Flag Tag: Credit Report Disaster Flags As Social Insurance Tags

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One Slide Summary

Research Question:

- Role for masking defaults during natural disasters to alleviate financial distress?

Data:

- TransUnion consumer credit reporting data.

Key Findings:

- Lenders voluntarily mask defaults during natural disasters ('disaster flags').
- Disaster flags widely used.
- Disaster flag defaults slightly riskier.
- Temporary $\uparrow$ credit scores concentrated among most financially distressed.
- Counterfactual masking all disaster defaults has limited predictive loss.

Disclaimer: Working paper so precise estimates & specifications in slidepack may evolve.

Paper Outline

1. Motivation
2. What Are Disaster Flags?
3. Disaster Flag Facts
4. Information in Disaster Flags
5. Consumer Benefits of Disaster Flags
6. Counterfactual Masking Disaster Defaults

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2. What Are Disaster Flags?
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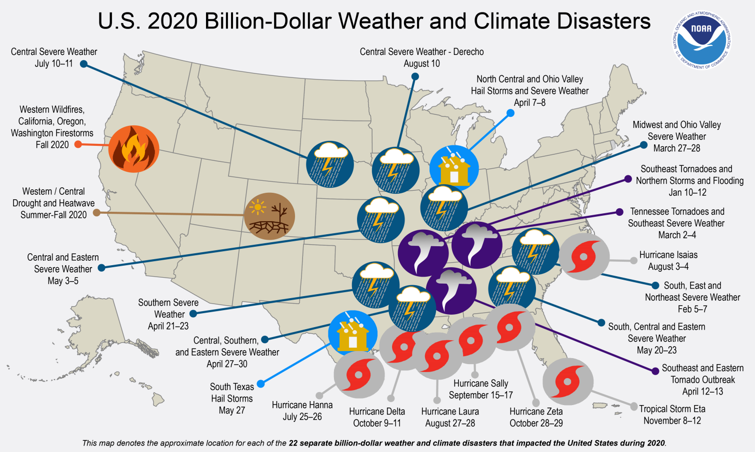
4. Information in Disaster Flags
5. Consumer Benefits of Disaster Flags
6. Counterfactual Masking Disaster Defaults

2020 had record-breaking 22 x $1+bn natural disasters…
+ COVID-19



- Not a 'one-off': US disasters more frequent + damaging in last 5-10 years (NOAA).

Motivation

- Natural disasters often considered shocks to households.
- Large government transfers & private sector forbearance.
- **What role for credit report relief from natural disasters?** (e.g. see CFPB; FinRegLab; NCLC; Urban Institute)

2. What Are Disaster Flags?

What are disaster flags?

- Applied by lenders to borrowers' credit reports.
- Voluntary.
- Eligible if affected by natural / declared disaster.

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- Applied by lenders to borrowers' credit reports.
- Voluntary.
- Eligible if affected by natural / declared disaster.
- Applied at account-level.
  (e.g. a mortgage not all credit report accounts)
- Removed at lender discretion.
- Separate field to default reporting.

3. Disaster Flag Facts

Data: 20+ years of anonymized monthly credit reporting data

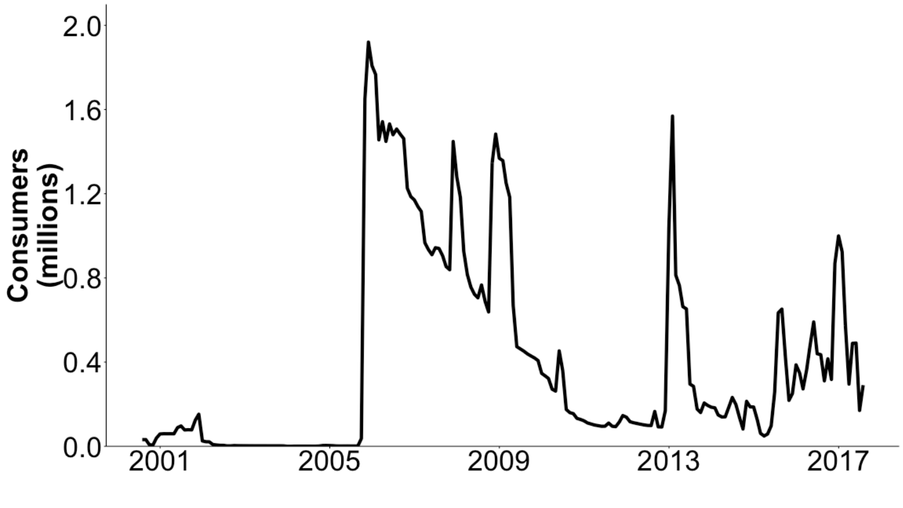
- TransUnion anonymized credit reporting data, 2000 - 2022.
- Booth's 1 in 10 sample of people with US credit reports.
- Contains, monthly, individual credit accounts + consumer-level information (e.g. credit score).
- Observe flags added or removed to accounts.
- Post-09 data more granular.

How many consumers have credit report disaster flags?

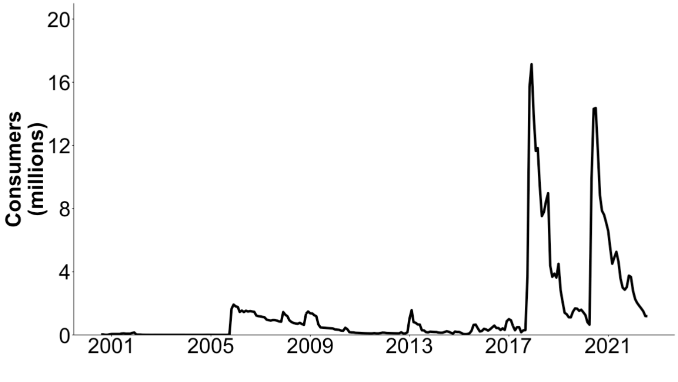
FACT 1:
59.2m people with disaster flag on their credit report
(2010 - 2020).

- 59.2m > 3.5 x number of bankruptcies (2010 - 2020).

Disaster flags mainly used since Hurricane Katrina in 2005

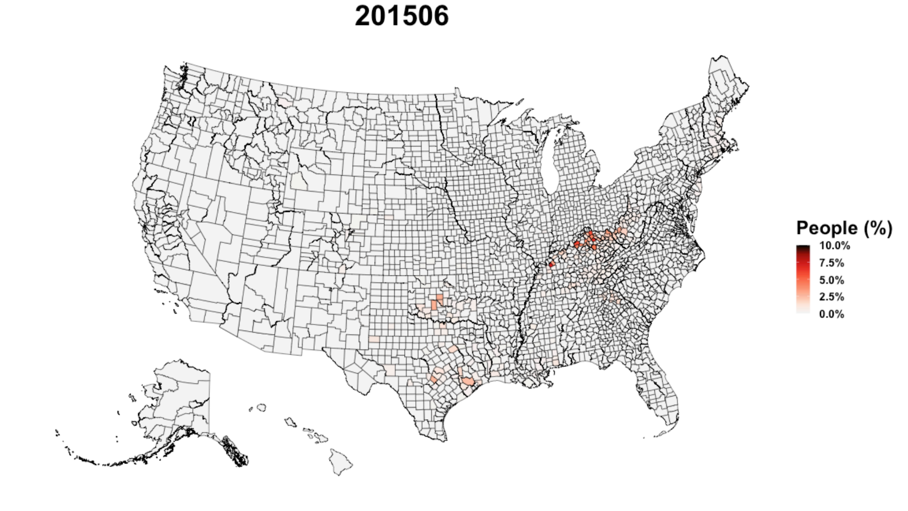


FACT 2: A level shift in disaster flag use occurred in 2017 driven by Hurricanes Harvey and Irma



Y-axis is 10x prior chart!

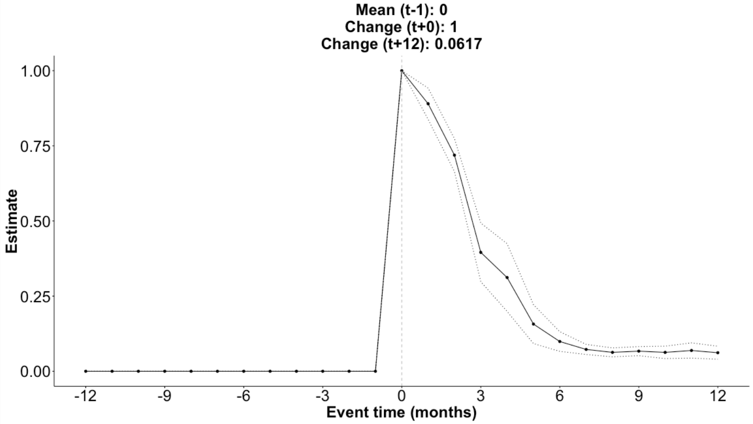
FACT 3. Growing geographic usage - especially during COVID-19



Top coded at 10%.

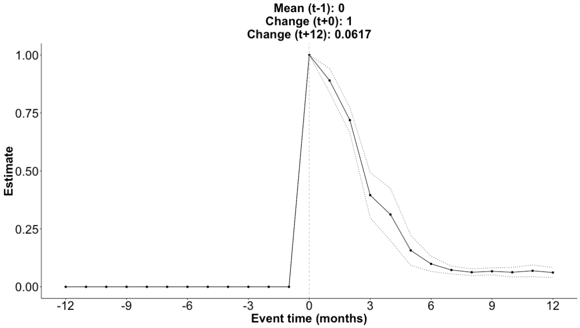
FACT 4. Flags typically only remain on a credit account for up to three months and rarely more than six months.

Any disaster flag on credit report

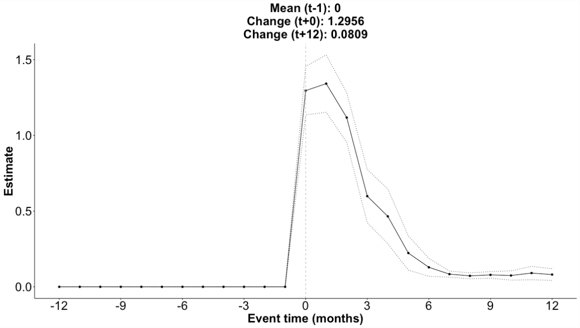


FACT 5. Flags are are only applied to subset of consumers' credit accounts.

A. Any disaster flag on credit report



B. Number of disaster flags on credit report



Who has disaster flags?

- **Flags used across credit products** (mortgage, credit card, autos, student loans, other) **& firm types** (banks, non-bank finance, credit unions).

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- **Lender selection into flag use:**
  - Among flagged counties, which lender x asset classes flag?
  R^2 : 0.13 $\rightarrow$ 0.16 (county + lender F.E.)
  - Among flagged people, which accounts flagged?:
  R^2 : 0.10 $\rightarrow$ 0.13 (individual F.E.) $\rightarrow$ 0.62 (individual + lender F.E.)
- **Mean flagged consumer (vs. unflagged in same geography):**
  - *more* credit products (8 vs. 5)
  - *more* debt balances ($141k vs. $88k)
  - *lower* credit score (695 vs. 703)

3. Information in Disaster Flags

What is π? Predictive value of flagged defaults.

Consider simple credit score model:

$$Pr(Y = 1) = f(X'\beta + \theta \ DEFAULT + \pi \ DEFAULTxFLAG) \tag{1}$$

- $Y = 1$ if new future default.
- X' is vector of non-default characteristics (e.g. balances, limits, utilization).
- θ increase in credit risk from a past default.

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Market temporarily imposes $\pi\ =-\theta$.
But are flagged defaults...
(a) $\pi>0$: riskier than non-flagged defaults.
(b) $\pi=0$: uninformative noise.
(c) $-\theta<\pi<0$ *Less* risky than non-flagged defaults.
(d) $\pi=-\theta$ Perfectly offset non-flagged default risk.
(e) $\pi<-\theta$ More than offset non-flagged default risk.

What is π? Predictive value of flagged defaults.

(1) Baseline:

$$Pr(Y = 1) = f(X'\beta + \theta \; DEFAULT) \tag{1}$$

(2) Baseline With Flag Interaction:

$$Pr(Y = 1) = f(X'\beta + \theta \; DEFAULT + \pi \; DEFAULTxFLAG) \tag{2}$$

(3) Masked:

$$Pr(Y = 1) = f(X'\tilde{\beta} + \tilde{\theta} \; DEF\tilde{A}ULT) \tag{3}$$

Flagged defaults riskier but masking them doesn't harm firms much

- (2) consistent with (a) $\pi > 0$: flagged defaults riskier than non-flagged defaults.
- Yet masking flagged defaults (3) has limited predictive loss to firms.

	(1) Baseline
Any Default: θ	0.110***
	(0.001)
Any Flagged Default: π	
Any Default After Flag Masking: $\tilde{\theta}$	
AUROC	0.8755
Balanced Accuracy	0.6352

N = 2,425,251. *** $p < 0.001$. Average marginal effects from logistic regression shown.
Controls: accounts, balances, product holdings, credit card limits, utilization, bankruptcy.
Outcome: Any new default in 12 months from March 2018.

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	(1) Baseline	(2) Baseline With Flag Interaction
Any Default: θ	0.110***	0.109***
	(0.001)	(0.001)
Any Flagged Default: π		0.073***
		(0.003)
Any Default After Flag Masking: $\tilde{\theta}$		
AUROC	0.8755	0.8757
Balanced Accuracy	0.6352	0.6357

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5. Consumer Benefits of Disaster Flags

Difference-in-difference (DiD) event study isolating effects of flags separate from disaster

- Event study of flag application.
- Exploit exogenous variation in timing (+ location) of natural disasters.
- Key identifying assumption is common trends.
- Estimating ATT: Average treatment effect of adding disaster flag for flagged (treated) consumers on household finances.

$$E[Y_{1,i} - Y_{0,i} | FLAG_i = 1]$$

Stacked DiD Methodology

1. 1st month person has disaster flag added.
2. Matched control in census block group-zipcode.
3. Keep observations ± 12 months to flag addition date.
   (cohorts first flagged Jan 2010 - July 2019)
4. Estimate parameter of interest (δ_τ):

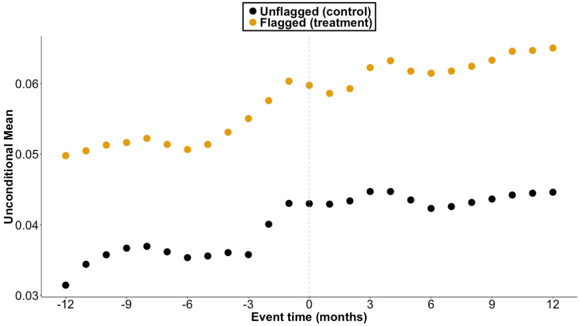
$$Y_{i,c,t} = \alpha_{i,c} + \lambda_{c,t} + \sum_{\tau \neq -1} \mu_\tau \mathbb{1}\{E_{c,t} = \tau\} + \sum_{\tau \neq -1} \delta_\tau \mathbb{1}\{E_{c,t} = \tau\} \cdot \mathbb{1}\{FLAG_i = 1\} + \varepsilon_{i,c,t} \quad (2)$$

c, t, e are cohort, calendar time, event time.
$FLAG_i = 1$ if consumer flagged (0 otherwise).

Standard errors clustered at group-level (e.g. Jan 2010 flagged + unflagged cohorts).

Defaults appear (A.) but masked by flags (B.) with zero effect from t+6

A. Any defaults
(unconditional means)



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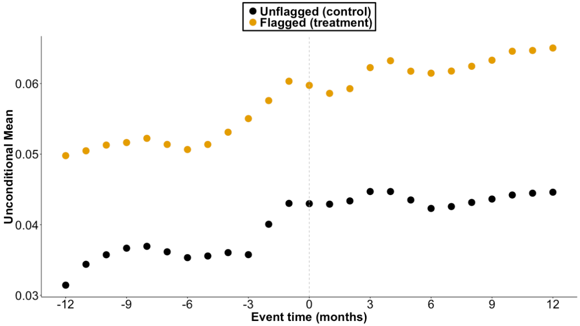
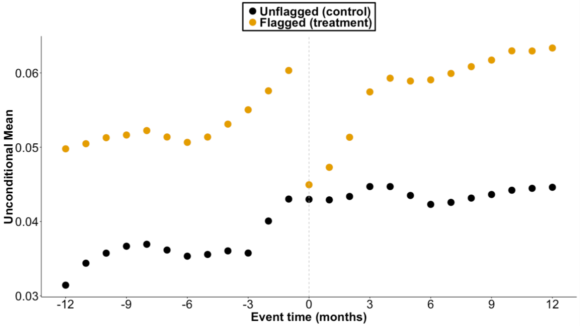
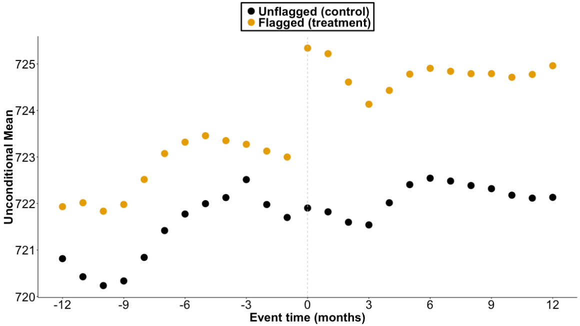


B. Any defaults *not masked by flags*
(unconditional means)

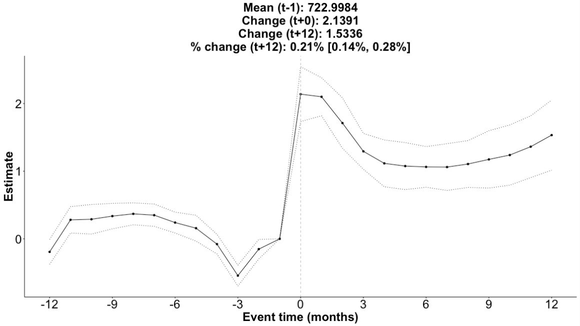


+2.1 [1.6, 2.7] initial jump in credit score goes to +1.5 [0.7, 2.3] after t+12

A. Unconditional means of credit score



B. δ_τ for credit score



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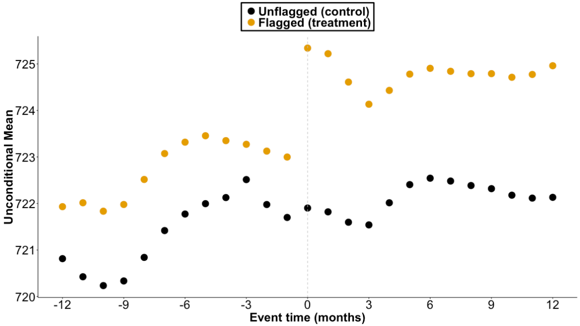

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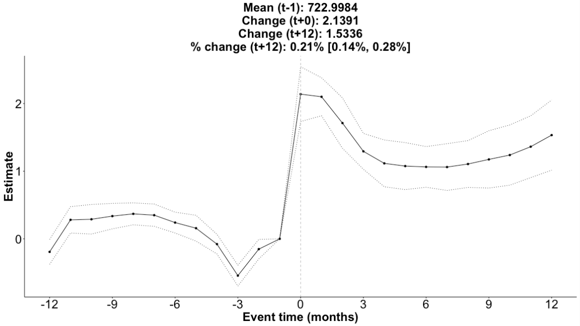

- Average increase in credit score ‘small’ & temporary

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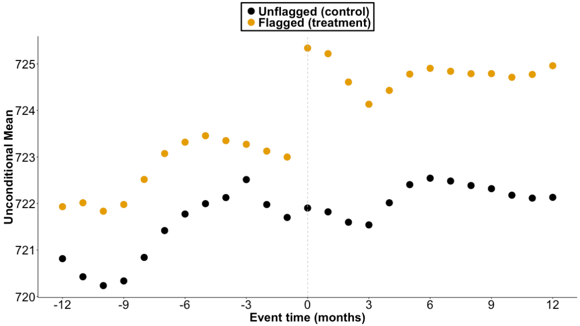

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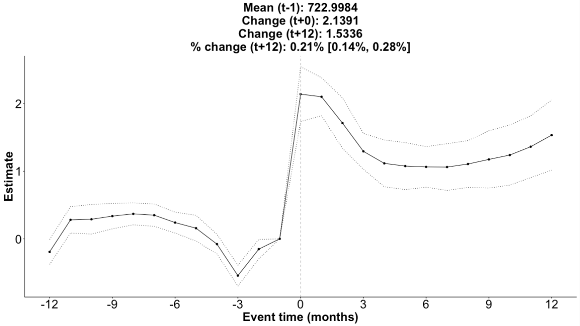
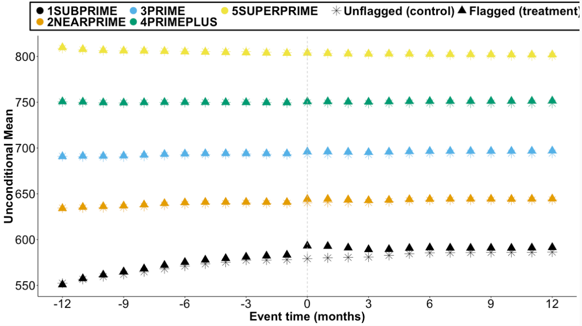


- Average increase in credit score ‘small’ & temporary
- Offseting approx. 30% of -ve effect of disaster.

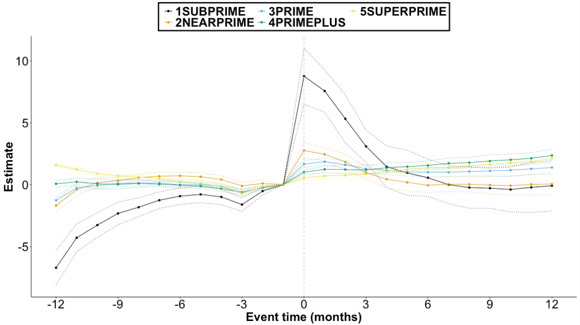
Effects concentrated in lowest pre-disaster credit score group (1SUBPRIME)

- Heterogeneous effects by t-12 credit score.
- Effects concentrated in lowest credit score group: **1SUBPRIME** (VantageScore <601).

A. Unconditional means of credit score



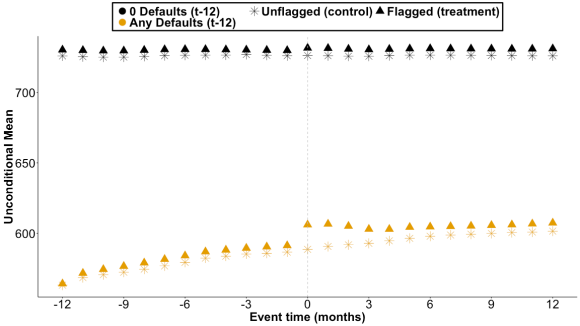
B. δ_τ for credit score



Effects concentrated among pre-disaster defaulters (Any Defaults, t-12)

- Heterogeneous effects by t-12 any default score.
- Effect for defaulters larger than bankruptcy flag removal, though only temporary.

A. Unconditional means of credit score



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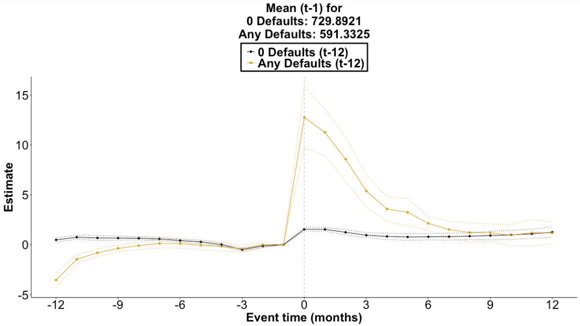

- Temporary positive effects do not translate into positive real effects on credit access.

6. Counterfactual Masking Disaster Defaults

How to evaluate information loss if *all* disaster defaults masked?

Consider counterfactual social insurance policy defaults automatically + permanently mask disaster defaults in credit reports (CARES Act-esque).

CFPB (2018), National Consumer Law Centre (2019), Urban Institute (2019), FinRegLab (2020)

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- Merge FEMA records of county + dates of natural disasters
- Tag default where new default appears on tradeline 6 months from disaster onset.

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- Tag default where new default appears on tradeline 6 months from disaster onset.

Analogous to earlier equation:

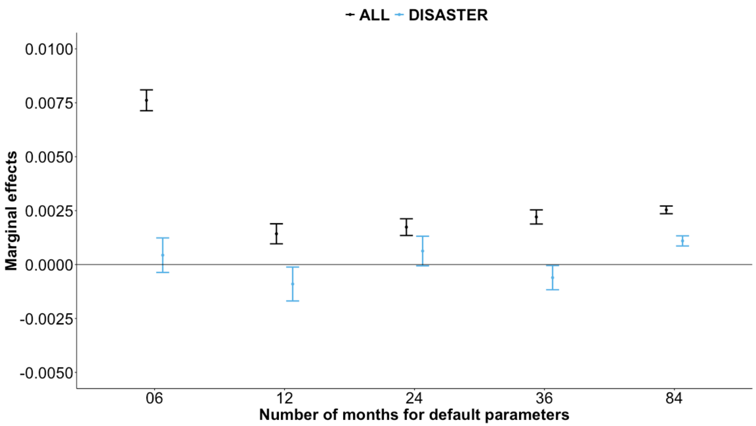
$$Pr(Y_{t+24} = 1) = f\big(X_t'\beta + \theta D_t + \phi(D_t \times FEMA_t)\big) \tag{4}$$

Two counterfactuals:

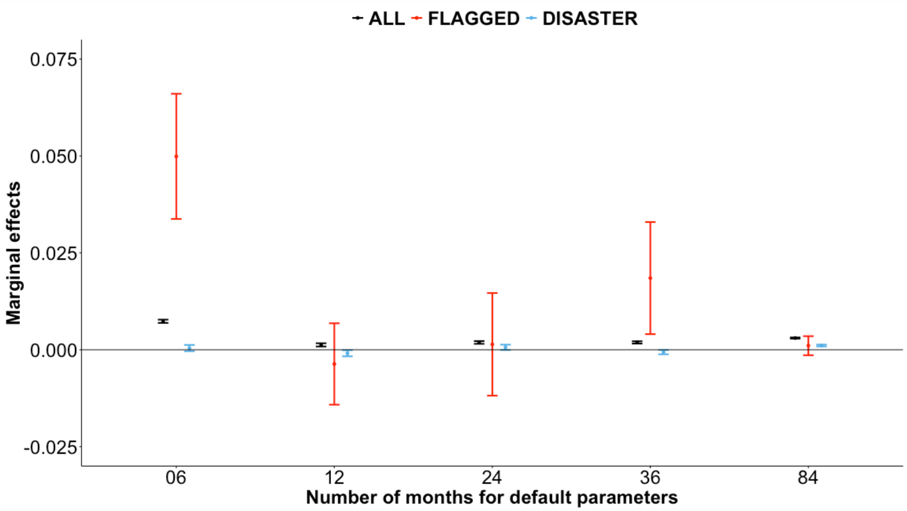
- **'Temporary':** Mask defaults occurring within six months from FEMA event. (lower bound)
- **'Permanent':** Mask defaults that *started* within six months from FEMA event. (upper bound)

$\phi = 0$: FEMA disaster defaults no riskier than other defaults

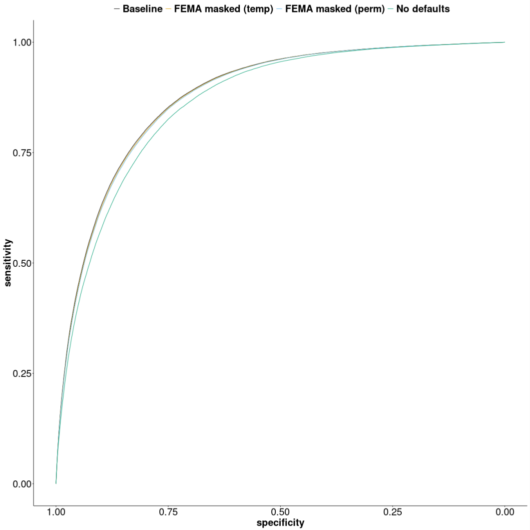
$$Pr(Y_{t+24} = 1) = f\big(X_t'\beta + \theta D_t + \phi(D_t \times FEMA_t)\big)$$



All, flagged & FEMA disaster defaults compared



Masking FEMA defaults (5, 6) far more efficient than masking all defaults (7)



Model	AUROC	Baseline %
Baseline	0.8790	
Flag masked	0.8786	-0.0005%
FEMA masked (temp)	0.8777	-0.0015%
FEMA masked (perm)	0.8764	-0.0030%
No defaults	0.8641	-0.0170%

FEMA masks 6.66% - 18.42% of all defaults.

Definitions: y-axis sensitivity: true positive cases identified [TP/(TP+FN)]. x-axis specificity: true negative cases identified [TN/(TN+FP)]

Conclusions

- Lenders voluntarily mask defaults during natural disasters ('disaster flags').
- Disaster flags widely used.
- Disaster flag defaults slightly riskier.
- Temporary $\uparrow$ credit scores concentrated among most financially distressed.
- Counterfactual masking all disaster defaults has limited predictive loss.

THANK YOU!

Appendix

Conceptual Framework

Consider generic credit risk model:

$$Pr(D_{t+j} = 1) = f\Big(X_t'\beta_0 + \theta_0 D_t\Big)$$

where D_t default, X_t' vector of non-default variables, f(.) function (e.g. logit).

Conceptual Framework

Allow default component (D_t) to differ for defaults during natural disaster ($N_t = 1$):

$$Pr(D_{t+j} = 1) = f\Big(X_t'\beta_1 + \theta_1 D_t + \pi_1(D_t \times N_t)\Big)$$

where D_t default, X_t' vector of non-default variables, f(.) function (e.g. logit).

How to define N_t?

- All in FEMA disaster zone
- May be more efficient to 'tag' subset of households (Akerlof, 78)

How costly is masking information?

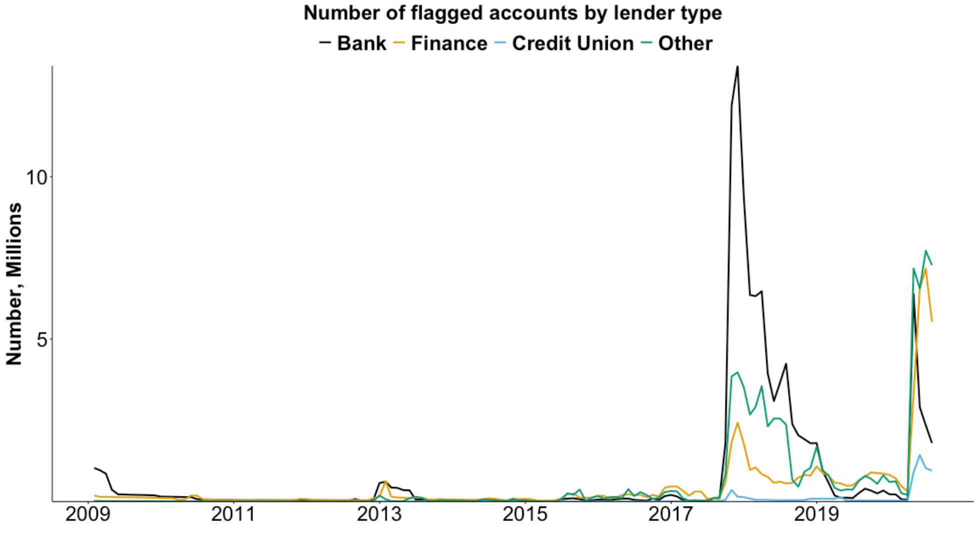
- $\pi_1 \lesseqgtr \theta_1$
- Predictive performance from masking disaster defaults

$$Pr(D_{t+j} = 1) = f\Big(X'\beta_2 + \theta_2 \tilde{D}_t\Big), \text{ where } \tilde{D}_t = \begin{cases} D_t \text{ if } N_t = 0 \\ 0 \text{ if } N_t = 1 \end{cases}$$

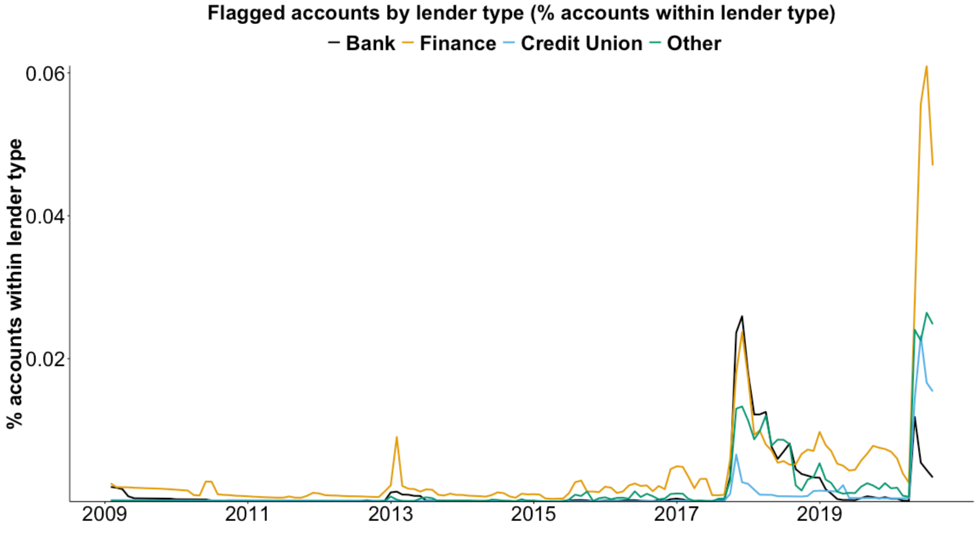
Example of Disaster Flag on Credit Report

Consumer: Ben		2019											
		Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Asset: Credit Card	Balance	6754	6694	6631	6554	6551	6660	6523	6543	6666	6822	6752	6683
Account Number: 01	Default	0	0	0	0	0	1	1	0	0	0	0	0
Lender: Ben's Bank	Flag	0	0	0	0	AND	AND	AND	0	0	0	0	0

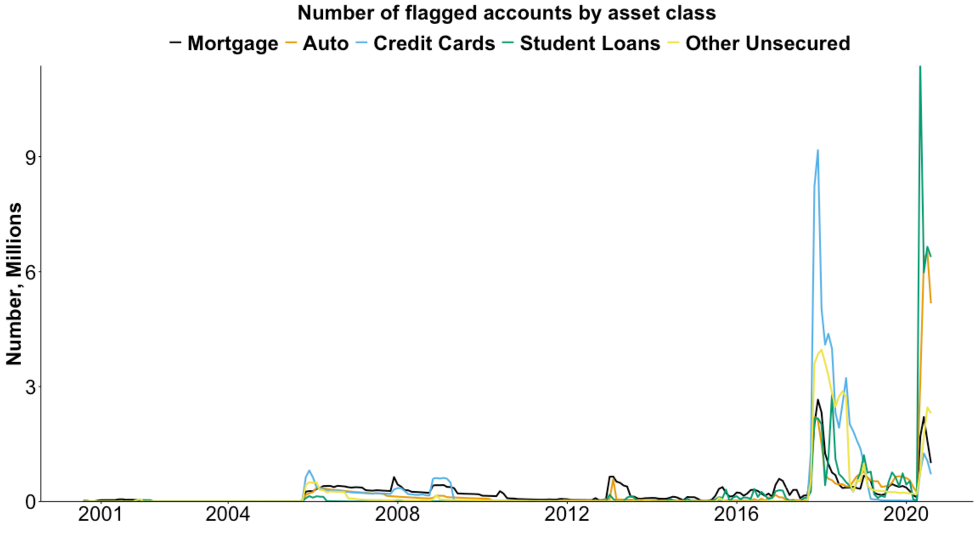
Number of accounts flagged by lender type (2009 - 2020)



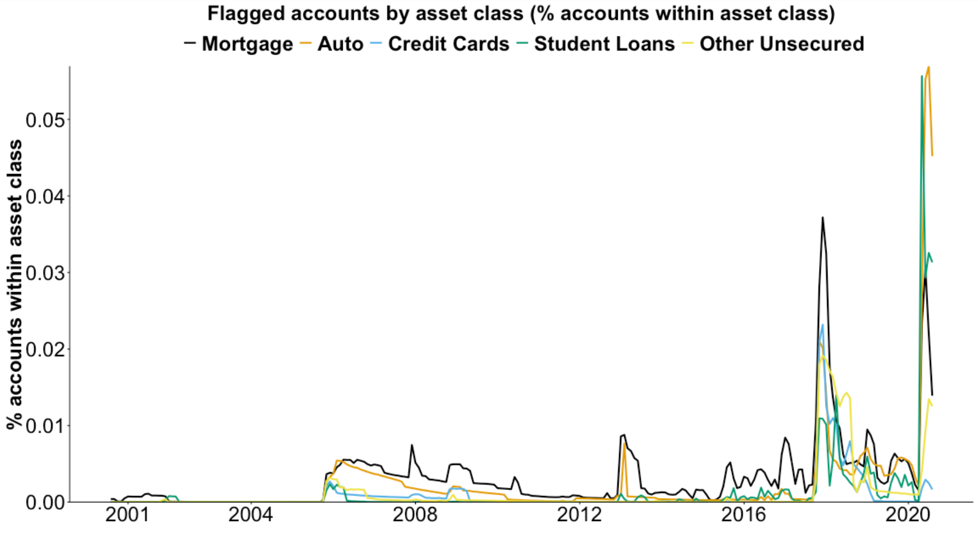
Percent of accounts flagged within lender type (2009 - 2020)



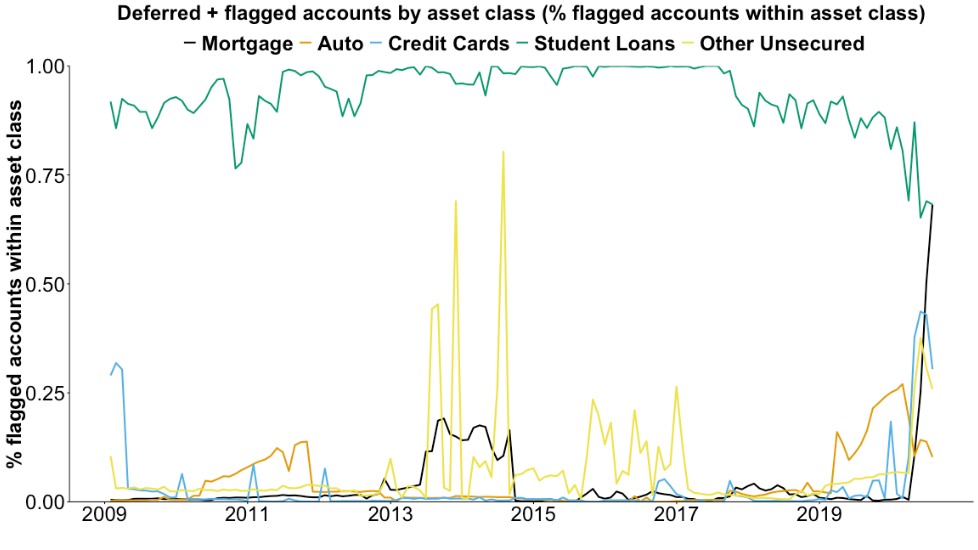
Number of accounts flagged by asset class (2000 - 2020)



Percent of accounts flagged within asset class (2000 - 2020)



Payments rarely deferred on flagged accounts *except* student loans & 2020



Selection into flags

- Mean flagged consumer likely to hold *more* credit products (8 vs. 5), more debt balances ($141k vs. $88k), & lower scores (695 vs. 703).

		Flag		Unflagged in CBGxZIP		Unflagged in US	
	Outcome	Mean	SD	Mean	SD	Mean	SD
1	Credit Score	695.59	98.32	703.59	98.32	703.79	99.93
2	Age	50.59	15.34	49.44	17.38	49.45	17.37
3	# Accounts	7.84	5.57	5.47	4.76	5.30	4.53
4	Any 30+ defaults	0.09	0.29	0.07	0.25	0.08	0.27
5	# 30+ defaults	0.17	0.83	0.12	0.63	0.13	0.63
6	Any Balance	0.97	0.18	0.89	0.31	0.89	0.31
7	Any Auto	0.53	0.50	0.38	0.48	0.34	0.47
8	Any Credit Card	0.80	0.40	0.71	0.46	0.68	0.47
9	Any Mortgage	0.45	0.50	0.31	0.46	0.33	0.47
10	Balances	141177.42	245303.85	88401.94	182325.43	86142.65	190829.88
11	Mortgage Balances	233733.45	299149.34	205811.69	248350.54	188588.59	257923.99
12	Non-Mortgage Balances	29347.42	40389.32	19131.69	37488.05	16273.00	45354.77
13	Auto Balances	21868.22	19649.76	19202.13	29307.38	16985.83	54424.18
14	Credit Card Balances	7984.61	12693.78	5865.76	12296.03	5533.44	10104.88
15	Credit Card Limits	32740.63	36379.93	26788.31	30842.55	24939.07	28261.46

Evaluating FEMA disasters as Akerlovian Tags

- **Social insurance = protecting against adverse shocks**
  (e.g. losing job, poor health, natural disaster - Feldstein, 05; Chetty & Finkelstein, 13).
- Challenge to provide **insurance for 'bad luck' minimizing moral hazard**.
- **'Tagging'** subset of people (Akerlof, 78) can be efficient.
  (e.g. allows for more generosity & reduced moral hazard concerns)
- Ideal Akerlovian tags: (rel.) **immutable characteristic** + **high correlation to target**.
  (e.g. income redistribution by height - Mankiw & Weinzierl, 10)

Are FEMA disasters good tags?

- Tag if *lived* in area affected by natural disaster.
  (moral hazard appears unlikely)
- Unclear currently voluntary system targeted to need.
  (e.g. 'low' take-up, many financially distressed do not do so, temporary)
- FEMA regime more efficient than blanket removal of default information.