The Effects of Extreme Wildfire and Smoke Events on Household Financial Outcomes

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Motivation

- Wildfire activity has become both more extreme and more destructive.
- There is an emerging literature on effects of wildfires.
 - Migration: Sharygin (2021), Winkler and Rouleau (2021)
 - Mortgage: Issler et al. (2020)
 - \circ Migration and household finance: McConnell et al. (2021)
 - Fires that have caused at least one building to be destroyed from 1999 to 2018
 - Heightened out-migration probability among tracts that experienced the most destructive wildfires
 - Significant drop in homeownership among those treated by major fires, concentrated in people over the age of 60.
 - Measures of credit distress, including delinquencies, bankruptcies, and foreclosures, improve rather than deteriorate after the fire, but the changes are not statistically significant.

Motivation

- Adverse effects of extreme wildfires extend beyond the perimeter of the fire owing to the broad diffusion of fire related **smoke** and particulate **pollution**.
- These air quality effects are typically not accounted for in assessments of wildfire economic effects.
- This paper studies the impact of **extreme** US wildfires and related **smoke** and **air pollution** events on household mobility, housing and financial outcomes.

Sample

- Four extreme wildfires, defined as those that damage or destroy 1,000 or more structures.
- Focus on Camp

 Table 1. List of Extreme Wildfires in the U.S. Between 2016-2020

	Fire Name	Destroyed Structures	Date	State
\leq	Camp	17,764	11/8/2018	CA
<	Central LND Complex	6,862	10/9/2017	CA
	Glendale	3,000	1/29/2016	OK
	North Complex	2,288	8/17/2020	CA
	Chimney Tops	2,018	11/23/2016	TN
\subset	Carr	1,610	7/23/2018	CA
	LNU Lightning Complex	1,469	8/17/2020	CA
	CZU AUG Lightning	1,329	8/16/2020	CA
	Beachie Creek	1,292	8/16/2020	OR
	Glass	1,198	9/27/2020	CA
\langle	Thomas	1,053	12/4/2017	CA



Figure 1. Extreme Wildfires in CA between 2016-2020 and the 1-, 5-, and 10- mile Peripheral Rings

Paper Strategy: Wildfires

• Diff-in-diff

- o Treatment: fire zones
- Control: 1- and 5-mile rings beyond the fire zone
- Tract: Migration & HPI
- Consumer: Financial outcomes

 $Y_{i,t} = \beta * Fire_{i,t} * Post_{i,t} + \tau_t + \zeta_i + \varepsilon_{it},$



Figure 2. Treatment and Control Areas in the Camp Fire Analyses *Notes*: This figure shows the treatment and control areas in the Camp fire analyses. The red area is the fire footprint, which is the treatment area; the brown area is a 1-mile peripheral ring, which we carve out in our analysis; the orange area is a 1- to 5-mile peripheral ring, which is the control area; and the yellow area is a 5- to 10-mile peripheral ring, which is an alternative control area. The border lines are census blocks in California.

Comments: Camp Fire

- Tract: HPI & Migration
 - o Pre-trends in HPI (Repeated Sales Median)
 - $\circ\,$ ATE for Migration \downarrow with \uparrow in the control group
- Robustness tests
 - Ccovariate balance
 - Longer pre-window
 - Different trends associated with local characteristics: $X'_{c,2018q3}\tau_t$, where $X'_{c,2018q3}$ is vector of tract-level characteristics as of 2018q3
 - Alternative control groups (e.g., PSM)
- Heterogeneity tests



 Table 2. Effects of Camp Fire on Net Migration

	1	2	3	4	5
	Move-in	Move-out	N	Net migration	
<i>Treated</i> \times <i>Post</i> 0 vs 5 miles	1.97	19.2***	17.7***		
	(2.87)	(1.92)	(5.27)		
<i>Treated</i> × <i>Post</i> 0 vs 10 miles				9.28***	
				(2.23)	
<i>Treated</i> × <i>Post</i> 0 vs 20 miles					3.2***
					(1.29)
Census tract FE	+	+	+	+	+
Year-qtr FE	+	+	+	+	+
Observations	470	470	470	674	1,023
R-squared	0.49	0.47	0.15	0.11	0.10
Dependent variable mean	36.02	33.18	6.96	2.31	2.67

Comments: Camp Fire

- Consumer: Balance & Delinquency
 - The total # of observations for the balance regressions is much smaller than that for the delinquency regressions.
 - Balance in level could have outliers.
- Robustness tests
 - \circ log(Balance) or log(1+Balance)
 - Poisson pseudo-likelihood regressions
 - Count-based delinquency (e.g., intensive vs. extensive margins)
 - Triple and quadruple DID
 - A different FICO threshold (e.g., 620 as in Billings, Gallagher, and Ricketts (2022))
- Interpretation
 - Homeowners/renters: insurance or ability to repay?
 - McConnell et al. (2021): credit distress ↓

Table 6. Heterogeneous Effects of Camp Fire on Credit Card Balance and Delinquency

	Home	owners	Ren	iters
	1	2	3	4
Panel A: Credit Balance	Credit Score ≤ 720	Credit Score > 720	Credit Score ≤ 720	Credit Score > 720
$Treated \times Post$	-3,195.09	-1,404.54*	-866.16	108.21
	(3,797.26)	(745.91)	(995.98)	(436.06)
Time-varying bor-	\checkmark	\checkmark	\checkmark	\checkmark
rower attributes				
Census tract FE	+	+	+	+
Year-qtr FE	+	+	+	+
Observations	691	4,505	6,282	6,282
R-squared	0.37	0.37	0.22	0.15
Dependent variable mean	7,382.2	3,674.5	3,125.1	2,114.1
Panel B: Delinquency	Credit Score ≤ 720	Credit Score > 720	Credit Score ≤ 720	Credit Score > 720
$Treated \times Post$	0.00	0.00	0.06***	0.00
i realea // i obr	(0.01)	(0.00)	(0.02)	(0.00)
Time-varying bor-	\checkmark	\checkmark	✓	\checkmark
rower attributes				
Census tract FE	+	+	+	+
Year-qtr FE	+	+	+	+
Observations	3.376	17.319	28,297	22,964
R-squared	0.14	0.04	0.14	0.04
Dependent variable mean	0.01	0.00	0.11	0.00

Paper Strategy: Pollution

- ZIP codes **outside** of the wildfire burn area but within **30 miles** from the fire perimeter.
- Rank order zip codes based on the level of **pollution** in the four weeks immediately following the onset of the fire
- Define the top quartile as Treatment and the **bottom quartile** as **Control** and drop remaining zip codes.
- Diff-in-diff

Consumer: Financial outcomes

$$Y_{i,t} = \gamma * \Delta PM2.5_z * Afterfire_{z,t} + X_{i,t}\vec{B} + \tau_t + \zeta_i + \varepsilon_{i,t}.$$

 $Y_{i,t} = \gamma * \widehat{PM2.5}_z * Afterfire_{z,t} + X_{i,t}\vec{B} + \tau_t + \zeta_i + \varepsilon_{i,t}.$

Month of the Fire:





Figure A.3. Wildfire Smoke Elevated PM2.5 After the Camp Fire

Comments: Pollution

- Robustness tests
 - o Ccovariate balance
 - Parallel trends for delinquency
 - \circ Longer pre-window
 - Different trends associated with local characteristics: $X'_{z,2018q3}\tau_t$, where $X'_{z,2018q3}$, vector of zip-level characteristics as of 2018q3
 - Delinquency based on count
 - Triple DID for heterogeneity tests
 - o Alternative FICO thresholds
 - Alternative control groups (e.g., 50 miles from fire, zips outside the 30-mile ring)

 Table 9. Heterogeneous Effects of Wildfire-Induced Pollution on Credit Card Spending and Payment: Different Credit Score Segments

	1	2
Panel A: Δ Spending	Credit Score ≤ 720	Credit Score > 720
$Treated \times Post$	140.061	535.442***
	(107.843)	(88.154)
Time-varying borrower attributes	\checkmark	\checkmark
Account FE	+	+
Year-month FE	+	+
Observations	249,317	449,846
R-squared	0.131	0.076
Dependent variable mean	-1,048.704	-36.189
Panel B: ∆ Payment	Credit Score ≤ 720	Credit Score > 720
$Treated \times Post$	-445.491***	-26.773
	(89.364)	(70.242)
Time-varying borrower attributes	\checkmark	\checkmark
Account FE	+	+
Year-Month FE	+	+
Observations	249,317	449,846
R-squared	0.093	0.052
-		

Comments: Pollution

- Treatment measures
 - ΔPM2.5 Difference between fire month PM2.5 and the same month PM2.5 in the prior year.
 - $\circ \widehat{PM2.5}$ Smoke-driven pollutants based on a machine learning model
- Alternative measures and tests
 - Both smoke and pollution could be caused by events other than wildfires. Could there be more direct measures (e.g., based on wind information)?
 - Placebo tests?



Figure 5. Delta Smoke and Pollution – Camp Fire

Notes: This figure shows the variation in changes in smoke and pollution (relative to the same months in 2015) two months before and after the Camp Fire. The red area is the fire footprint. The black circle is a radius of 30 miles from the fire. The border lines are ZIP Codes. Each ZIP Code is colored in gray or blue according to the change in the number of smoke days in the current month relative to the same month in 2015 (the base year). The dots represent the pollution monitors, where shades of green represent a decline in pollution levels compared with the same month in 2015 (the base year). The orange-red color of the pollution monitors means an increase in pollution levels compared with the same month in 2015.

Comments: Pollution

- Pollution vs. wildfires.
 - Pollution has similar impact as wildfires.
- Interpretation

• Why?

	1 Mortgage	Credit Card	3 Personal Loan	4 Retail/Store Card
	Delinquency	Delinquency	Delinquency	Delinquency
Treated×Post	0.02*	0.02***	0.05*	0.02
	(0.01)	(0.01)	(0.03)	(0.02)
Consumer FE	+	+	+	+
Year-qtr FE	+	+	+	+
Observations	20,686	71,964	11,544	17,282
R-squared	0.54	0.77	0.74	0.73
Dependent variable mean	0.01	0.04	0.08	0.12

Table 4. Effects of the Camp Fire on Consumer Financial Distress

Table 7. Effects of Camp Fire-Induced Pollution on Credit Outcomes

	1	2	3	4
Panel A	Mortgage	Credit Card	Personal Loan	Retail/Store Card
	Delinquency	Delinquency	Delinquency	Definquency
Treated imes Post	0.01***	0.02***	0.05**	0.02***
	(0.00)	(0.00)	(0.00)	(0.00)
Time-varying borrower attributes	\checkmark	\checkmark	\checkmark	\checkmark
Borrower FE	+	+	+	+
Year-qtr FE	+	+	+	+
Observations	5,846	20,730	3.023	5,007
R-squared	0.31	0.78	0.76	0.79
Dependent variable	0.01	0.04	0.13	0.10

Conclusions

• My take

 \circ Nice motivation

 \circ Interesting data (e.g., smoke, pollution)

 \odot Intriguing and detailed results

- My comments
 - Wildfires Robustness checks
 - Pollution Alternative treatment measures, placebo tests

o Interpretation (e.g., why does pollution have similar impact as wildfires?)