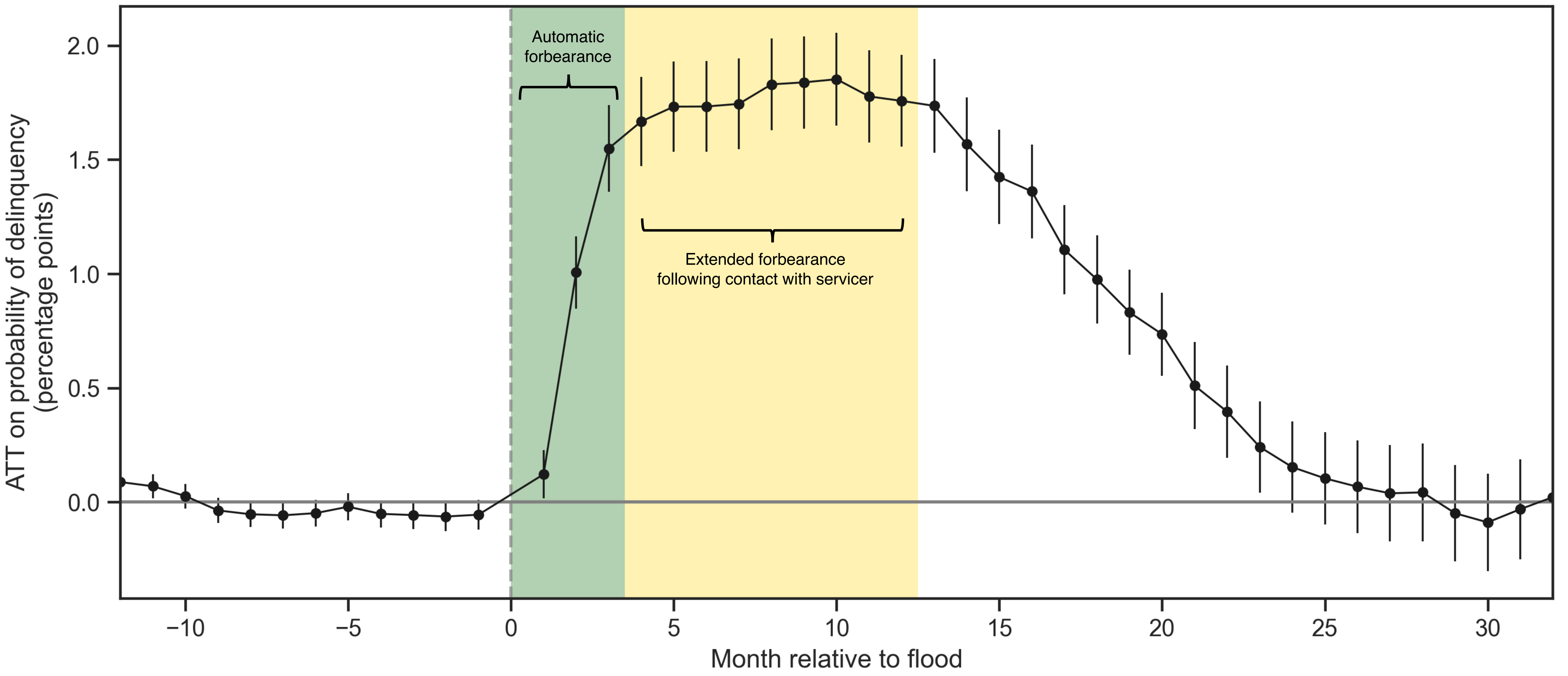
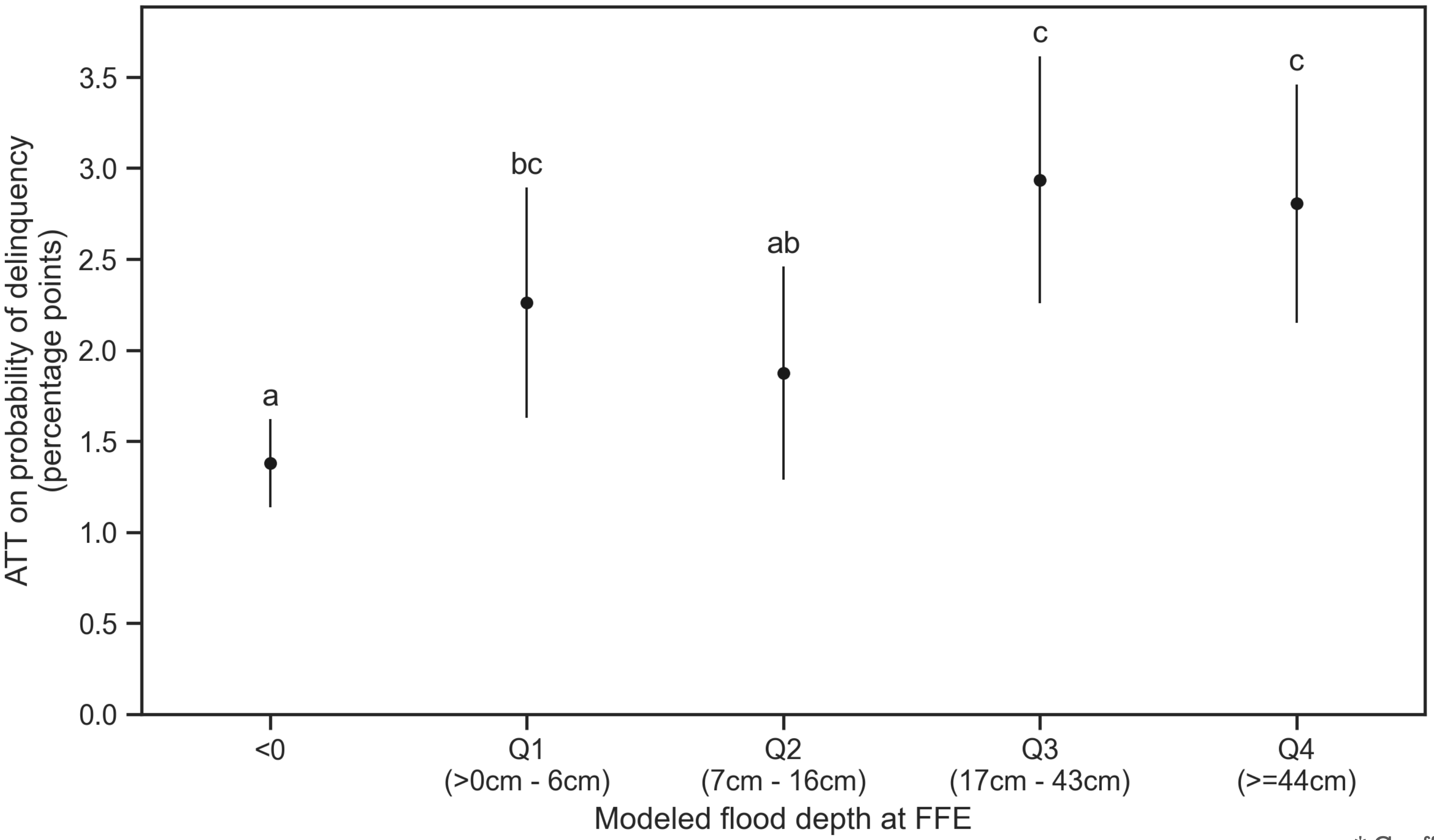
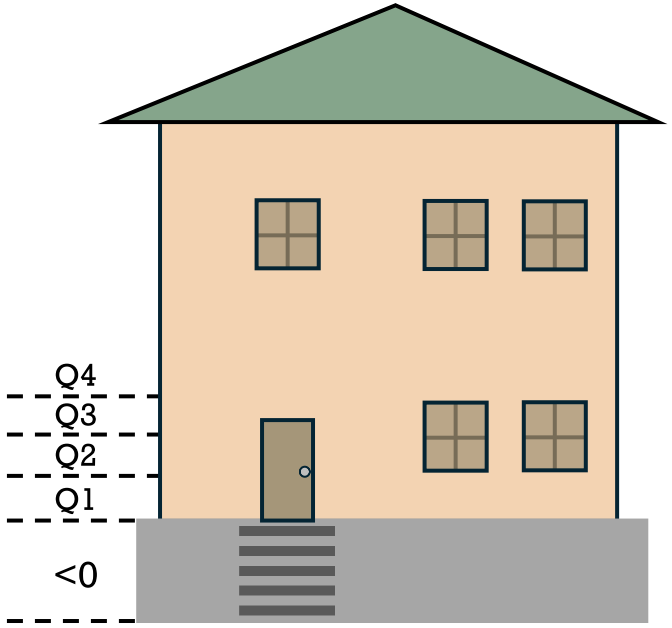


# Heterogenous treatment effects – Flood depth

ATT increases by ~1.5pp for observations with above-median inundation depth at FFE compared to observations where depth is below FFE

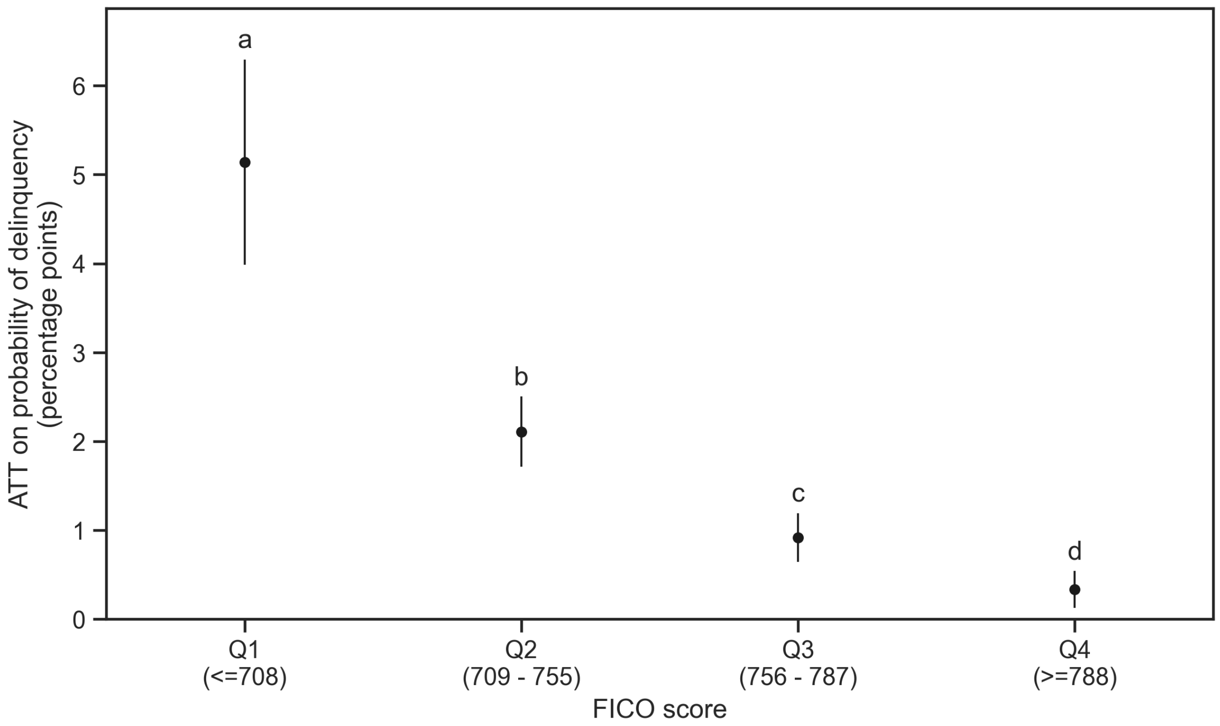



* Coefficients with the same letter indicate pairwise comparisons where we fail to reject the null hypothesis that $\beta = \beta'$

# Heterogenous treatment effects – FICO & DTI

## Borrowers with lower credit scores are more likely to become delinquent following flood events

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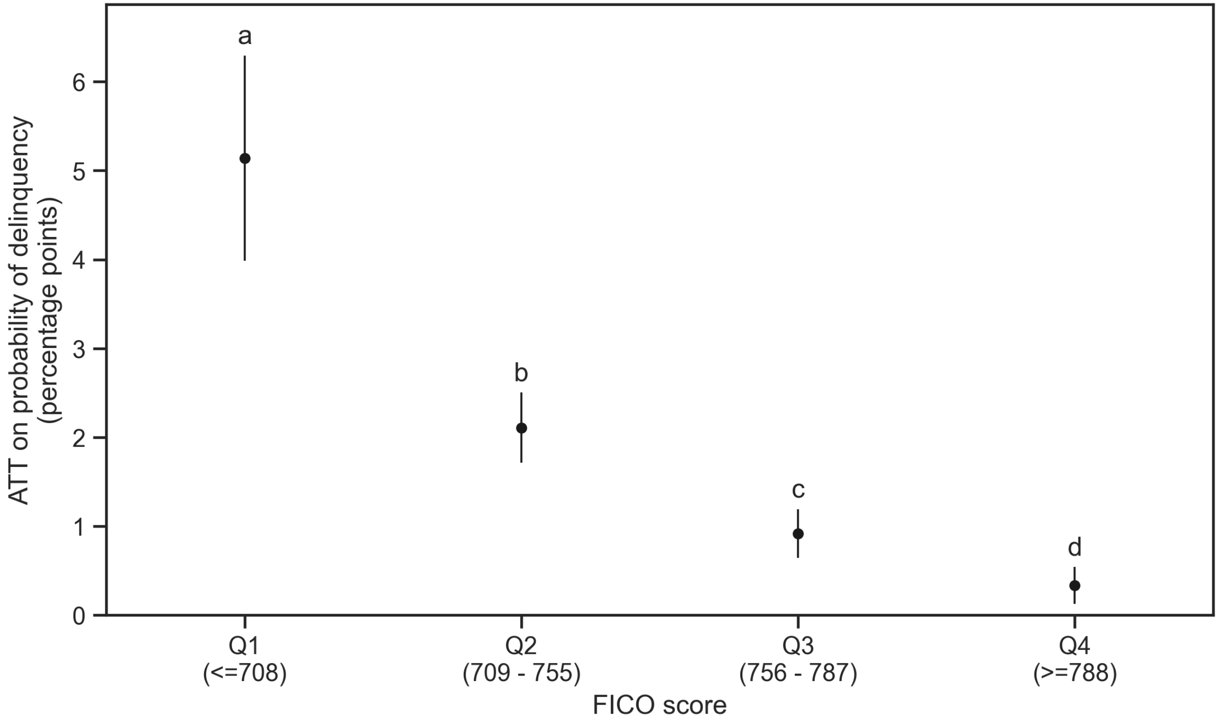
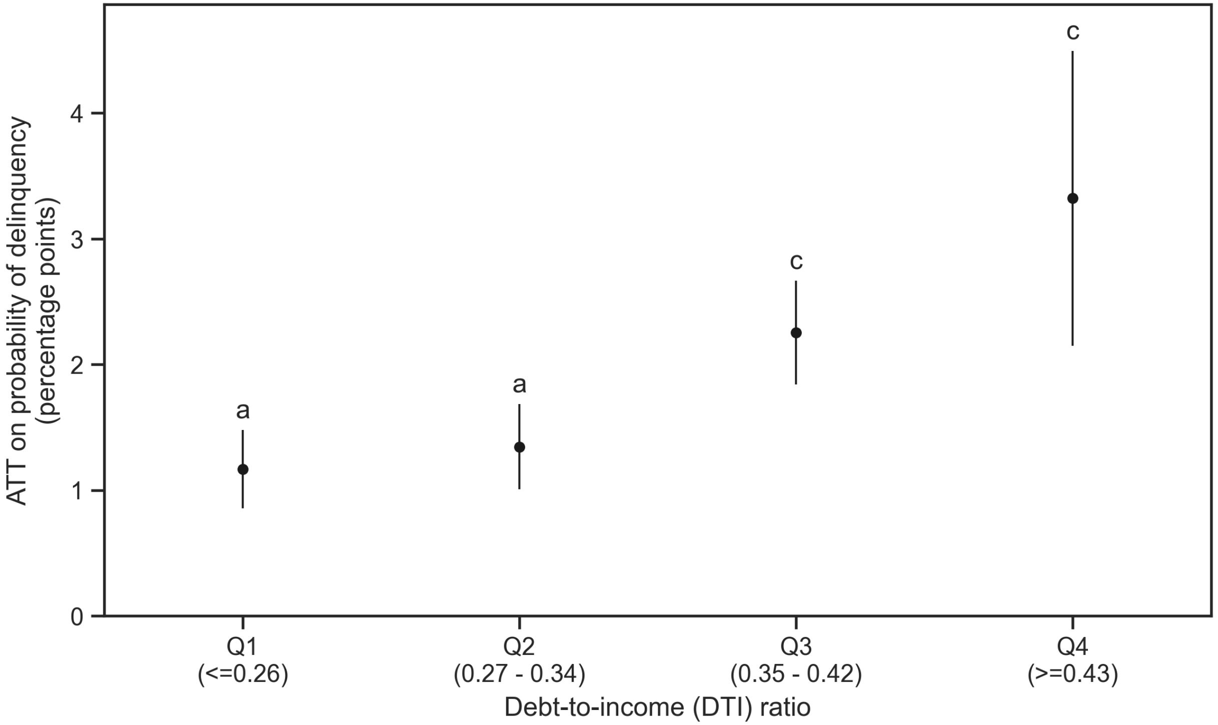



## Similar yet smaller differences as DTI ratios increase

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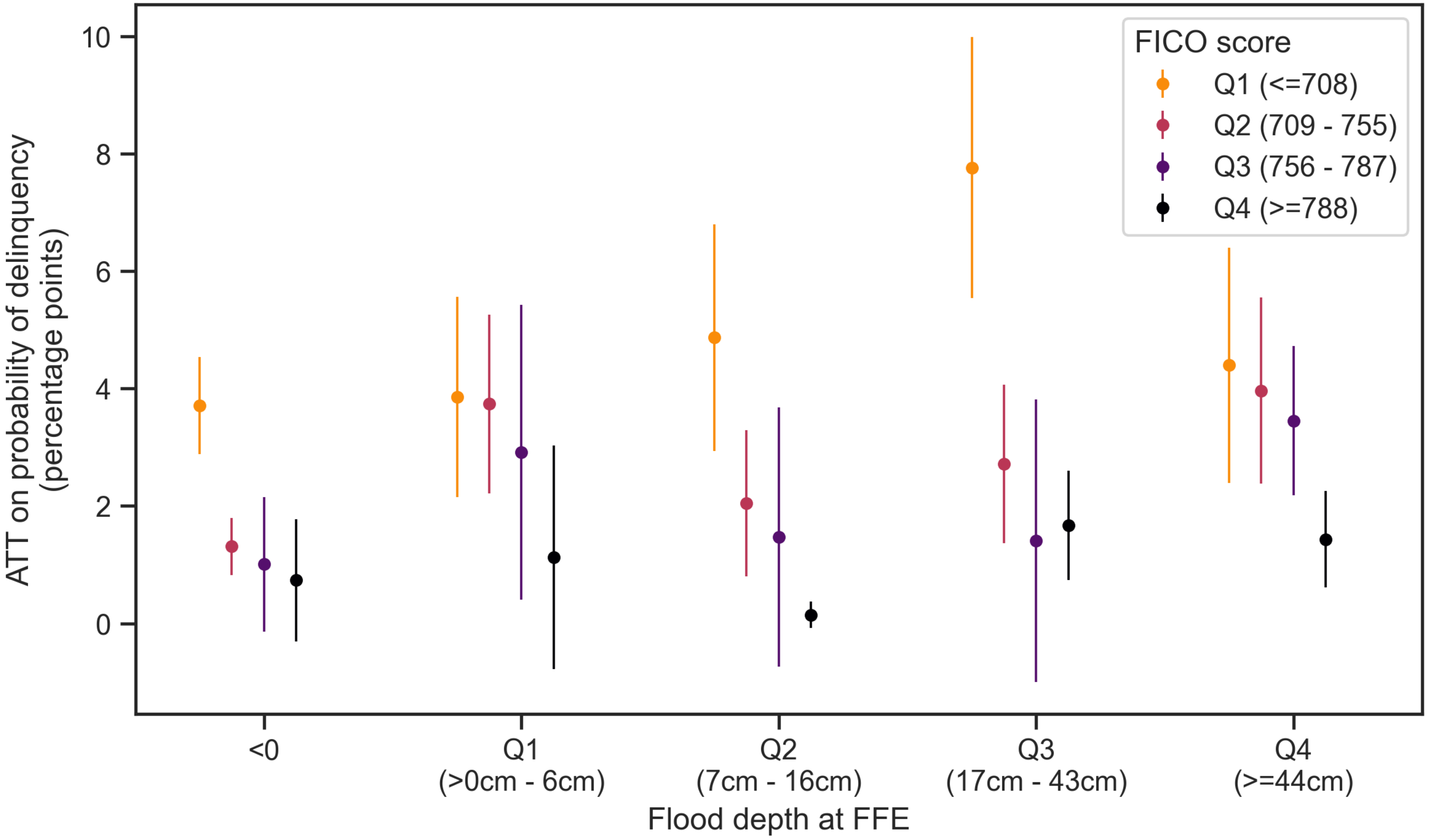
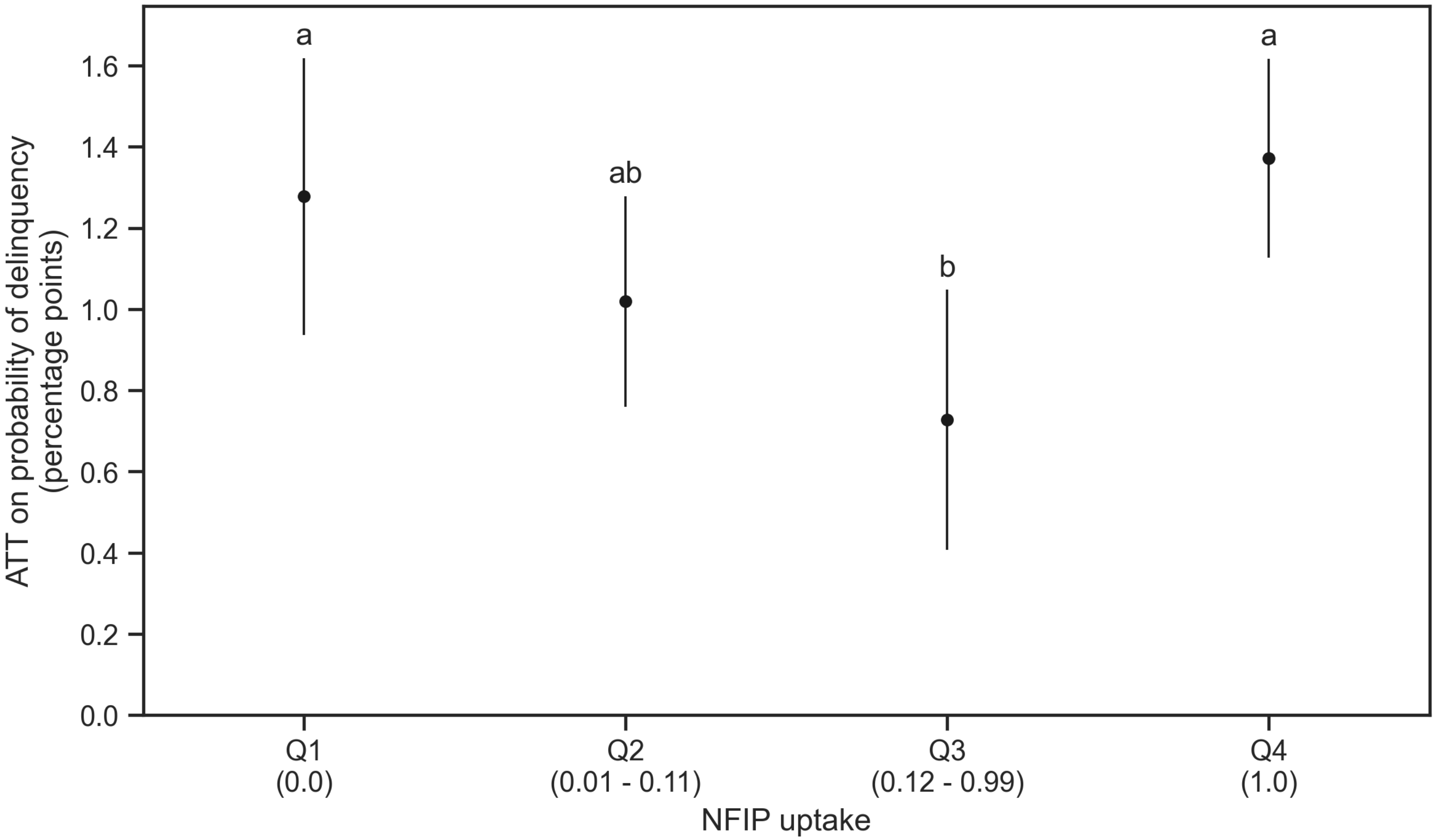
# Heterogenous treatment effects – Flood depth & FICO



# Heterogenous treatment effects – NFIP uptake




$$Uptake_{it} = \frac{PIF_{bzt}}{AtRisk_{bz}}$$

Where:

$Uptake_{it}$ is the NFIP uptake rate associated with loan $i$ at time $t$

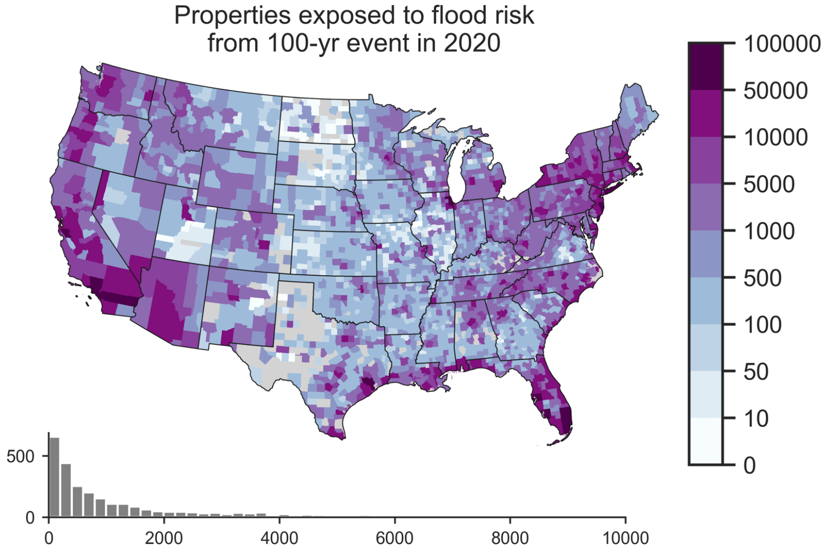
$PIF_{bzt}$ is the number of policies-in-force in block group $b$ in flood zone $z$ (SFHA or non-SFHA) at time $t$

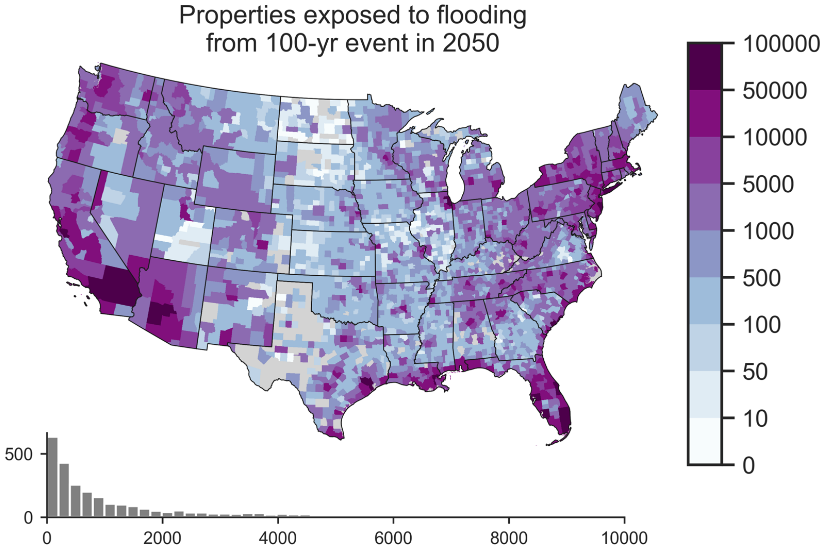
$AtRisk_{bz}$ is the number of 1-4 unit homes that First Street estimates to be at risk of flooding from a 100-year event in 2020 in block group $b$ in flood zone $z$ (SFHA or non-SFHA)

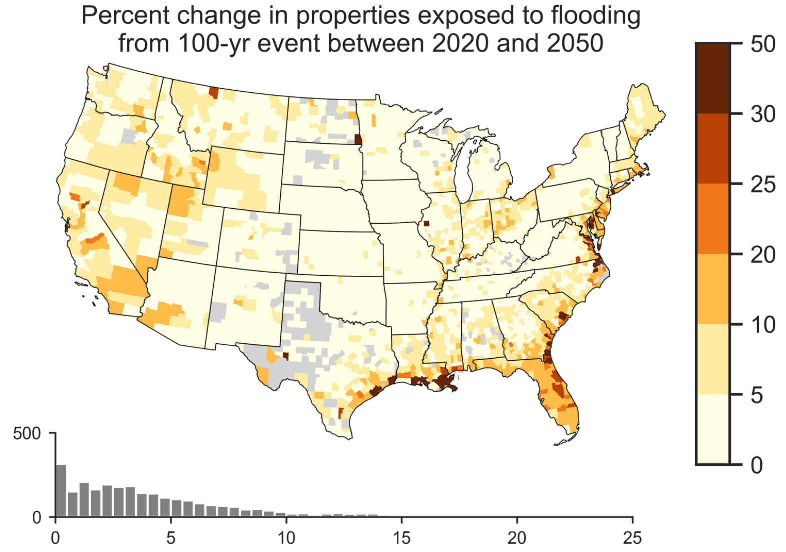
* For named storm-events, the average time from loss until claim payment is 93 days.

* Coefficients with the same letter indicate pairwise comparisons where we fail to reject the null hypothesis that $\beta = \beta'$

# Projecting impacts of 100 and 500-year events

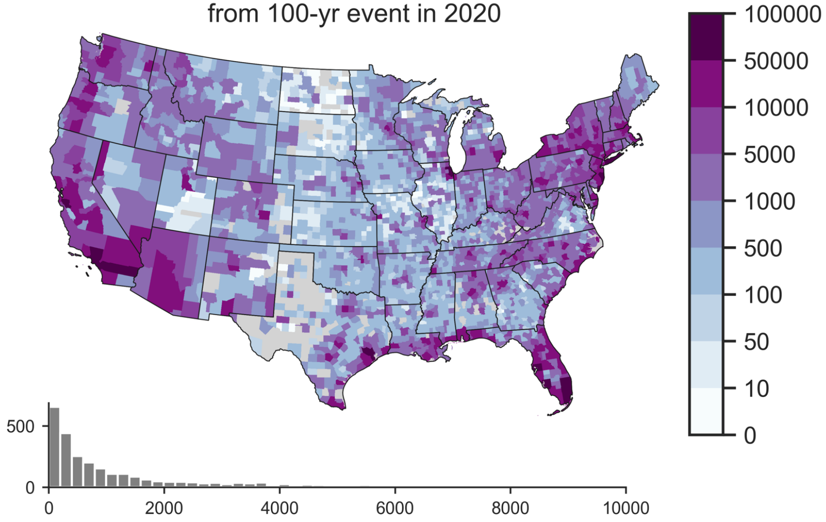


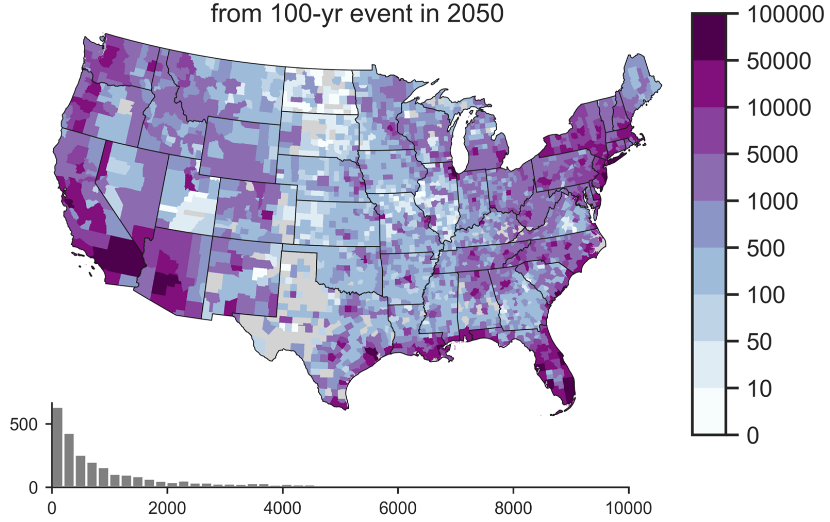



# Projecting impacts of 100 and 500-year events

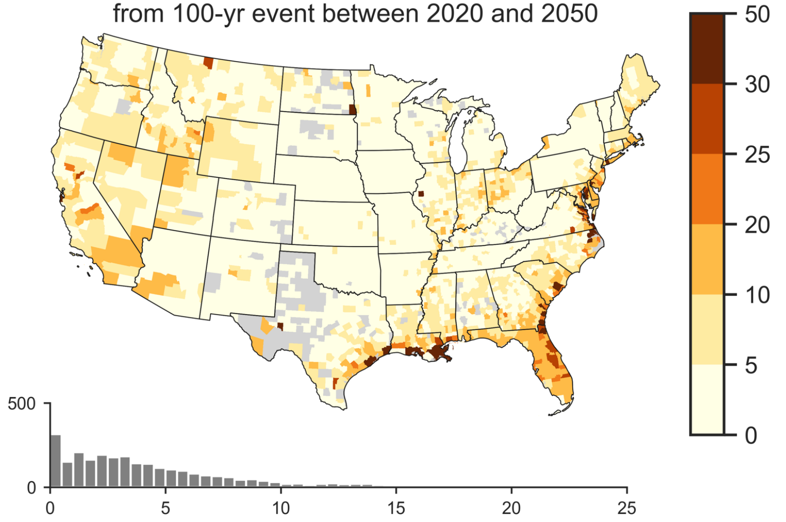
Properties exposed to flood risk
from 100-yr event in 2020



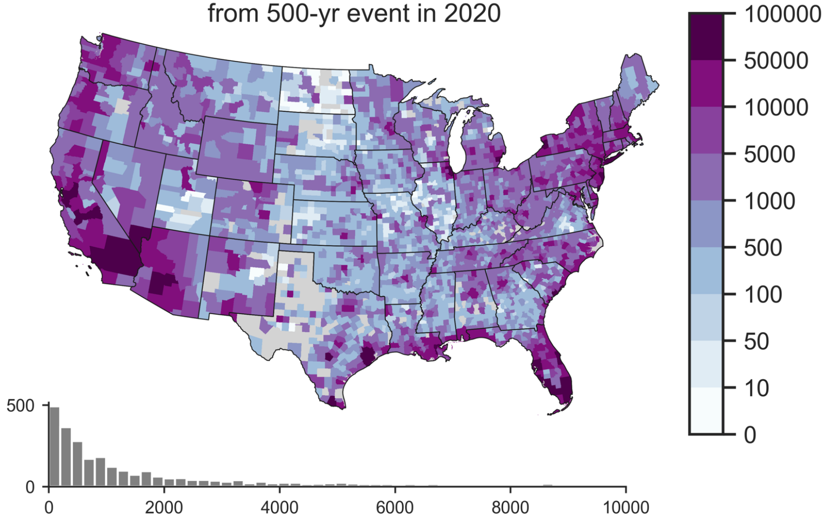

Properties exposed to flooding
from 100-yr event in 2050




Percent change in properties exposed to flooding
from 100-yr event between 2020 and 2050




Properties exposed to flooding
from 500-yr event in 2020




Properties exposed to flooding
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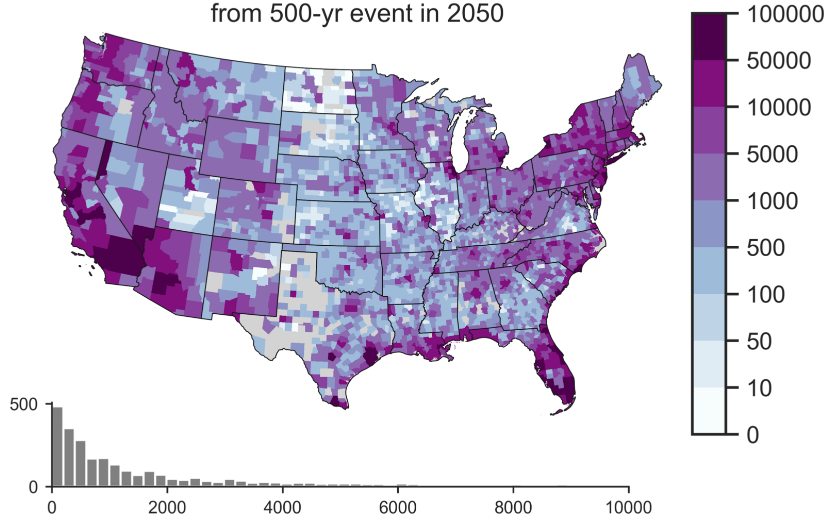


Percent change in properties exposed to flooding
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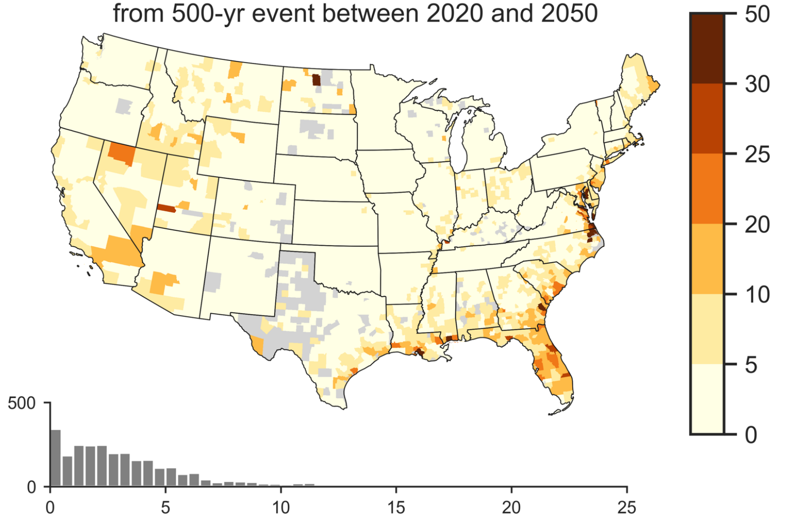
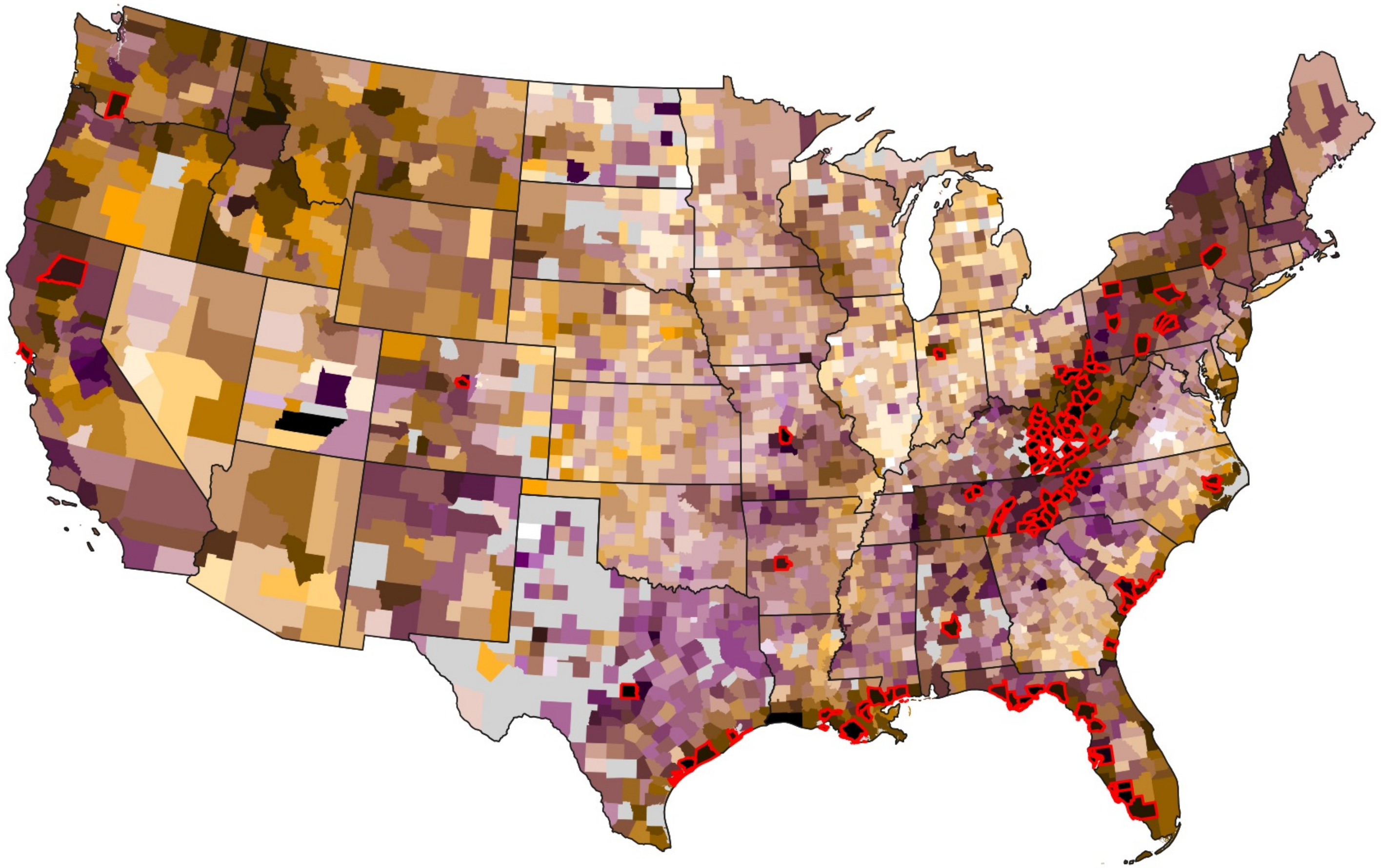
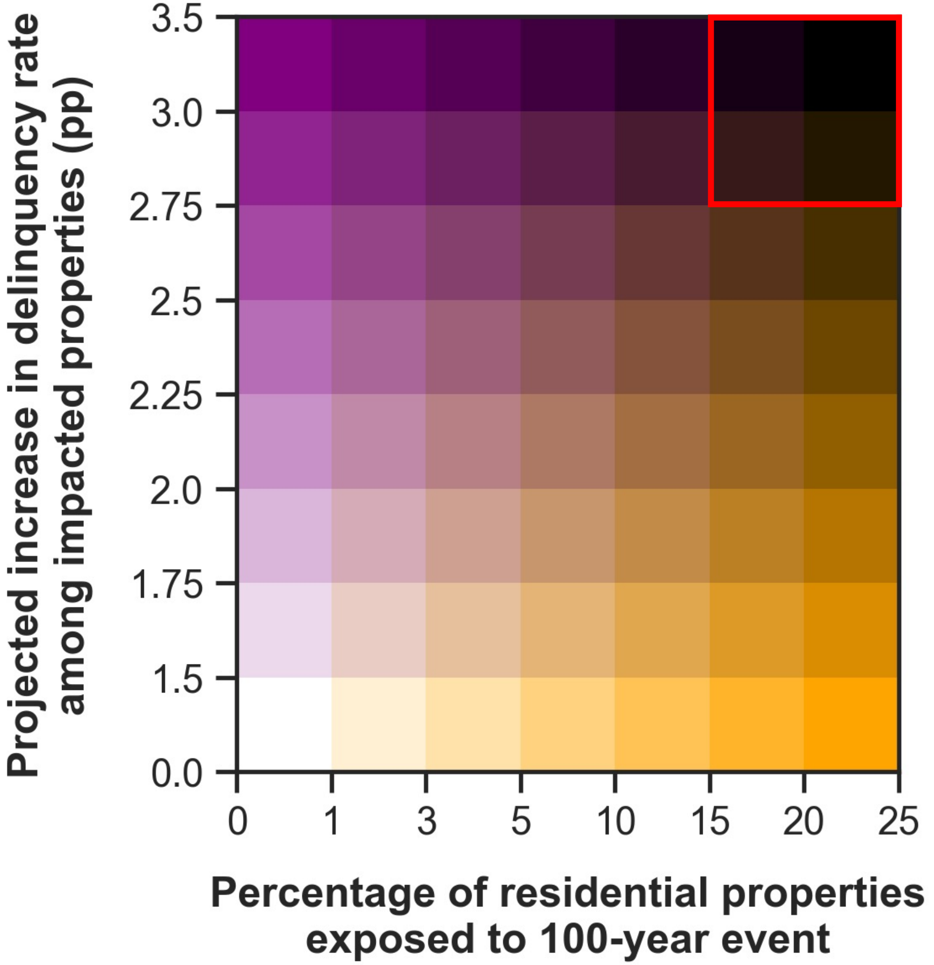


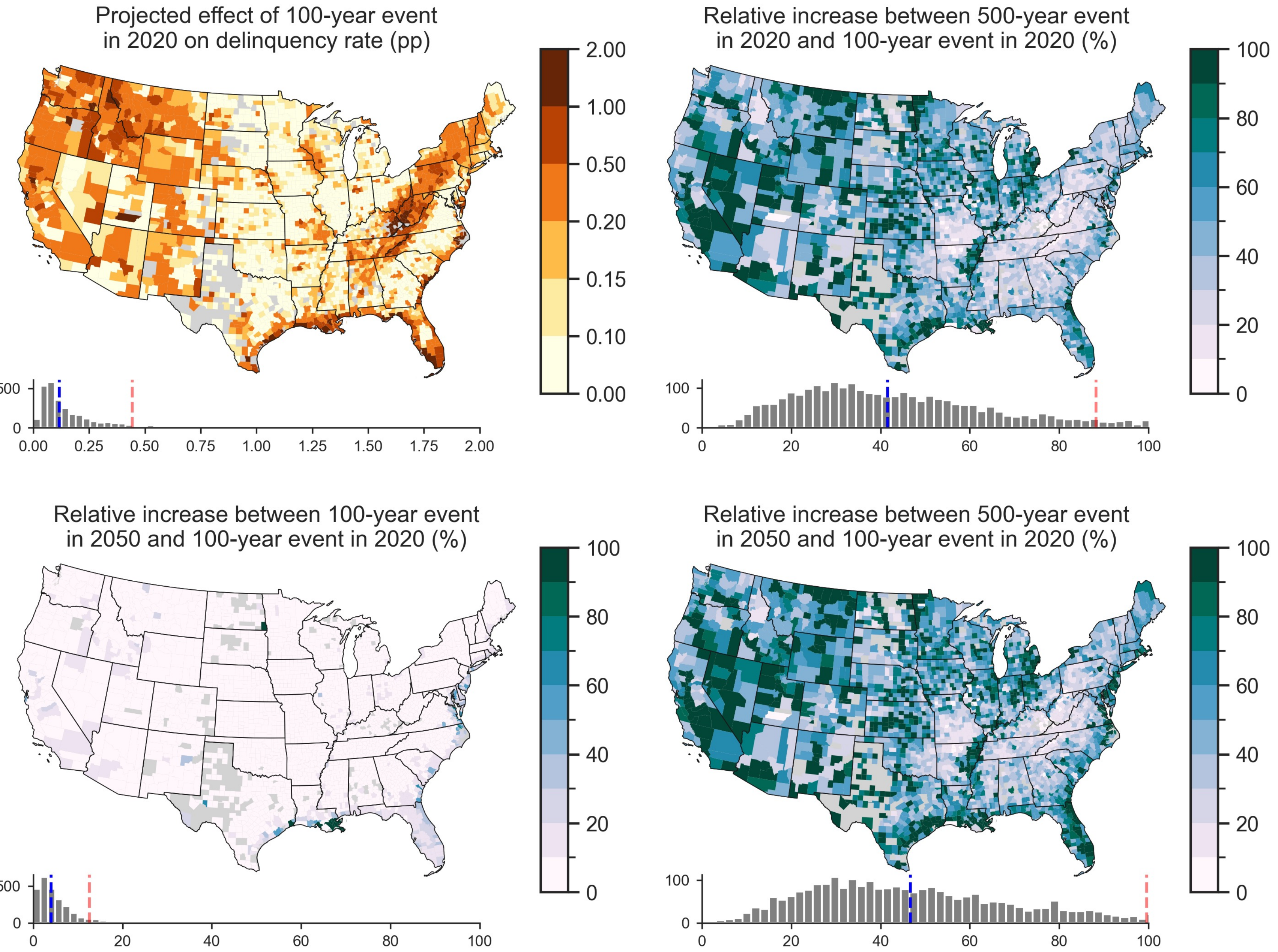
# Projecting impacts of 100-year flood events

Extrapolating estimated effects reveals hotspots of credit risk associated with flooding in Appalachia and Gulf and Atlantic coastal regions



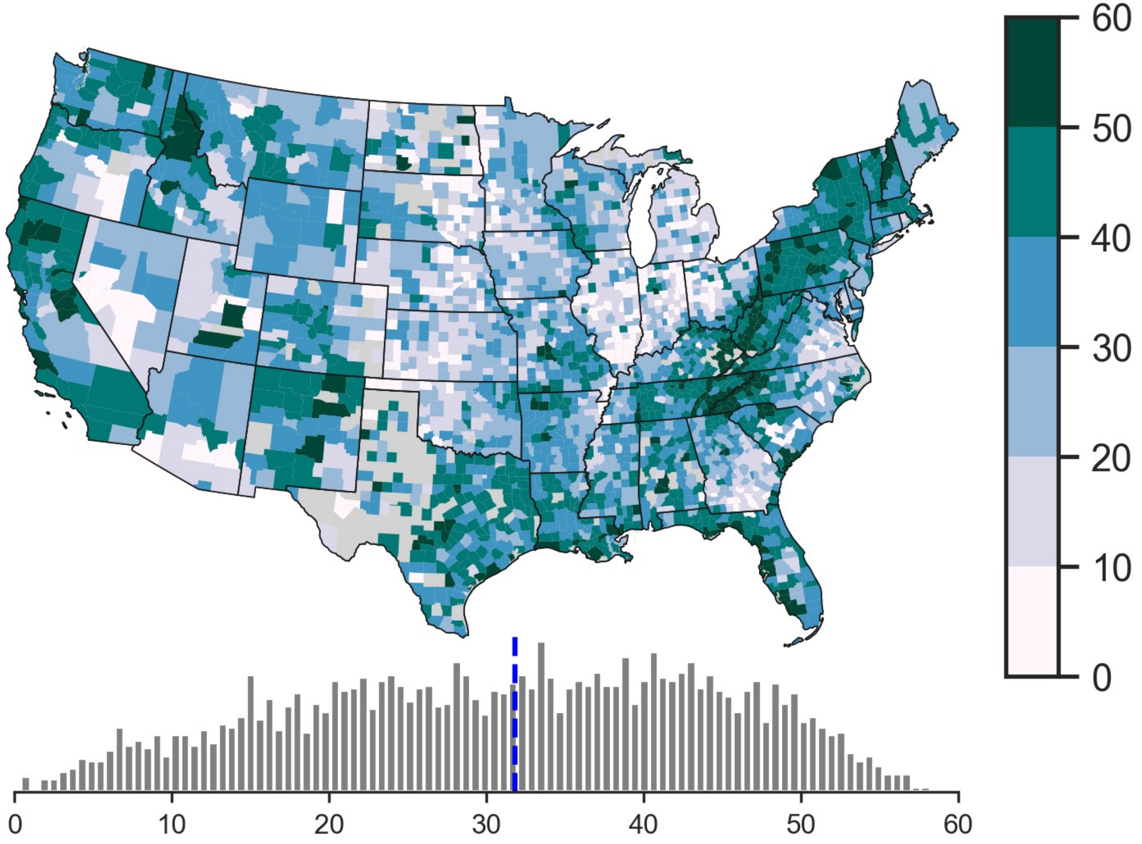


# Projecting impacts of more severe flood events



# Projecting impacts of alternative scenarios

Reducing flood depths to below FFE decreases delinquencies by a median of 32% across counties



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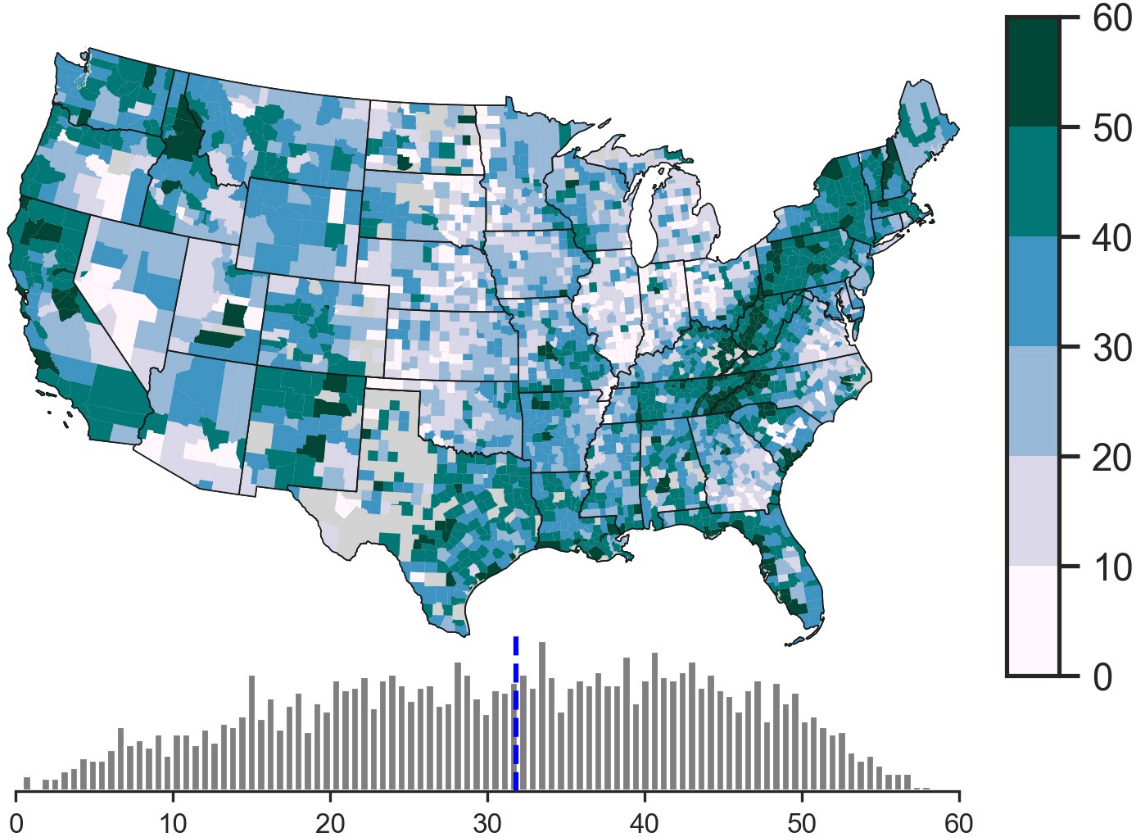
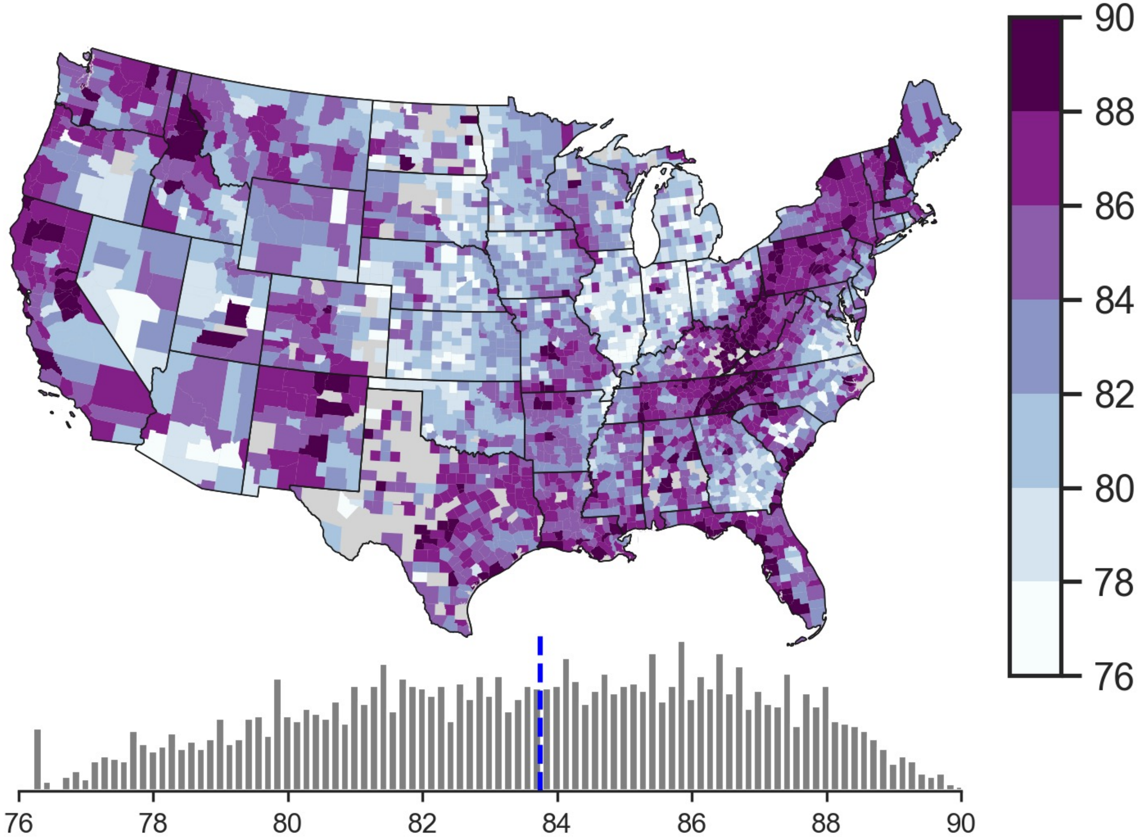



Restricting lending to borrowers in highest FICO quartile decreases delinquencies by a median of 84% across counties



# Main conclusions

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- Rates of delinquency are expected to increase under more extreme events and from future climate change
- Mitigating flood risk and tightening lending standards may reduce delinquencies caused by flood event

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- Include observations from non-hurricane flood events to sample

# Thank you

Please reach out with comments or questions!

Email: jgourevitch@edf.org

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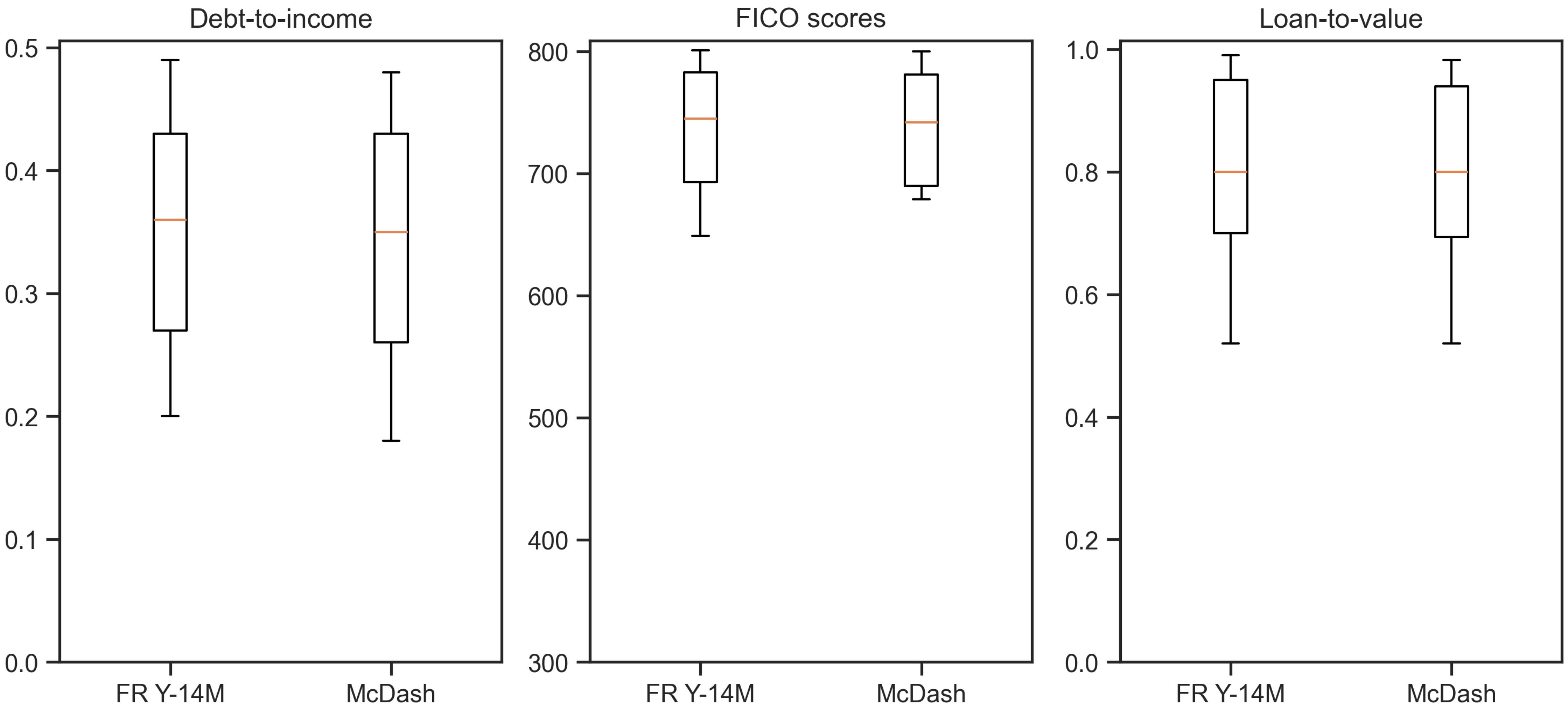
# Extra Slides

# Comparing FR Y-14M and McDash loan characteristics




(link back)

# Validation of modeled historical flood events

| Site Name | (a) Fathom hindcast model | | | | (b) NWC hindcast model | | | |
|---|---|---|---|---|---|---|---|---|
| | HR | FAR | CSI | EB | HR | FAR | CSI | EB |
| Tres Palacios River | 0.89 | 0.41 | 0.55 | 5.59 | 0.67 | 0.43 | 0.45 | 1.54 |
| Upper Brazos River | 0.89 | 0.18 | 0.74 | 1.68 | 0.52 | 0.19 | 0.46 | 0.26 |
| Lower Brazos River | 0.93 | 0.04 | 0.90 | 0.61 | 0.50 | 0.05 | 0.48 | 0.06 |
| Cow Bayou | 0.77 | 0.11 | 0.70 | 0.42 | 0.51 | 0.12 | 0.47 | 0.14 |
| Big Cow Creek | 0.65 | 0.16 | 0.57 | 0.35 | 0.54 | 0.19 | 0.48 | 0.27 |
| East Matagorda Bay | 0.76 | 0.15 | 0.67 | 0.55 | 0.33 | 0.25 | 0.30 | 0.17 |
| Matagorda Bay | 0.79 | 0.37 | 0.54 | 2.19 | 0.58 | 0.21 | 0.50 | 0.37 |
| Upper San Bernard River | 0.55 | 0.15 | 0.50 | 0.21 | 0.13 | 0.05 | 0.13 | 0.01 |
| Middle San Bernard River | 0.79 | 0.04 | 0.76 | 0.16 | 0.34 | 0.04 | 0.34 | 0.02 |
| Lower San Bernard River | 0.95 | 0.25 | 0.72 | 6.01 | 0.75 | 0.27 | 0.58 | 1.10 |
| San Jacinto River | 0.76 | 0.35 | 0.54 | 1.74 | 0.45 | 0.25 | 0.39 | 0.28 |
| Lower Neches River | 0.79 | 0.07 | 0.74 | 0.29 | 0.37 | 0.07 | 0.36 | 0.05 |
| Upper Neches River | 0.70 | 0.02 | 0.69 | 0.06 | 0.36 | 0.03 | 0.36 | 0.02 |
| Pine Island Bayou | 0.67 | 0.04 | 0.65 | 0.08 | 0.44 | 0.07 | 0.43 | 0.06 |
| **MEAN** | **0.78** | **0.17** | **0.66** | **1.42** | **0.46** | **0.16** | **0.41** | **0.31** |

(c)

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| HR: | 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 |
| FAR: | 1 | 0.9 | 0.8 | 0.7 | 0.6 | 0.5 | 0.4 | 0.3 | 0.2 | 0.1 | 0 |
| CSI: | 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 |
| EB: | ∞ | 100 | 50 | 20 | 10 | 5 | 2.5 | 2 | 1.5 | 1.25 | 1 |
| | 0 | 0.01 | 0.02 | 0.05 | 0.1 | 0.2 | 0.4 | 0.5 | 0.66 | 0.8 | 1 |

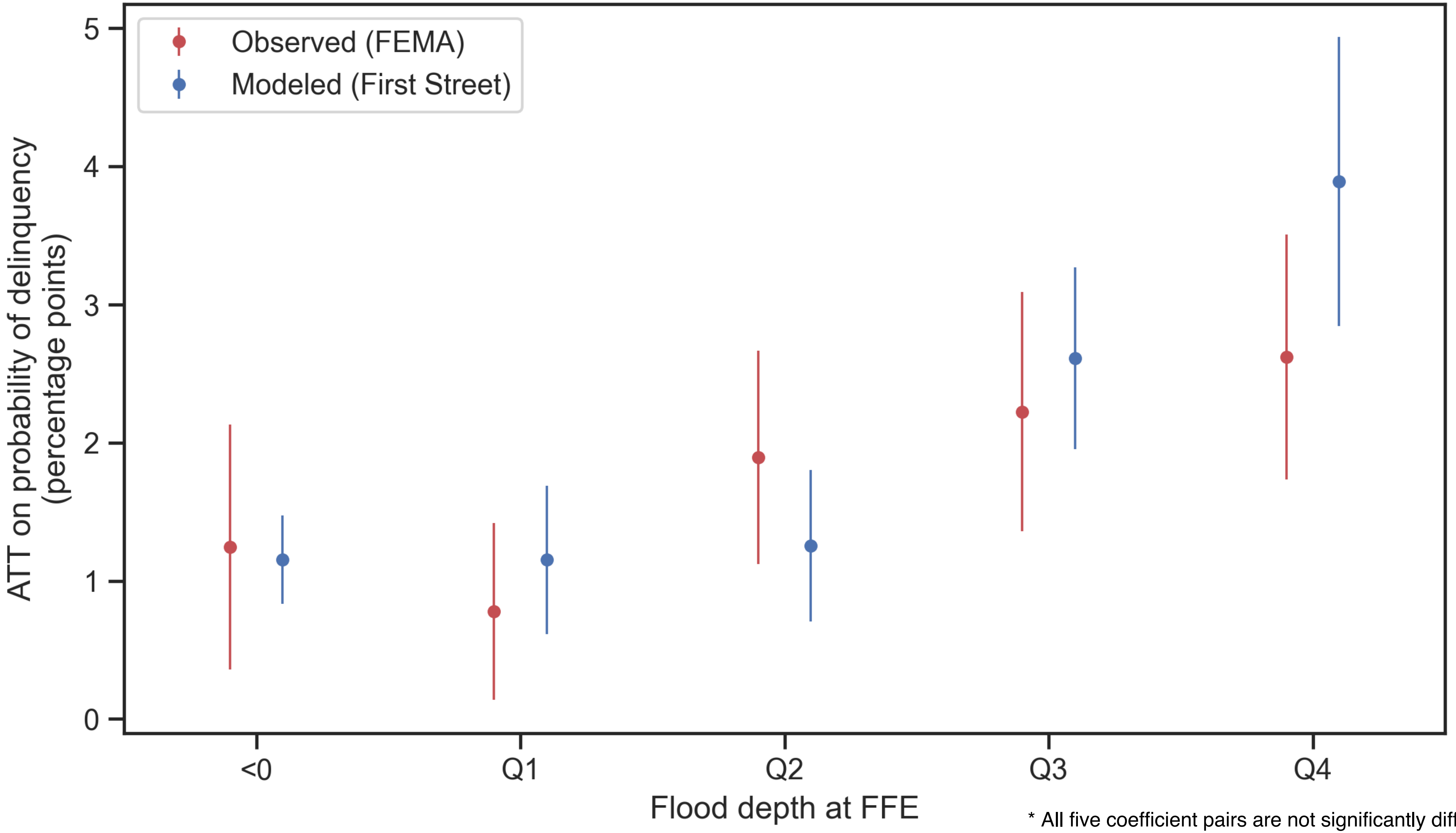
Wing, et al. (2019) "A flood inundation forecast of Hurricane Harvey using a continental-scale 2D hydrodynamic model." *Journal of Hydrology X* 4: 100039.

| **Flood Event Location** | **Bias (m)** | | | **Error (m)** | | | **Critical success index** | | |
|---|---|---|---|---|---|---|---|---|---|
| | *0.8*Q* | *1.0*Q* | *1.2*Q* | *0.8*Q* | *1.0*Q* | *1.2*Q* | *0.8*Q* | *1.0*Q* | *1.2*Q* |
| Eastern Iowa | −0.87 | −0.55 | −0.17 | 1.31 | 1.13 | 0.96 | 0.9 | 0.92 | 0.94 |
| Central Iowa | −0.61 | −0.39 | −0.10 | 0.71 | 0.53 | 0.39 | 0.84 | 0.88 | 0.91 |
| Eastern Missouri | −4.27 | −3.75 | −2.95 | 4.27 | 3.75 | 2.95 | 0.59 | 0.7 | 0.82 |
| Southern Indiana | −0.65 | −0.42 | −0.08 | 0.65 | 0.45 | 0.31 | 0.78 | 0.82 | 0.86 |
| Eastern Nebraska | −1.53 | −1.11 | −0.70 | 1.53 | 1.12 | 0.74 | 0.73 | 0.8 | 0.85 |
| Central South Carolina | 0.89 | 1.44 | 2.07 | 1.5 | 1.84 | 2.35 | 0.85 | 0.86 | 0.87 |
| Northen Pennsylvania | −1.31 | −0.94 | −0.60 | 1.96 | 1.85 | 1.85 | 0.81 | 0.82 | 0.83 |
| Texas / Louisiana border | −1.28 | −0.93 | −0.59 | 1.28 | 0.97 | 0.66 | 0.81 | 0.85 | 0.88 |
| New England | 0.29 | 1.05 | 1.58 | 1.08 | 1.22 | 1.7 | 0.59 | 0.88 | 0.85 |

Wing, et al. (2021) "Simulating historical flood events at the continental scale: observational validation of a large-scale hydrodynamic model." *Natural Hazards and Earth System Sciences* 21.2: 559-575.

(link back)

# Estimates using modeled & observed flood depths for Harvey




* All five coefficient pairs are not significantly different ($p > 0.05$)

# GSE loss given default summary stats (Goodman & Zhu 2015)

## Outcomes following 180+ days delinquent or foreclosure

| | | Paths without an Eventual Loss | | | | | Paths with an Eventual Loss | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | Already Liquidated | | | |
| Year | LTV | Current w/o Modification | Modified, Current | Prepay w/o Modification | Prepay After Modification | Total | Modified, Not Current | In Pipeline w/o Modification | REO | Foreclosure Alternatives | Total | Total |
| 1999–2004 | ≤60 | 6 | 9 | 26 | 3 | 43 | 6 | 19 | 18 | 14 | 32 | 57 |
| | 60–80 | 4 | 9 | 12 | 2 | 28 | 6 | 15 | 36 | 15 | 51 | 72 |
| | >80 | 3 | 7 | 9 | 2 | 22 | 6 | 11 | 49 | 12 | 62 | 78 |
| | Total | 4 | 8 | 12 | 2 | 26 | 6 | 13 | 41 | 14 | 55 | 74 |
| 2005 | ≤60 | 5 | 15 | 12 | 2 | 35 | 9 | 21 | 17 | 18 | 36 | 65 |
| | 60–80 | 3 | 13 | 3 | 1 | 20 | 8 | 17 | 30 | 25 | 56 | 80 |
| | >80 | 3 | 9 | 2 | 1 | 15 | 7 | 16 | 43 | 19 | 61 | 85 |
| | Total | 3 | 12 | 4 | 1 | 20 | 8 | 17 | 32 | 23 | 55 | 80 |
| 2006 | ≤60 | 5 | 18 | 9 | 1 | 34 | 9 | 21 | 18 | 18 | 36 | 66 |
| | 60–80 | 3 | 13 | 2 | 1 | 19 | 8 | 16 | 30 | 27 | 57 | 81 |
| | >80 | 2 | 10 | 2 | 1 | 15 | 8 | 15 | 43 | 19 | 62 | 85 |
| | Total | 3 | 13 | 3 | 1 | 19 | 8 | 16 | 32 | 24 | 56 | 81 |
| 2007 | ≤60 | 5 | 17 | 11 | 1 | 34 | 9 | 24 | 18 | 15 | 33 | 66 |
| | 60–80 | 3 | 14 | 2 | 1 | 21 | 8 | 17 | 29 | 25 | 54 | 79 |
| | >80 | 3 | 12 | 1 | 1 | 16 | 9 | 16 | 38 | 20 | 59 | 84 |
| | Total | 3 | 14 | 3 | 1 | 20 | 9 | 17 | 31 | 23 | 54 | 80 |
| 2008 | ≤60 | 6 | 15 | 14 | 2 | 37 | 11 | 27 | 13 | 11 | 24 | 63 |
| | 60–80 | 4 | 16 | 3 | 1 | 24 | 9 | 20 | 25 | 22 | 47 | 76 |
| | >80 | 3 | 14 | 2 | 1 | 19 | 9 | 18 | 33 | 21 | 54 | 81 |
| | Total | 4 | 15 | 4 | 1 | 24 | 9 | 20 | 26 | 21 | 47 | 76 |
| 2009–2010 | ≤60 | 8 | 5 | 20 | 1 | 33 | 6 | 43 | 10 | 8 | 18 | 67 |
| | 60–80 | 5 | 8 | 6 | 0 | 19 | 8 | 36 | 21 | 17 | 38 | 81 |
| | >80 | 3 | 7 | 2 | 0 | 12 | 6 | 30 | 27 | 25 | 52 | 88 |
| | Total | 5 | 7 | 7 | 0 | 20 | 7 | 36 | 20 | 17 | 37 | 80 |
| 2011–2013 | ≤60 | 13 | 2 | 16 | 0 | 31 | 4 | 60 | 0 | 5 | 5 | 69 |
| | 60–80 | 5 | 5 | 8 | 0 | 18 | 8 | 59 | 8 | 7 | 15 | 82 |
| | >80 | 3 | 4 | 5 | 0 | 12 | 8 | 53 | 13 | 14 | 27 | 88 |
| | Total | 6 | 4 | 8 | 0 | 18 | 7 | 58 | 8 | 8 | 16 | 82 |
| Total | ≤60 | 6 | 14 | 15 | 2 | 37 | 8 | 23 | 17 | 15 | 32 | 63 |
| | 60–80 | 3 | 12 | 6 | 1 | 23 | 8 | 17 | 31 | 22 | 53 | 77 |
| | >80 | 3 | 9 | 5 | 1 | 19 | 7 | 14 | 44 | 16 | 60 | 81 |
| | Total | 3 | 11 | 6 | 1 | 22 | 7 | 16 | 34 | 20 | 54 | 78 |

## Loss severity given liquidation (severity = % unpaid balance lost)

| Year | FICO | LTV ≤60 | LTV 60–80 | LTV >80 | Total |
|---|---|---|---|---|---|
| 1999–2004 | ≤700 | 26.0 | 38.9 | 21.1 | 29.3 |
| | 700–750 | 21.9 | 36.5 | 24.0 | 31.0 |
| | >750 | 23.7 | 36.5 | 27.1 | 32.8 |
| | Total | 24.5 | 38.0 | 22.1 | 30.0 |
| 2005 | ≤700 | 36.7 | 49.1 | 33.5 | 44.2 |
| | 700–750 | 33.6 | 47.1 | 34.9 | 43.9 |
| | >750 | 32.8 | 45.8 | 35.6 | 43.2 |
| | Total | 35.0 | 47.9 | 34.1 | 44.0 |
| 2006 | ≤700 | 44.7 | 54.8 | 36.2 | 49.1 |
| | 700–750 | 41.1 | 52.3 | 39.2 | 49.5 |
| | >750 | 38.2 | 50.0 | 37.3 | 47.5 |
| | Total | 42.5 | 53.0 | 37.0 | 48.9 |
| 2007 | ≤700 | 49.1 | 55.9 | 38.2 | 48.4 |
| | 700–750 | 42.6 | 52.3 | 38.3 | 47.8 |
| | >750 | 39.3 | 48.9 | 36.1 | 45.2 |
| | Total | 45.3 | 53.3 | 37.9 | 47.6 |
| 2008 | ≤700 | 41.7 | 53.6 | 36.7 | 46.2 |
| | 700–750 | 35.9 | 48.8 | 33.4 | 42.6 |
| | >750 | 29.8 | 45.0 | 30.7 | 39.3 |
| | Total | 37.5 | 49.8 | 34.3 | 43.3 |
| 2009–2010 | ≤700 | 27.7 | 41.9 | 22.1 | 37.3 |
| | 700–750 | 25.9 | 36.8 | 18.2 | 32.0 |
| | >750 | 22.6 | 33.4 | 18.0 | 29.3 |
| | Total | 25.7 | 36.7 | 18.8 | 32.1 |
| 2011–2013 | ≤700 | 0.0 | 28.4 | 9.3 | 21.0 |
| | 700–750 | 12.4 | 30.3 | 11.5 | 19.1 |
| | >750 | 0.0 | 25.2 | 11.6 | 18.3 |
| | Total | 9.9 | 27.7 | 11.1 | 19.2 |
| Total | | 37.1 | 48.3 | 31.0 | 42.0 |