Unequal Recovery after Wildfires: Income, Infrastructure, and Community Return

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Introduction

- **Wildfires are large, frequent, and costly.** In 2024, the U.S. saw 64,897 fires that burned 8.9 million acres. (National Interagency Fire Center)
- **Economic losses are immense.** NOAA's billion-dollar disaster database shows a persistent rise in costly fire events; Western wildfire damages in 2017–2021 exceeded $90B. The Jan 2025 Los Angeles fires alone are estimated at $28–35B insured losses, with broader losses potentially far higher.
- **Climate change is amplifying risk.** Warmer, drier conditions increase "fire weather" and fuel aridity; mainly through man-made activities. Projections indicate further increases in fire danger and suppression costs this century. (NOAA)
- **Post fire recovery is uneven.** (McConnell & Braneon, 2024)
- This paper explores the time and heterogenity of post Wildfire recovery in California.

Motivation

- Understanding the length of disruption: provide idea of post-fire recovery period, understanding the scope and length of economic loss, at a high resolution scale.
- Explore if recovery timing differ based on income. Identifying systematic wealth patterns in disaster recovery, and better allocate recovery efforts.
- Whether the presence of critical infrastructure speed up recovery, identifying infrastructures that speed-up recovery process.
- Together these results can help policymakers to better prepare for natural disasters like wildfires and how to better allocate post-disaster recovery efforts.

Previous Literature

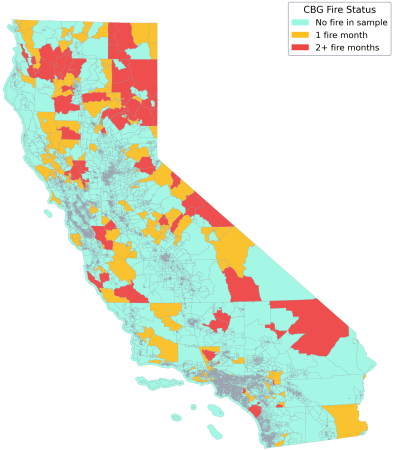
- The government spends more to fight fires where there are more houses, which ends up acting like a hidden subsidy for living in fire-prone places. (Baylis & Boomhower, 2023)
- House prices and rents are lowered post natural disaster. (Boustan et al., 2020)
- Community earnings were seen to first dip following disaster, but increased more than non-affected counterparts in the long run. (Deryugina et al., 2018)
- However, rental units were replaced by owner occupied housing post disaster, and increased rents in areas, signaling a gentrification effect. (McConnell & Braneon, 2024)
- There are significant socioeconomic and racial disparities in resilience capacity and evacuation patterns. (Hong et al., 2021)

Contribution

- Explores the underlying causal factors that determine disaster recovery, using monthly data at a Census Block Group (CBG) level.
- The paper explores a high-frequency and high-resolution measure of post disaster heterogeneity in recovery.
- This paper is also the first of its kind in exploring the role of critical infrastructure in post-disaster recovery.

Data: Wildfires

- Wildfire data collected from the Monitoring Trends in Burn Sensitivity (MTBS) platform
- Years covered: 2018–2022
- Unit of analysis: Census Block Groups (CBGs)
- Fire Stats:
  - Total CBG-fire months: 510
  - Unique CBGs with fire: 421
  - CBGs with multiple fire: 67



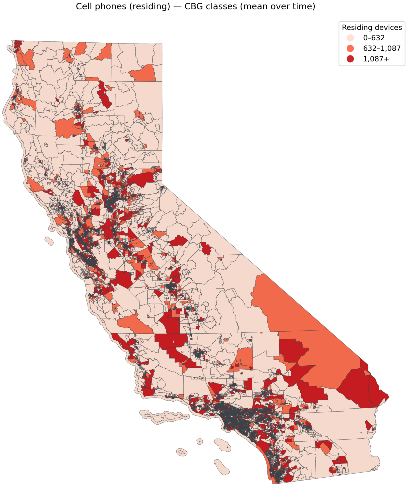
Data: Cell Phone Location Data

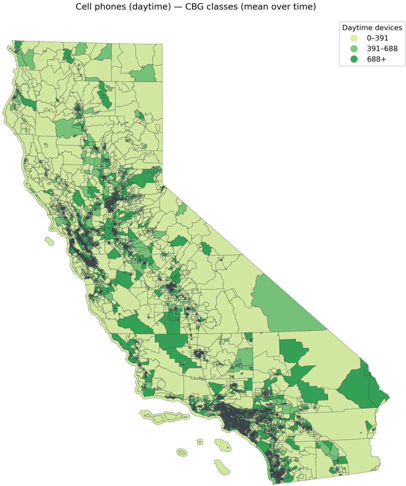
- Cell phone location data collected from Advan (Dewey Data Platform).
- It counts number of devices during daytime, as well as during night-time, enabling us to separate primary-working CBG vs primary-residence CBG.
- The data is aggregated to a month for each CBG each year. Future iterations will focus on a weekly analysis.

Variable	N	Mean	SD	Min	Max
Residing devices	18,759	588.89	753.55	3.8	42,317
Daytime devices	18,759	367.61	570.64	0.0	34,097

Table: Summary statistics of cell phone devices by CBG (2018–2022)

Daytime vs Night-time





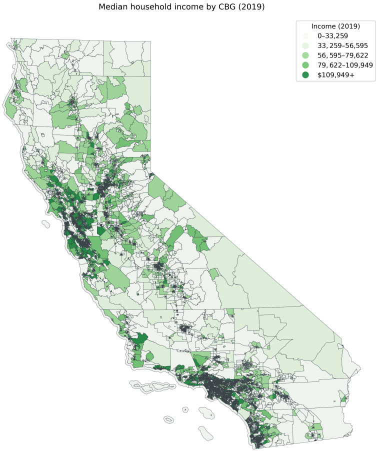
Data: Income Data

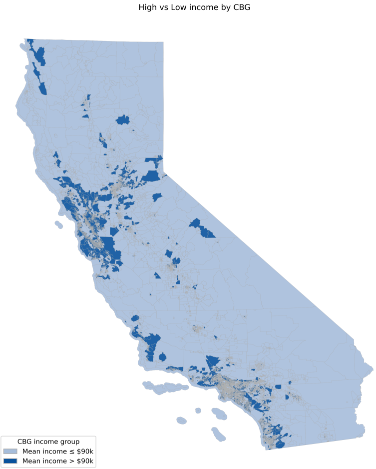
- Income data is collected as median household incomes on a CBG level from ACS 5-year estimates.
- CBGs above the mean are considered high income, and below are low income.

Variable	N	Mean	SD	Min	Max
Median household income	18,648	90,789	45,113	2,499	250,000

Table: Summary statistics of mean household income across California Census Block Groups (2018–2022).

Income Distribution



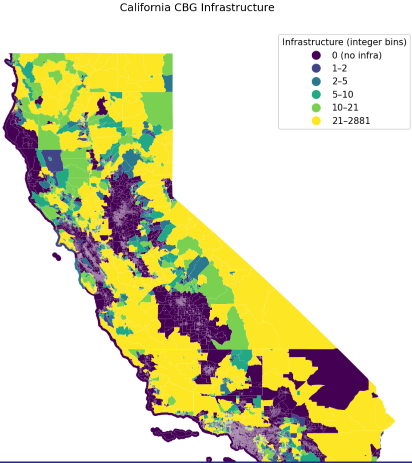


Data: Infrastructure Data

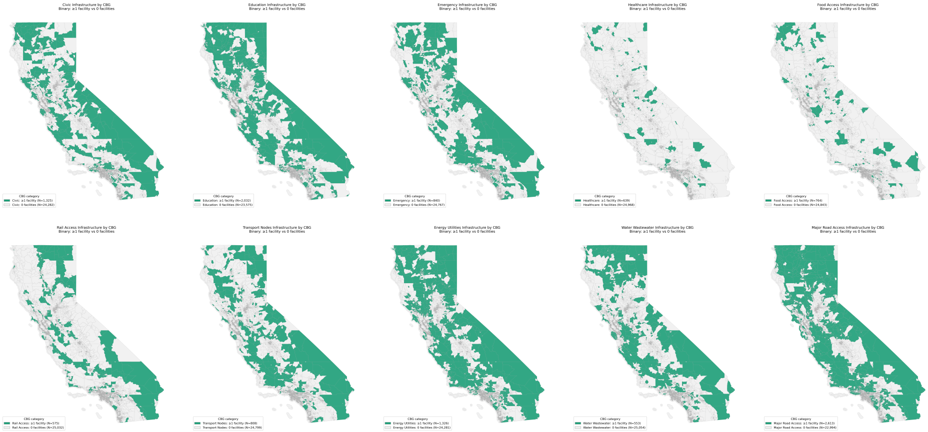
- Infrastructure per CBG is enumerated from Open Street Maps (OSM) using tagged location attributes into multiple categories such as: emergency, energy utilities, communication towers, water treatment, healthcare, emergency services, etc.
- An infrastructure index was created by adding the number of infrastructures across the categories.
- CBGs were distributed into a high infrastructure CBG vs a low infrastructure CBG, if they exceeded the median threshold of 13 infrastructure objects.

OSM Infrastructure Categories & Example Map

Category	Included OSM tags (key: values)
healthcare	amenity: hospital, clinic, doctors, pharmacy
emergency	amenity: fire_station, police, ambulance_station emergency: ambulance_station
education	amenity: school, college, university, kindergarten
transport_nodes	public_transport: station, stop_position railway: station, halt amenity: bus_station, ferry_terminal aeroway: aerodrome, heliport, terminal
energy_utilities	power: plant, substation, generator
water_wastewater	man_made: water_works, water_tower, pumping_station, wastewater_plant, sewage_works
communications	man_made: communications_tower
civic	amenity: townhall, courthouse, post_office, community_centre, shelter
food_access	shop: supermarket, hypermarket amenity: marketplace

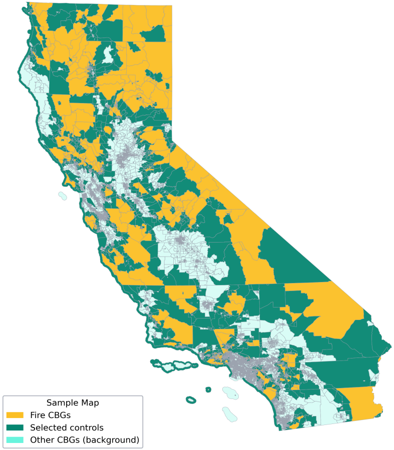


Infrastructure Distribution



Treatment Assignment

- Treatment: If ever had fire
  Control: Never Fire
- Event time: Month of first fire, then always treated
- Control Selection: Near neighbor method, surrounding CBG.
  Truncated sample, due to computing power limitations.
- Fire Stats:
  - Total Treated CBG: 421
  - Total Control CBG: 4363



Methodology: Staggard Diff-in-Diff, (csdid) model

Units/timing. CBGs i, months t. First-treatment (wildfire) cohort $G_i \in \mathcal{T} \cup \{\infty\}$. Outcome Y_{it} (e.g., night devices).

Subgroups (heterogeneity). Pre-treatment $S_i \in \{A, B\}$ (e.g., Low vs High income; Infra exposed vs Not).

Group–time effect within subgroup s:

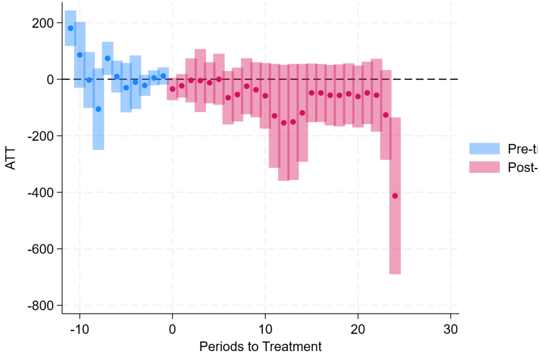
$$ATT_s(g,t) \;=\; E\big[\, Y_{it}^{(1)} - Y_{it}^{(0)} \mid G_i = g,\, S_i = s \,\big], \qquad t \geq g.$$

Interpretation. $ATT_s(g,t)$ is the causal effect for cohort g at time t using valid not-yet-/never-treated comparisons within s.

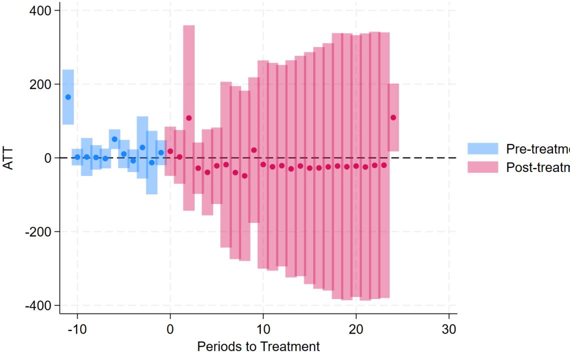
Design notes.

- G_i = first qualifying wildfire (once-treated-always-treated).
- Never-treated set buffered to limit spillovers; S_i fixed pre-treatment.
- Primary outcome normalized to unit pre-fire mean.

Daytime Devices: High vs Low Income

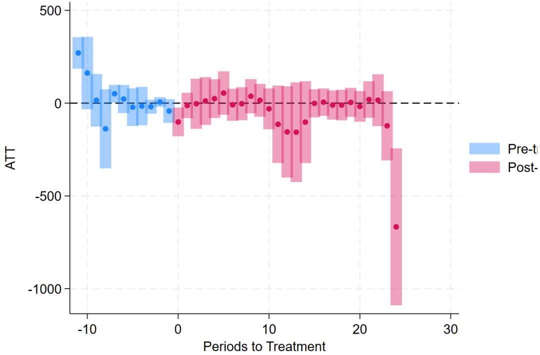


High Income

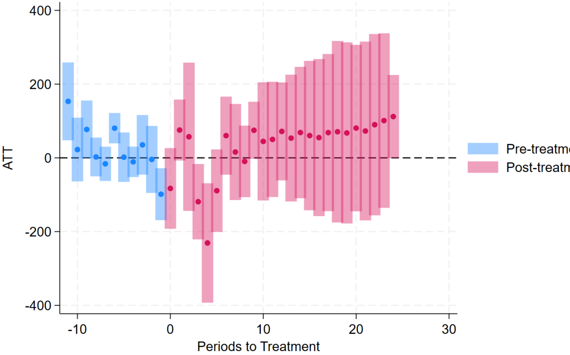


Low Income

Nighttime Devices: High vs Low Income

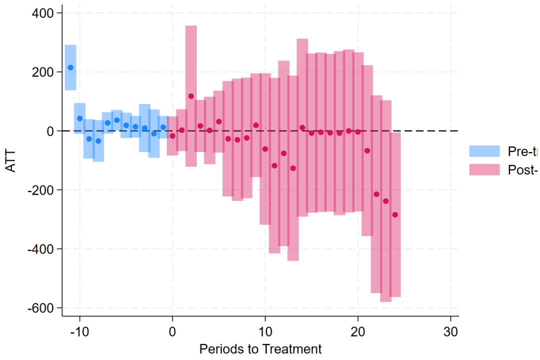


High Income

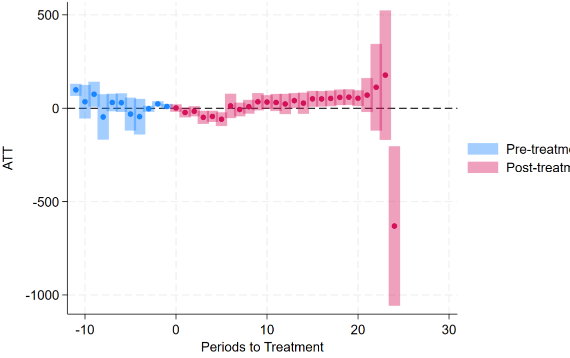


Low Income

Daytime Devices: High vs Low Infrastructure



Infra high



Infra low

Further Work

- Using fire intensity to undertake high intensity fires.
- Use controls and FE
- Handle areas with multiple fires.
- Undertake different variations and individual subset of infrastructure.
- Create an infrastructure index.
- Undertake a CBG-Week level analysis, as the month maybe too long and effects can be absorbed.

Thank you!

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