The Effects of China's Waste Import Ban on Pollution Relocation in the U.S.

Shan Zhang, University of Oregon

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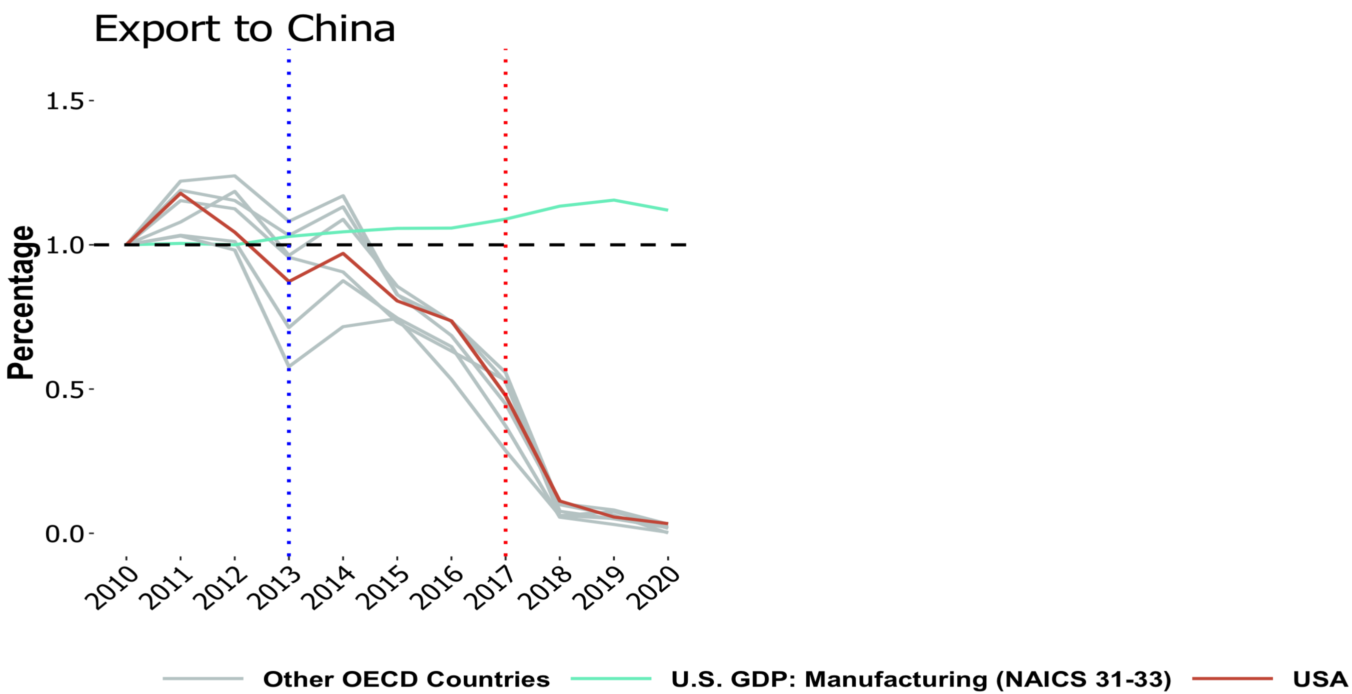
Introduction

- Recycling rate **7% → 32%** from 1960s to present
- For many years, most U.S. recyclables exported to developing countries
- China was the biggest importer of U.S. recyclables
- In 2017, China implemented its **Green Sword (GS) Policy** banning almost all recyclable waste imports
- Considerable domestic environmental costs
    - **air pollution** from re-processing of these materials
    - **landfill methane (GHG) emissions**
    - **land and water pollution**
    - **ocean disposal**
- U.S. has no **economical or efficient** recycling infrastructure
    - Recyclables went to landfills.

GS Policy and Trade

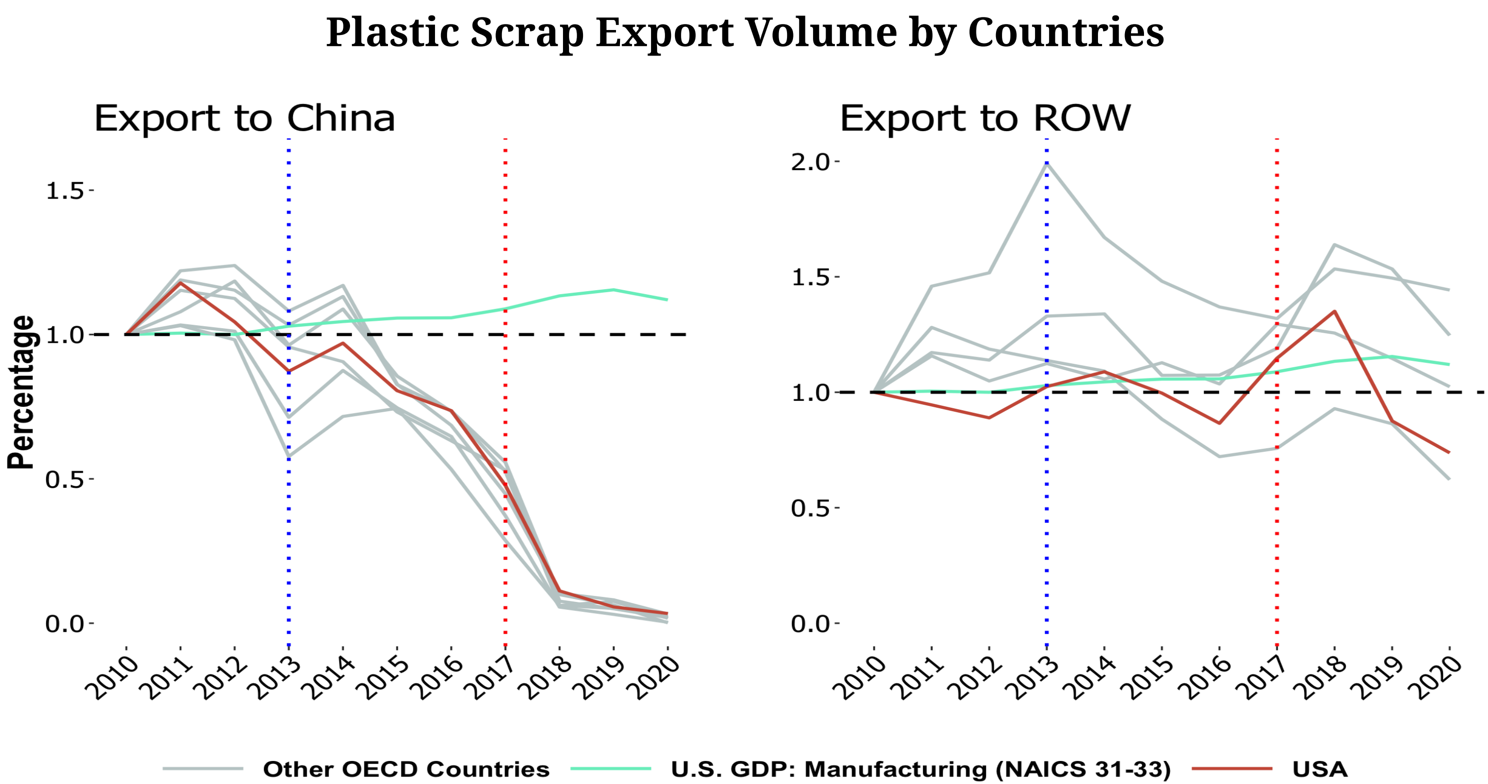
Plastic Scrap Export Volume by Countries



UN Comtrade Data

- U.S. plastic scrap exports to China dropped by **99%**

GS Policy and Trade



UN Comtrade Data

- U.S. plastic scrap exports to China dropped by **99%**
- U.S. plastic scrap exports to ROW **increased, then decreased** after China's GS policy

Research Questions

- For the **U.S.**
  - What has been the effect of China's GS policy on **Domestic Emissions** from landfill facilities?
  - What are the key features of states that drive **Heterogeneous Changes** in domestic emissions?
- For the state of **California**
  - What are the **Distributional Effects** of the GS policy on pollution relocation for local communities at census-block levels?
  - What are **Environmental Justice (EJ)** implications? What's the mechanism?

Relevance

Trade and Environment *Shapiro (2016), Shapiro (2018), Shapiro (2021)*

→ My innovation: Study a trade policy that directly restricts externality export and explore the policy's causal effects on local emissions in the U.S.

Environmental Gentrification and Environmental Justice *Baden and Coursey (2002), Cameron and McConnaha (2006), Banzhaf and Walsh (2008), Depro et al. (2011), Banzhaf and Walsh (2013), Depro et al. (2015), Banzhaf et al. (2019), Ho (2020), Hernandes and Meng (2020), Shapiro and Walker (2021)*

→ My innovation: Examine how an exogenous intl. trade policy affects U.S. EJ problems.

The efficiency of curbside recycling programs *Adaland and Caplan (2006), Bohm et al. (2010), Kinnaman (2014), Kinnaman et al. (2014)*

→ My innovation: Show that in the absence of an overseas market for recyclables, the U.S. recycling system is inefficient even though it has the "efficient" recycling rate.

Behavioral Economics of Curbside Recycling *Kurz et al.(2000), Halvorsen (2010), Ashenmiller (2009), Ashenmiller (2011), Best and Kneip (2019), Berck et al. (2020), Berck et al. (2021)*

→ My innovation: Use this exogenous trade policy as a tool to explore the relationship between the recycling programs and local environmental outcomes in the U.S.

Data

- U.S. EPA Greenhouse Gas Reporting Program (GHGRP)
    - Methane emissions from landfill facilities
    - 2010 to 2020 annually
- Approximately 8,000 facilities required to report emissions annually
- High compliance rates
- Covered industries include power plants, petroleum and natural gas systems, minerals, chemicals, pulp and paper, refineries, waste, etc.
- Data generation process:
    - Facilities in waste industry report annual **amount of wastes accepted**
    - Methane emissions are calculated using a complicated model embedded in U.S. EPA

Data

- California Department of Resources Recycling and Recovery (CalRecycle) Disposal Flow Data
    - Captures the amount of disposal transported by origin jurisdiction and destination facility
    - 2002 to 2021 quarterly
    - Contains 464 origin jurisdictions and 263 disposal facilities
- Other Data Sources
    - U.S. Trade Census
    - EPA Enforcement and Compliance Historical data
    - Bureau and Labor and Statistics (BLS) Quarterly Employment and Wages at county level
    - U.S. Census racial mix, median income at census-block level
    - Statewide Database (SWDB) election data at precinct level

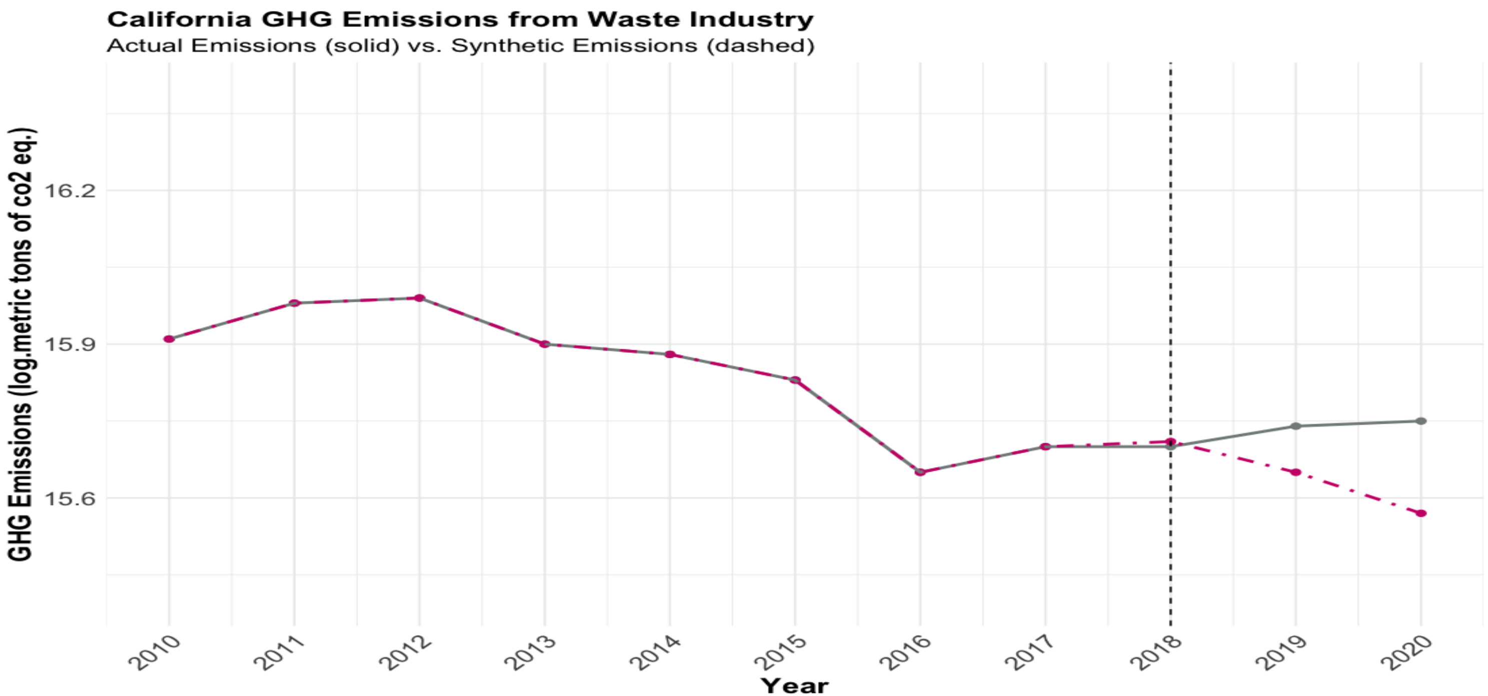
Identification: Synthetic Control Method

- Rely on exogenous variation in methane emissions across **all other industries** in the EPA GHGRP
    - Power plants, petroleum and natural gas systems, minerals, chemicals, pulp and paper, refineries, etc. (**not** waste)
- Take advantage of the fact that other industries which also emit GHGs were not affected by China's GS policy
- Use other industries (all states) as donor pool for synthetic control group
- Train the model using the pre-policy period **2010-2017**
    - Calculate state-industry pair weights to minimize prediction error

$$\hat{Y}_{1t}^{N} = \sum_{j=2}^{J+1} w_j Y_{1t}$$

- Predict counterfactual methane emissions in the absence of GS policy using post-policy period (**2018-2020**)

Results

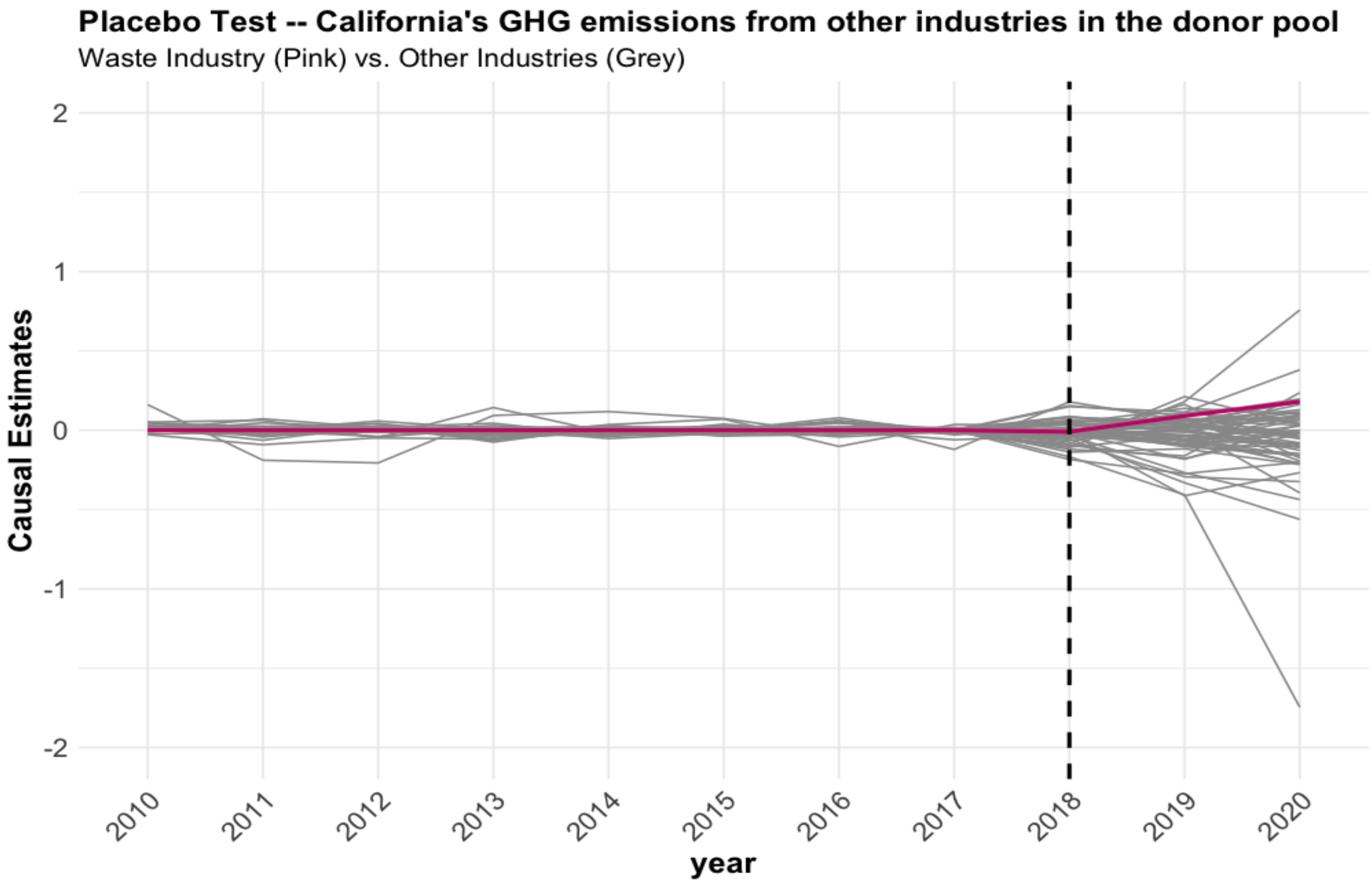


California

- The difference between actual emissions and synthetic emissions is the causal effect of China's GS policy on U.S. landfill methane emissions

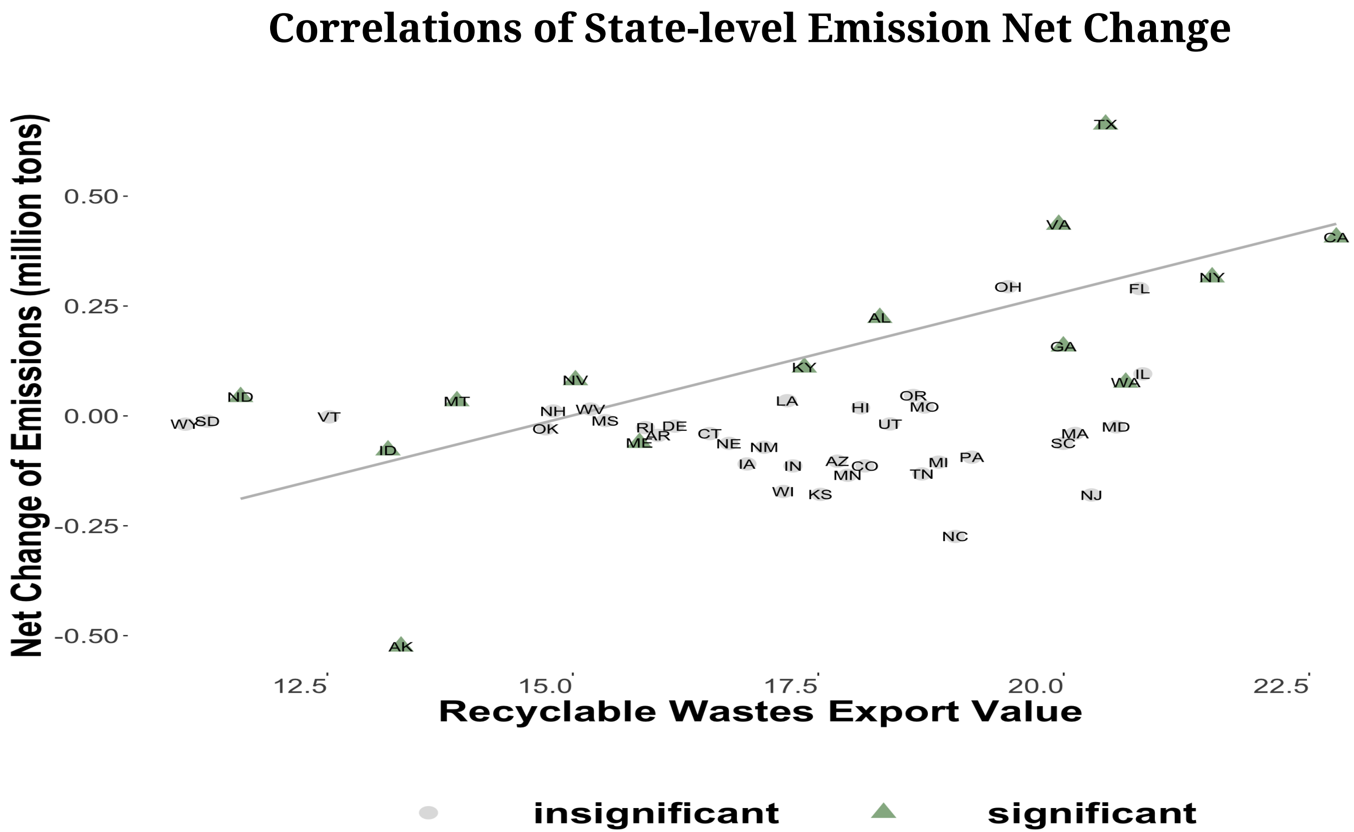
$$\hat{\tau_{1t}} = Y_{1t} - \hat{Y_{1t}^{N}}$$

Placebo Tests



Placebo Test using "Fake" Treatment Industries

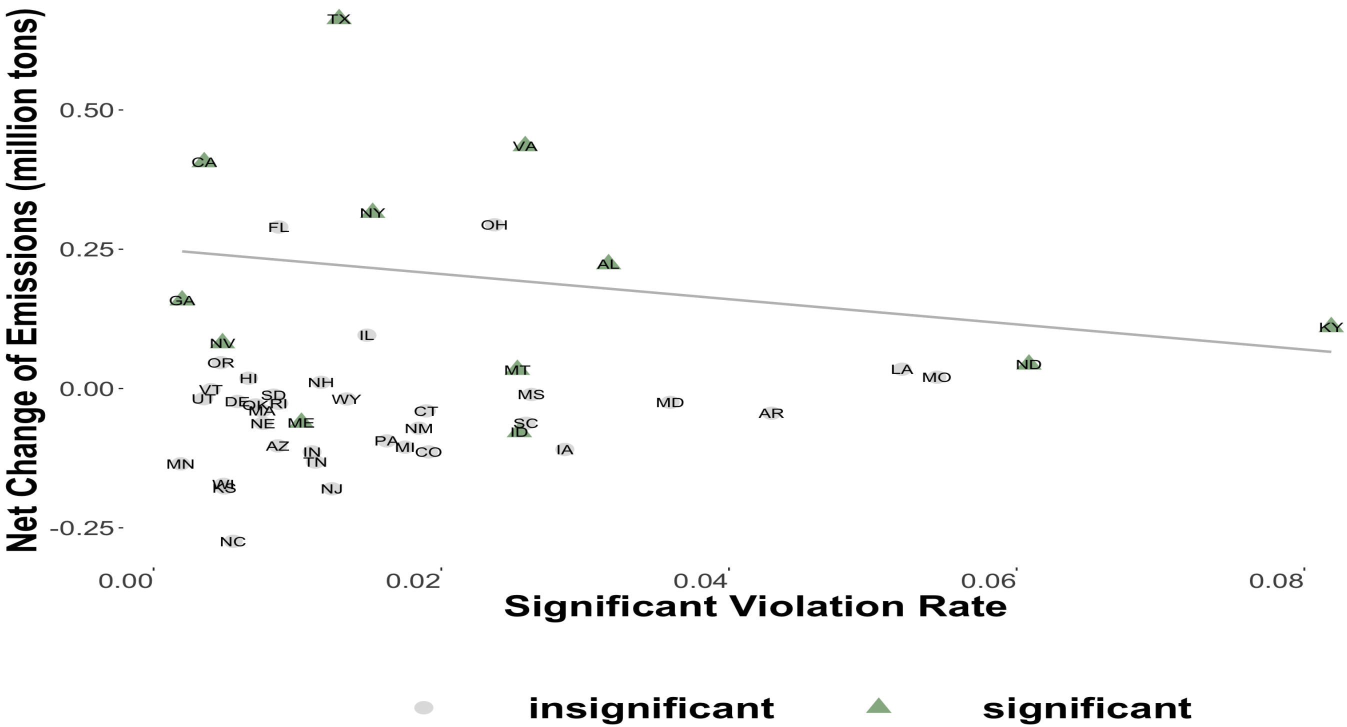
Results



- ↑ **Recyclable wastes a state exported** → ↑ increase in methane emissions.

Results

Fig.7 **Correlations of State-level Emission Net Change**

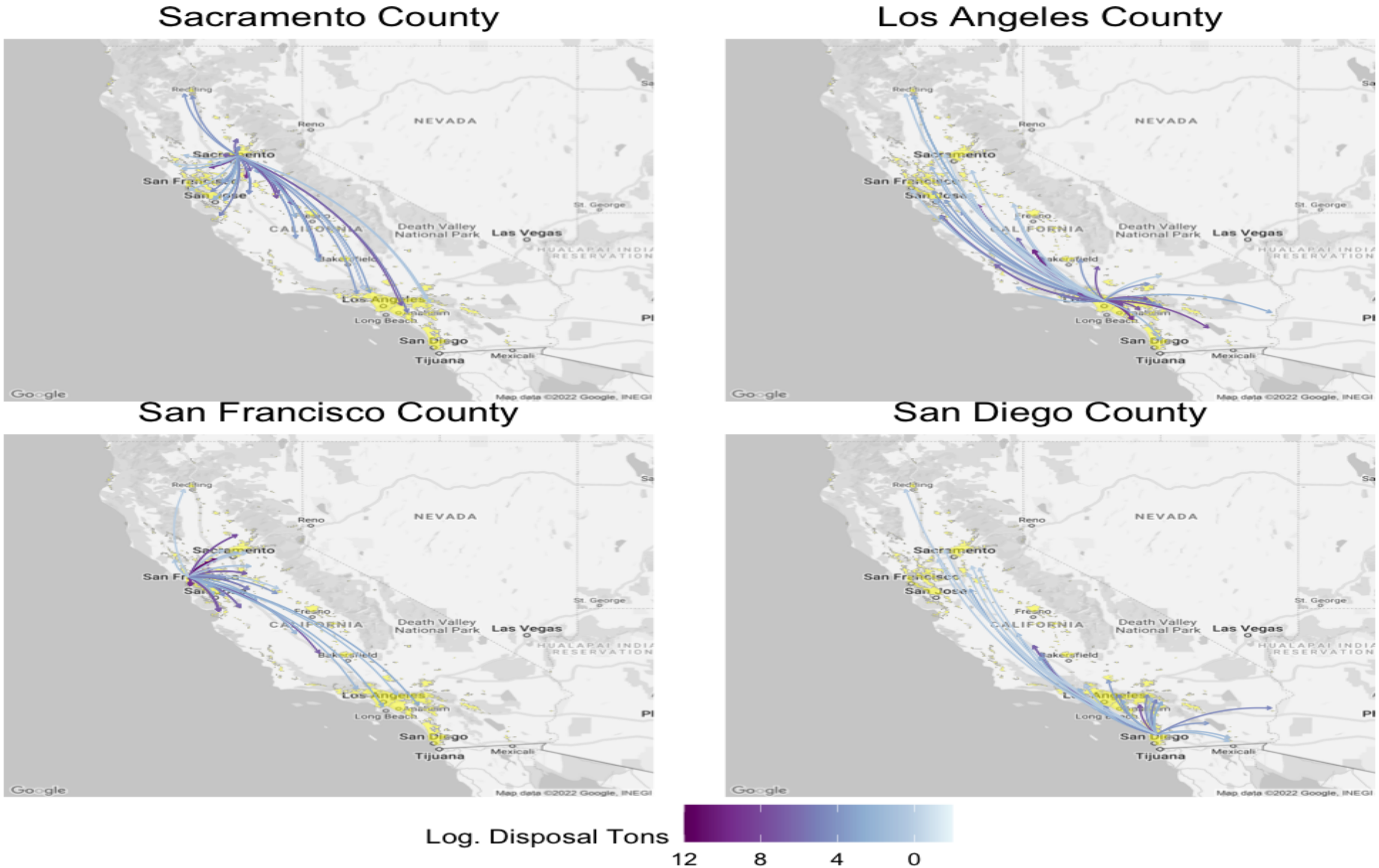


- ↑ **State-level rate of "significant" environmental violations** → ↓ increase in methane emissions.

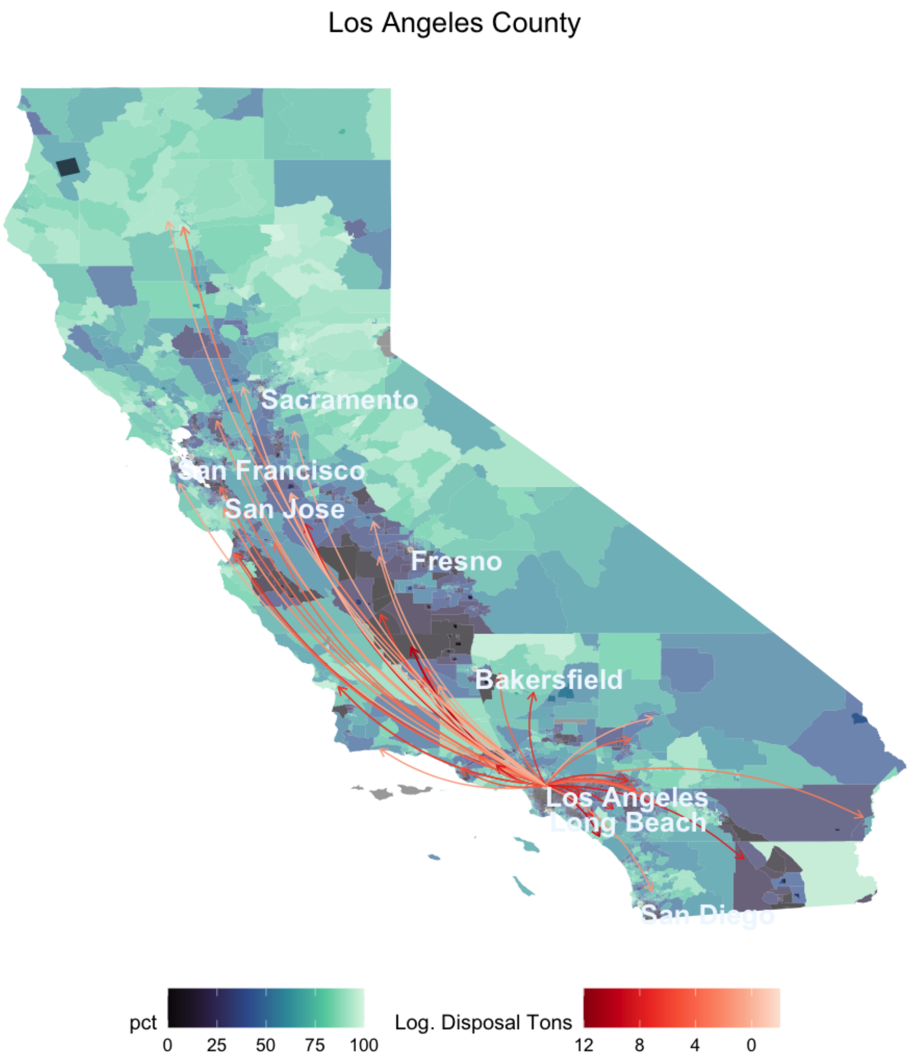
Pollution Relocation in California and Environmental Justice

Pollution Relocation

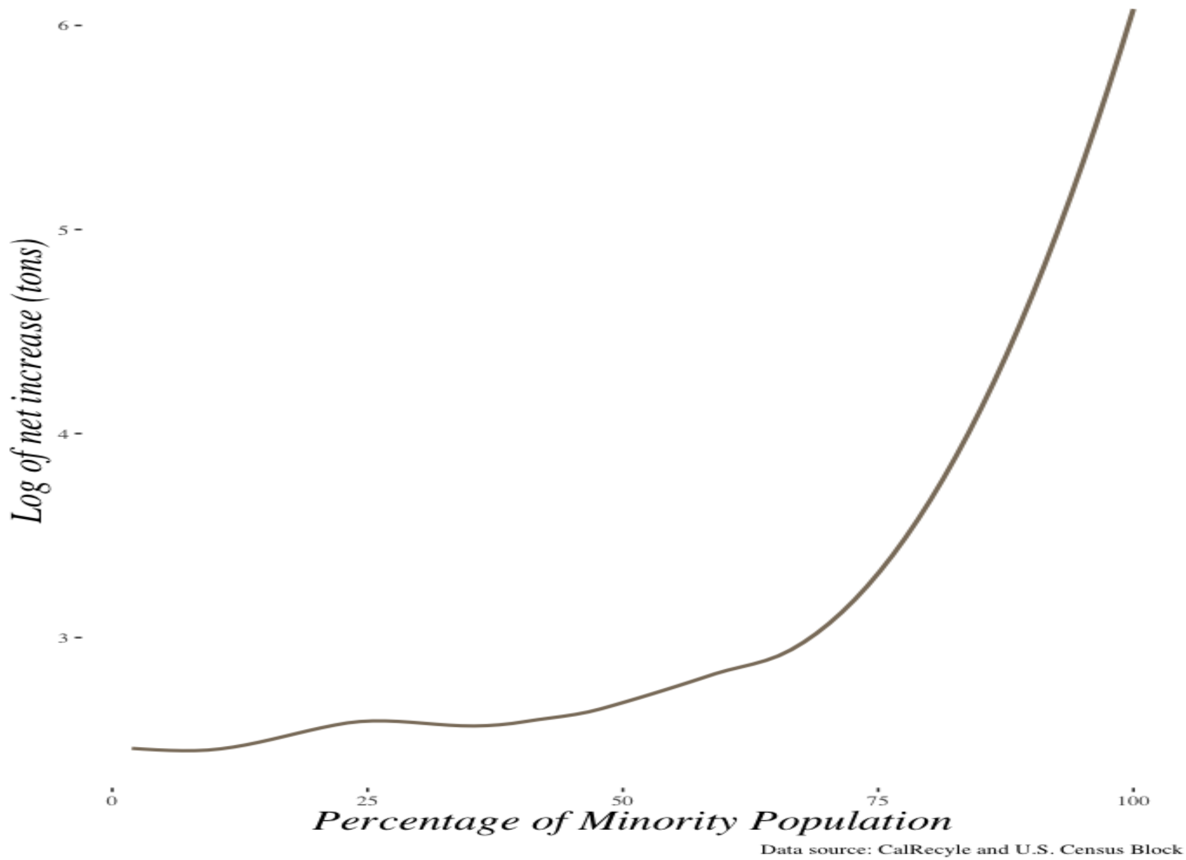
Average net increase in waste flows across regions after the GS policy



Pollution Relocation by Racial Composition



Pollution Relocation by Racial Composition



Average net increase in waste flows across regions after the GS policy

Gravity-type Model

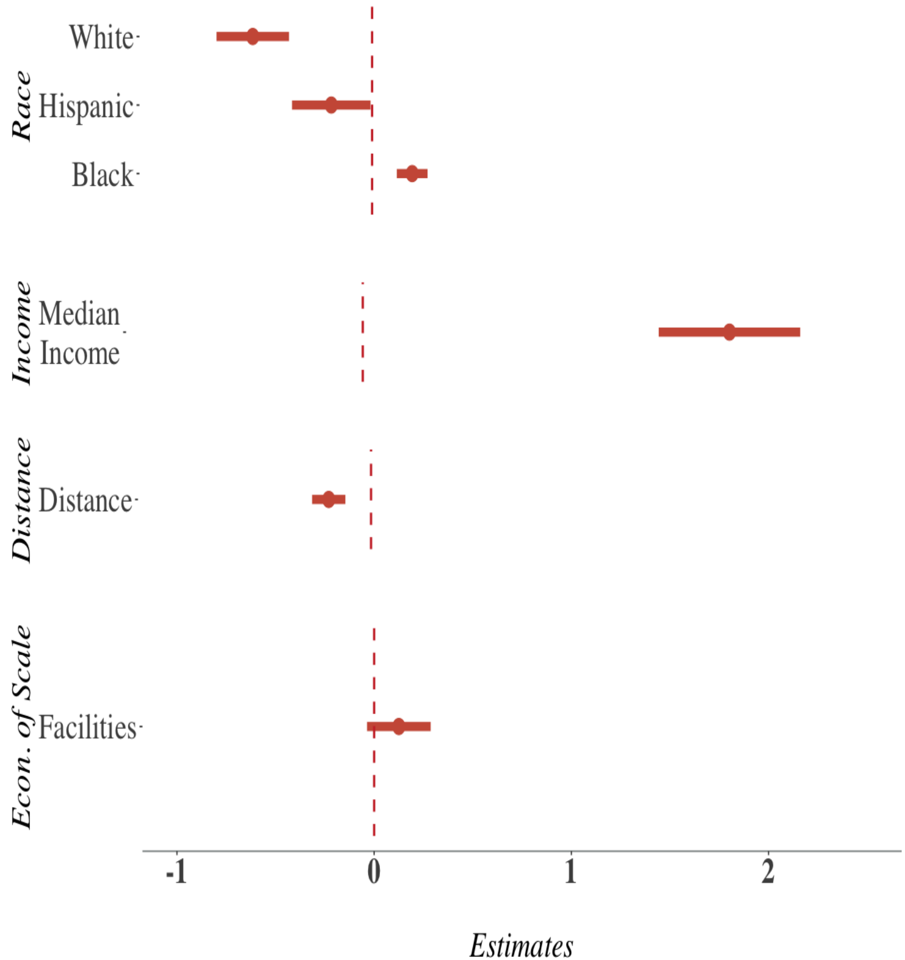
$$log(Y_{ijt}) = \alpha + \beta_1 log(Dist_{ij}) + \beta_2 log(R_j) + \beta_3 log(X_{jt})$$

$$+\beta_5 GS_{post} * log(R_j) + \beta_6 GS_{post} * log(X_{jt})$$

$$\epsilon_o + \theta_d + \mu_{od} + \eta_t + \lambda_{odt}$$

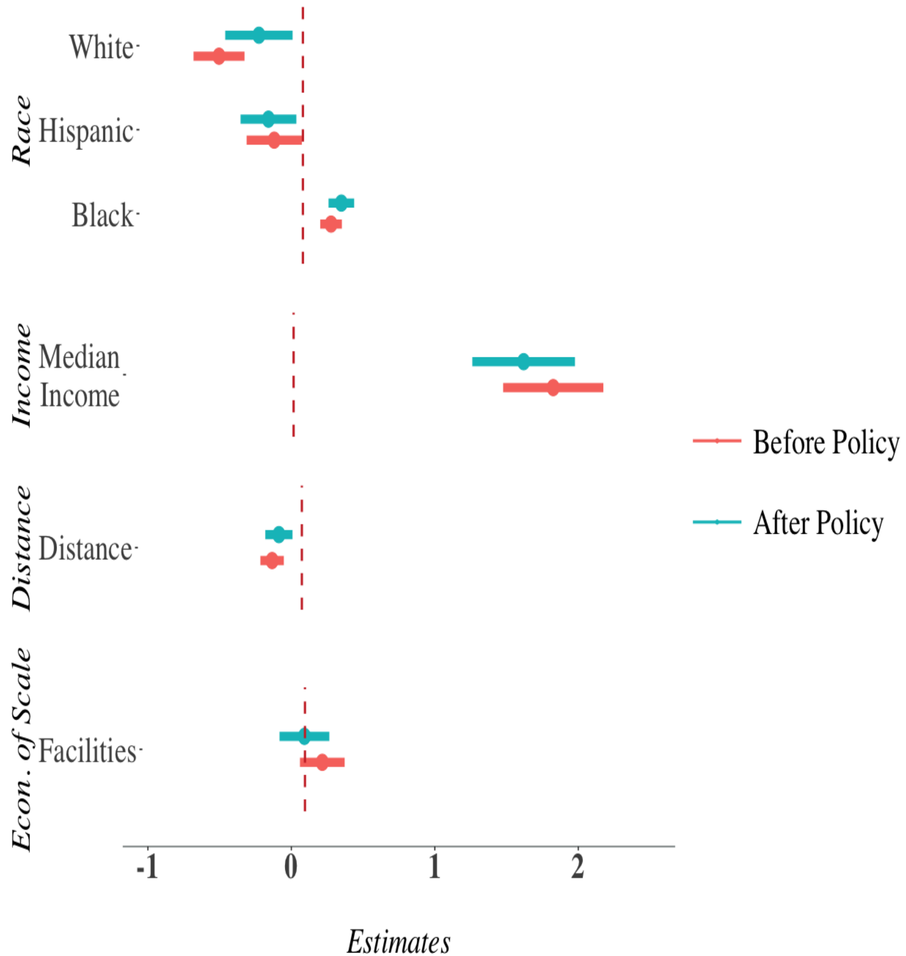
- i origin jurisdiction of California; o origin county
- j area that is a 3km buffer within the destination facility; d destination county
- t year-quarter
- R_{jt} **racial compositions of destination** j
- Y_{ijt} **tons of the disposal transported from** i **to** j **in year quarter** t
- GS_{post} **dummy variable for the GS policy**
- $Dist_{ij}$ distance between origin i and destination j
- X_{jt} median income, regulation of environmental stringency, and economies of scale of waste industry of destination j
- Fixed-effects: ϵ_o, θ_d, μ_{od}, η_t, λ_{odt}

Results prior to the GS Policy



Gravity Model: Key coefficient Estimates at Census-Block level

Results after the GS Policy



Gravity Model: Key coefficient Estimates at Census-Block level

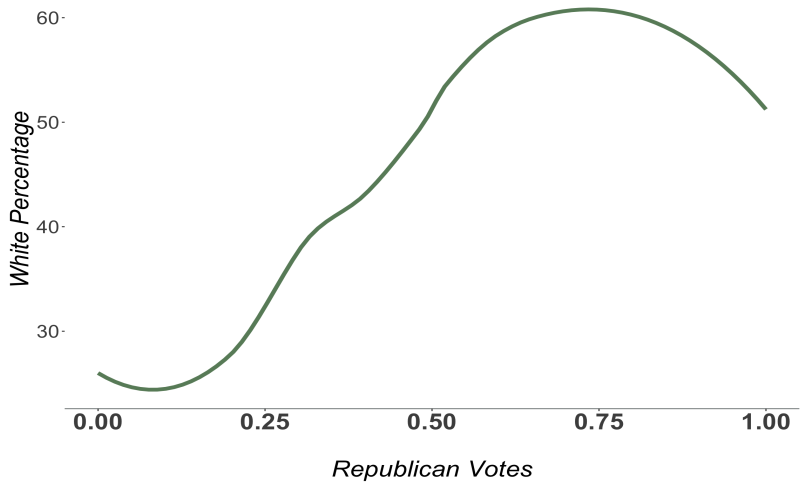
Preliminary Results

California Pollution Relocation

- Before China's GS policy
    - Waste tends to flow to **minority communities**
- After China's GS policy
    - Inflows increased more for **lower-income white communities**
- Counterintuitive?

Mechanism -- Political Costs

- Racial composition of the destination community is highly correlated with voting patterns



Correlation between White percentage by census blocks and Republican share by voting precincts

- Higher Republican votes, higher percentage of White population

- Do disposal inflows to Republican communities increase more due to political costs?

Pollution Relocation and Political Costs: Simple model

- Pollution relocation depends on **transportation costs** and **political costs**

$$Y_{ij} = \frac{\overline{Y}_i}{C_{ij}(d_{ij} \cdot f_{ij}) \cdot P_{ij}(Vjc)}$$

  - Y_{ij} is pollution relocated from jurisdiction i to facility j
  - $\overline{Y}_i$ is the waste pollution generated by jurisdiction i
  - $C_{ij}(d_{ij} \cdot f_{ij})$ is a transportation cost function w.r.t distance (overseas/domestic) and fuel price per mile
  - $P_{ij}(Vjc)$ is a political cost function w.r.t. votes in district where facility j located

- Political costs depend on the distance between precinct(destination) votes and state-incumbent votes

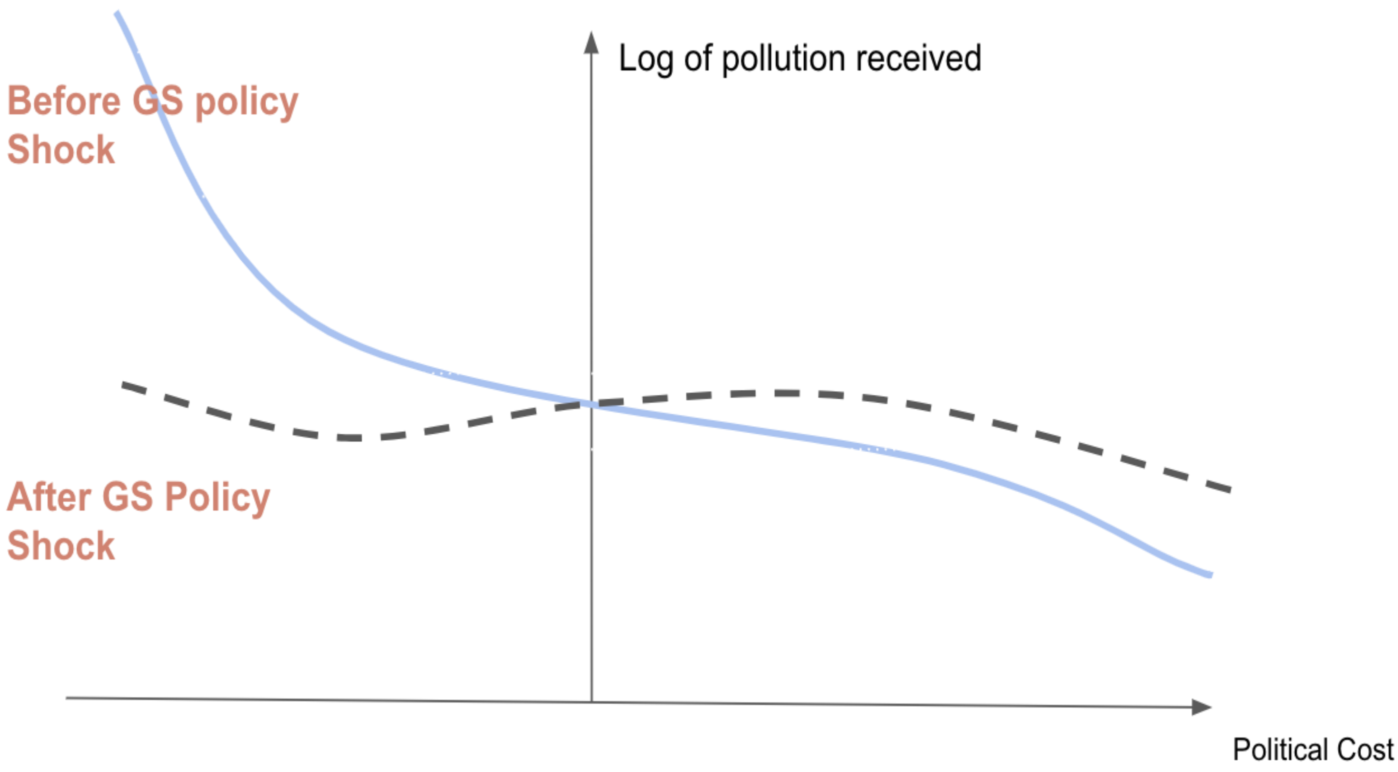
$$Vjc = v_j - \overline{v}_c$$

  - v_j is the votes of the district
  - v_c is California's incumbent votes
  - V_{jc} is the political cost of the destination community

- Before China's policy shock
  - $C_{ij}(d_{ij} \cdot f_{ij})$ << $P_{ij}(Vjc)$
  - Political costs prevail

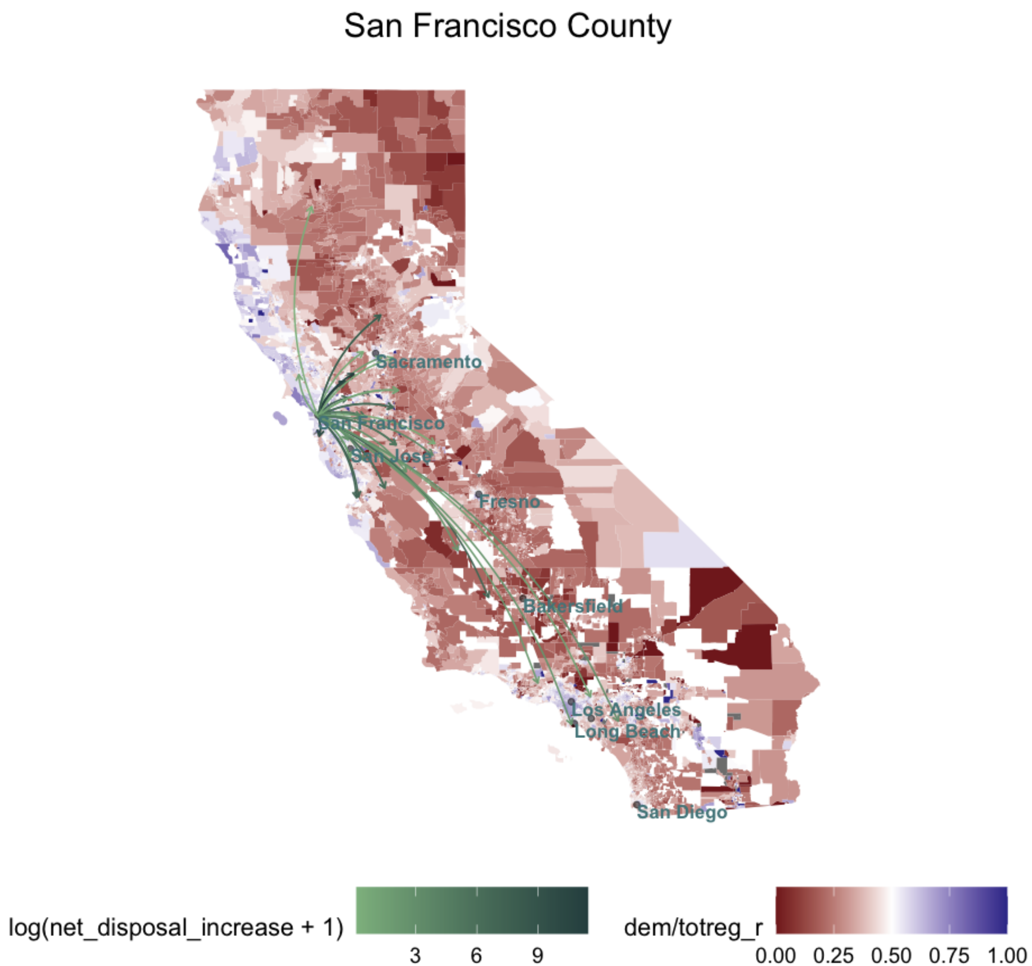
- After China's policy shock
  - $C_{ij}(d_{ij}))$ >> $P_{ij}(Vjc)$
  - Marginal political costs deminished

Intuition



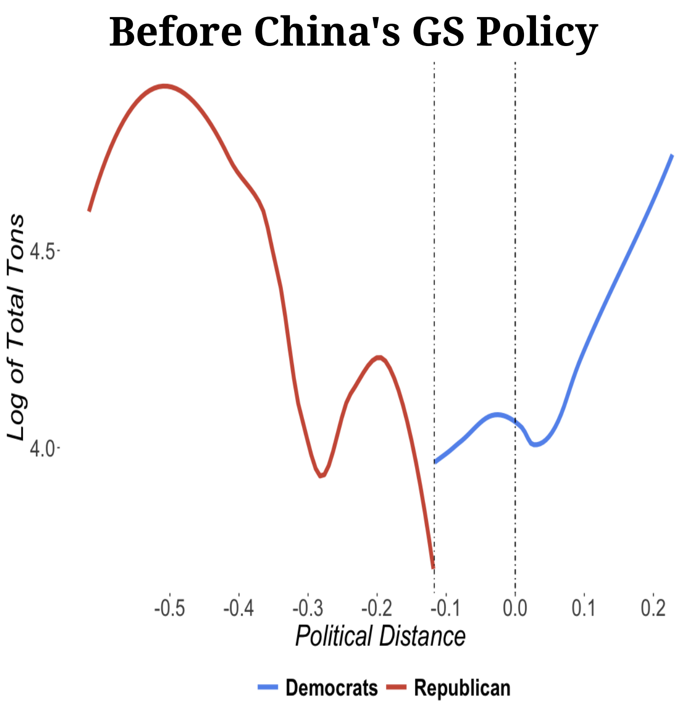
- China's GS policy shock shifts the curve flatter (less elastic)
- Excessive pollution relocation shifted from Republican communities to Democratic communities

California Voting by Precinct



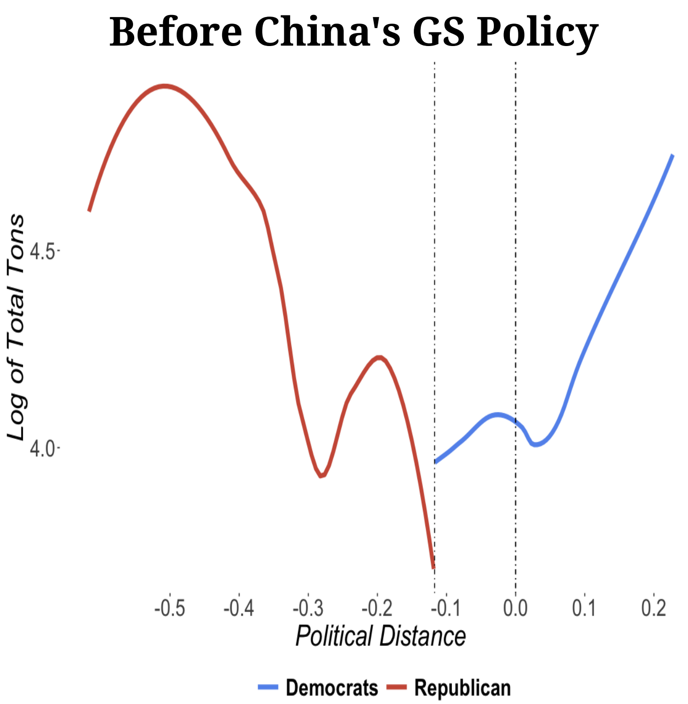
Disposal flow and Voting by precinct in California

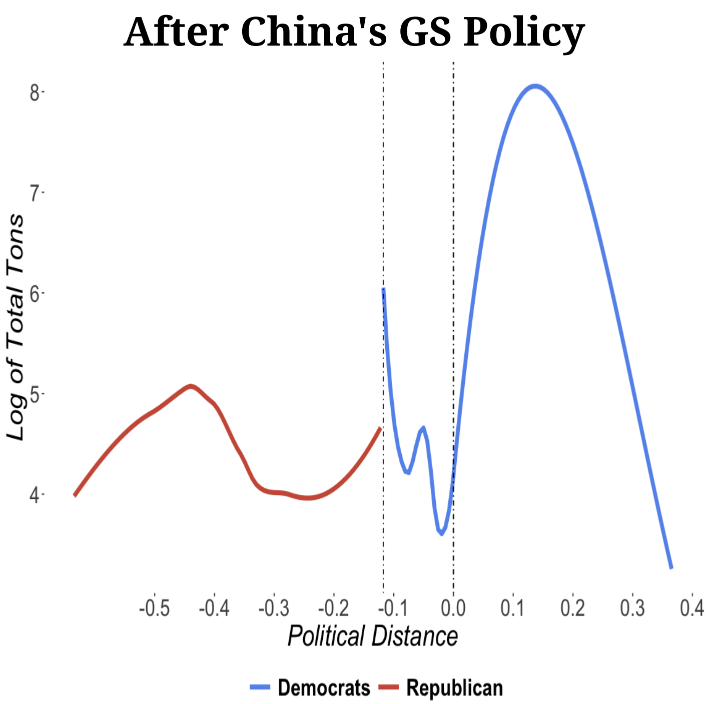
Mechanism -- Political Costs



- Facilities in Republican communities (low political costs) received more waste pollution

Mechanism -- Political Costs





- Facilities in Republican communities (low political costs) received more waste pollution

- Facilities from Democratic communities (relatively higher political costs) received more waste pollution

Conclusion Preliminary Findings

- **U.S. State-level Methane Emissions**
  - Many states: statistically significant increases in methane emissions
  - Relate to historical trade volume, stringency of envir. regulations
- **California Pollution Relocation**
  - Before China's GS policy

  Waste tend to relocate to minority communities

  - After China's GS policy

  Inflows increased more for remote lower income white communities

  - Potential mechanism

  Waste tended to relocate to places that have **lower political costs**. After GS policy shock, pollution relocated more to higher political costs places

Thank you

Questions?

Shan Zhang, Department of Economics, University of Oregon

szhang6@uoregon.edu

Placebo Tests

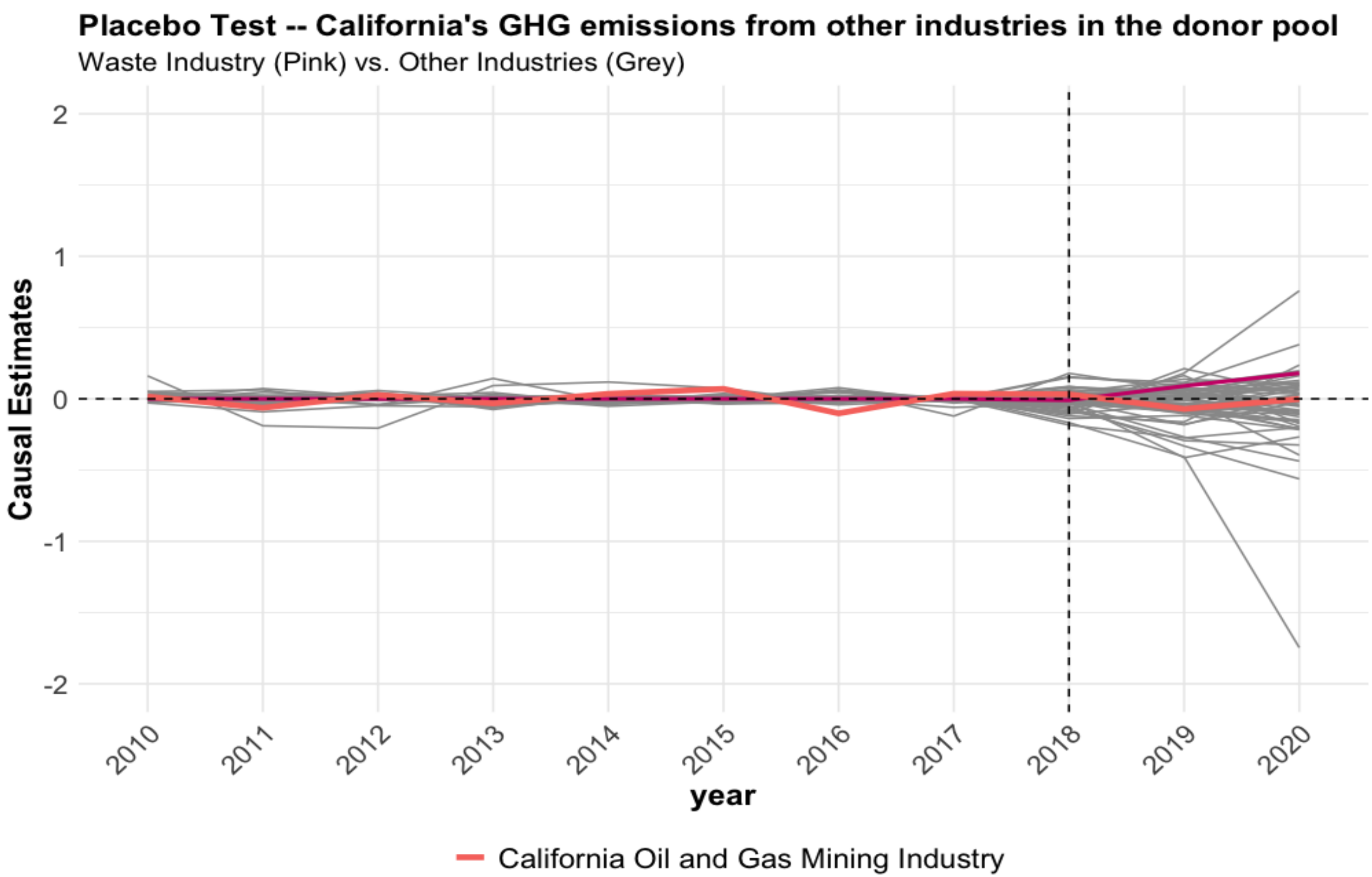


Fig.6 **Placebo Test using "Fake" Treatment Industries**

Placebo Tests

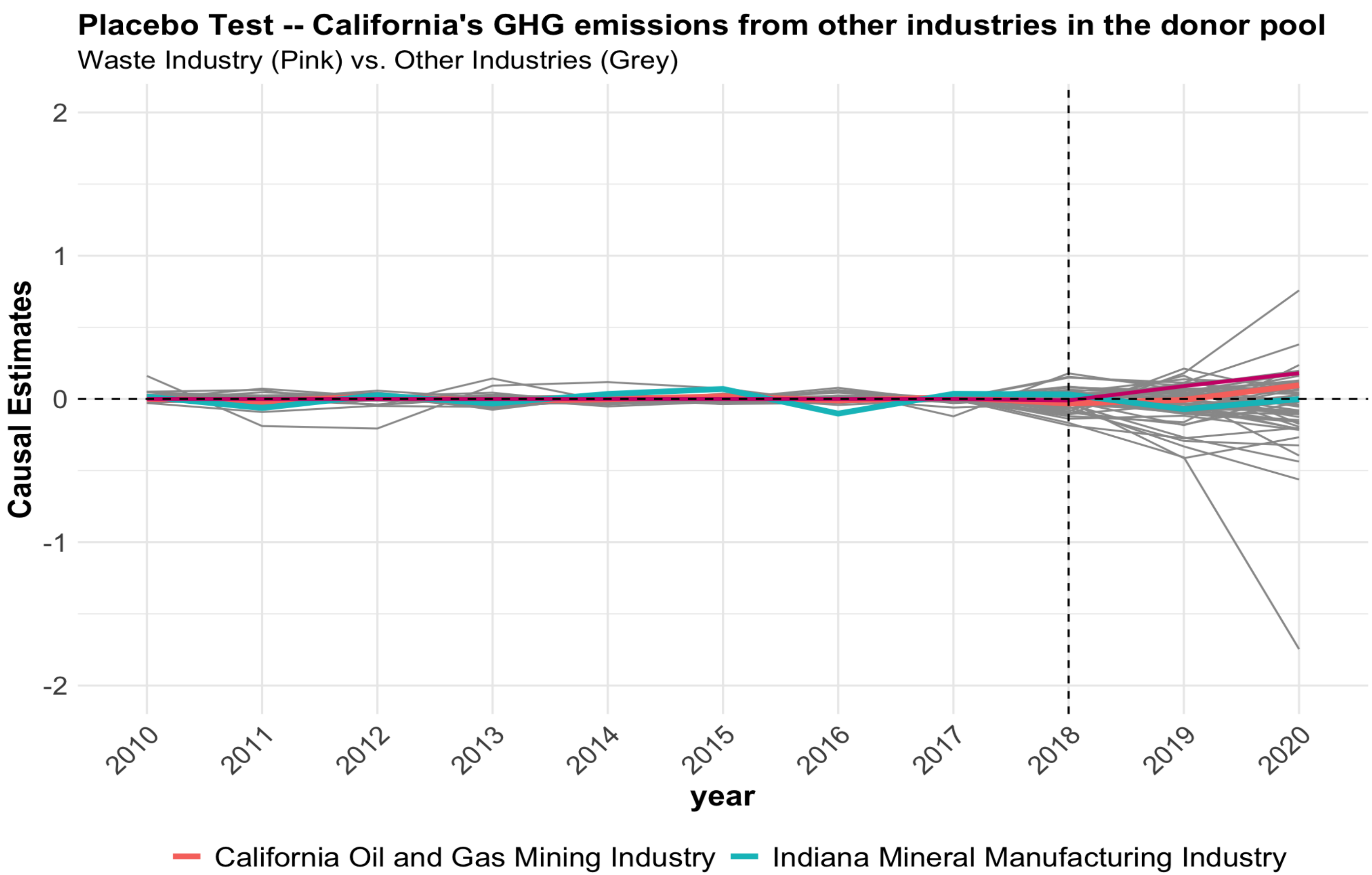


Fig.6 **Placebo Test using "Fake" Treatment Industries**

Appendix: Environmental Outcome Measurement

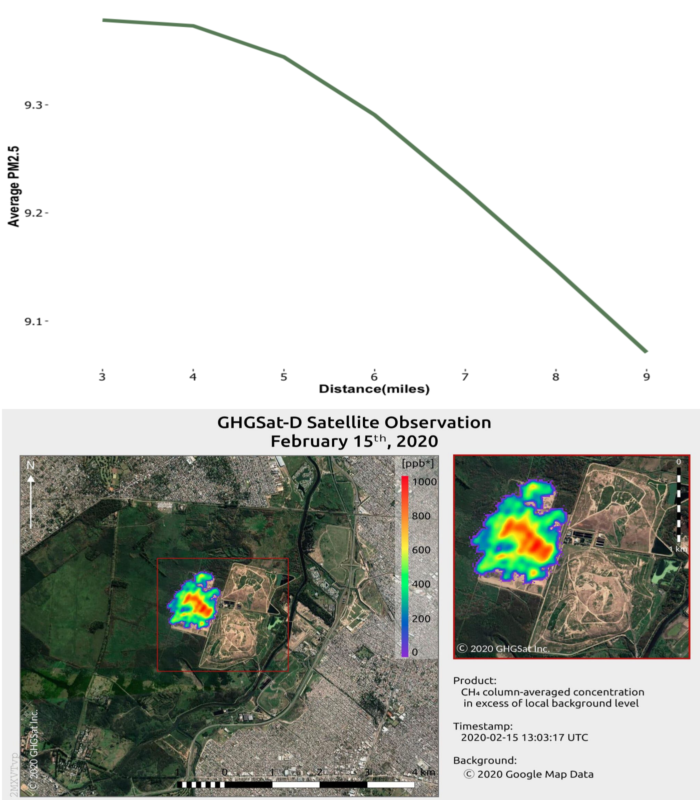


Fig.4 **PM2.5 from landfill sources by distance upper) and GHGSat's satellite showed methane from landfills (bottom)**

- Why use **methane** emissions?
  - Need consistently measured emissions data from 2010 to 2020
  - They are a **proxy** for general pollution emissions:**organic hazardous air pollutants (HAP), volatile organic compounds (VOC), hydrogen sulfide**, etc.
  - Methane is far more potent at trapping the sun's heat than carbon emissions

Appendix: Racial variation

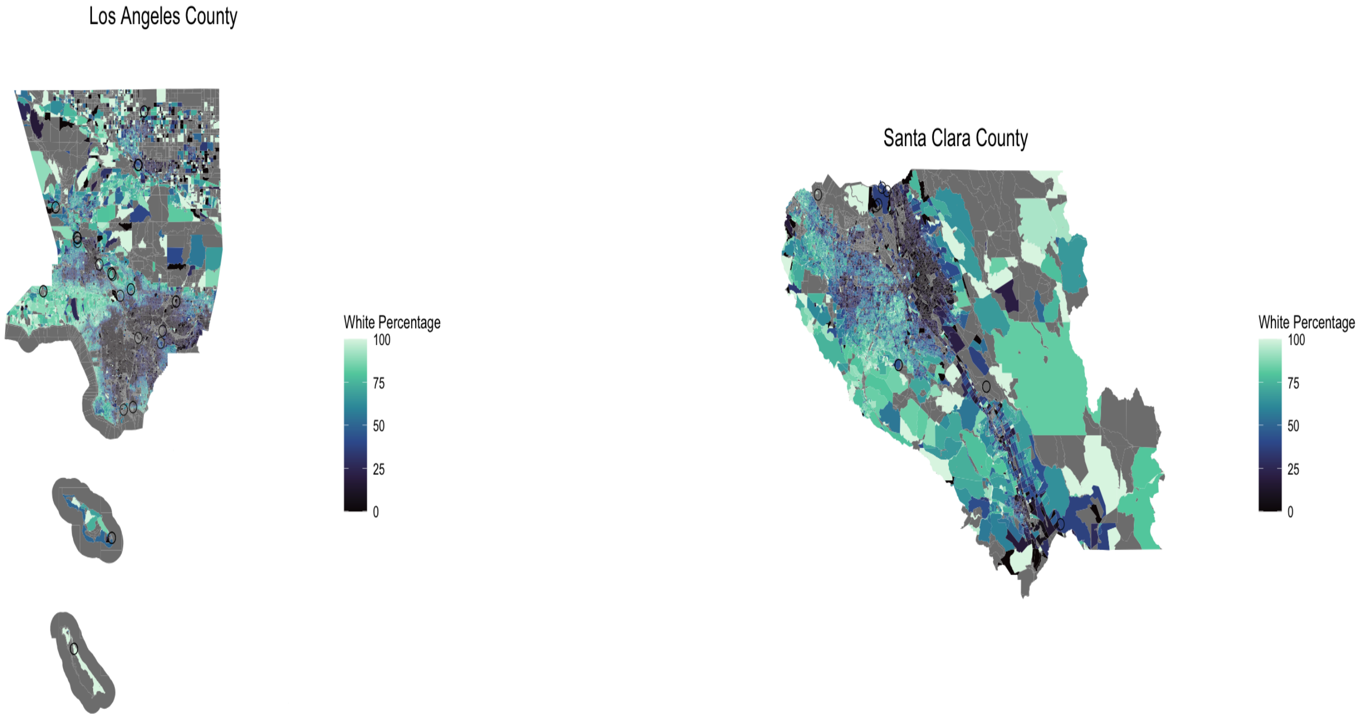
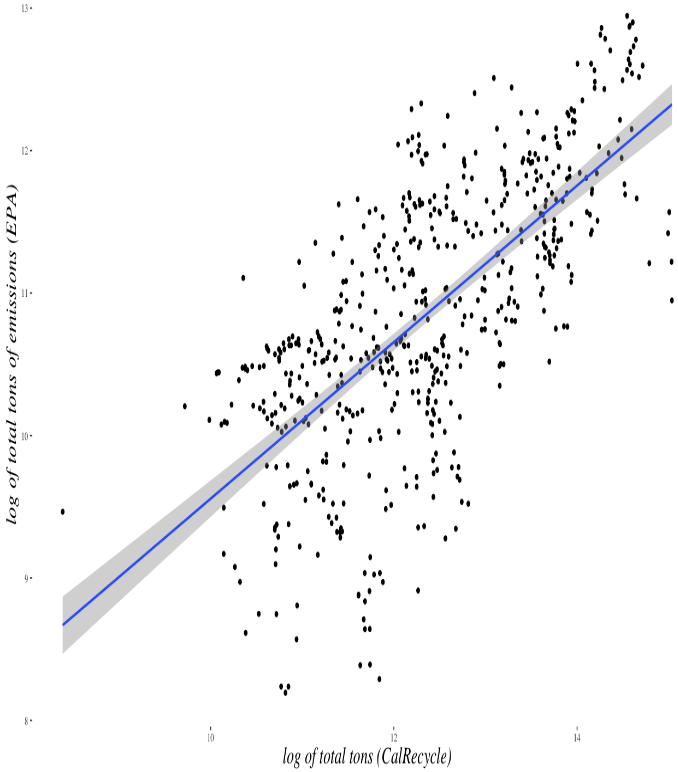
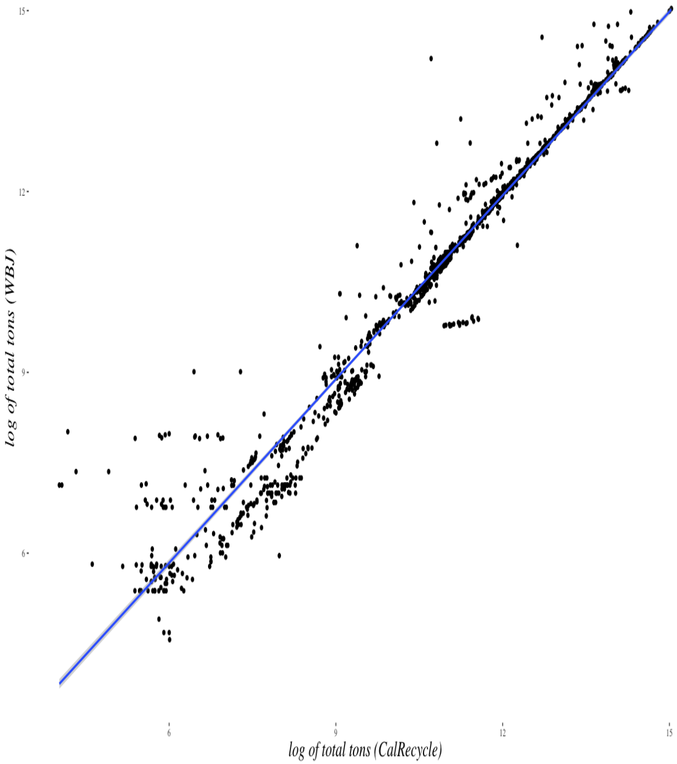


Fig.10 **Racial variation within the county**

Appendix: Data Source Comparison





Voting variation

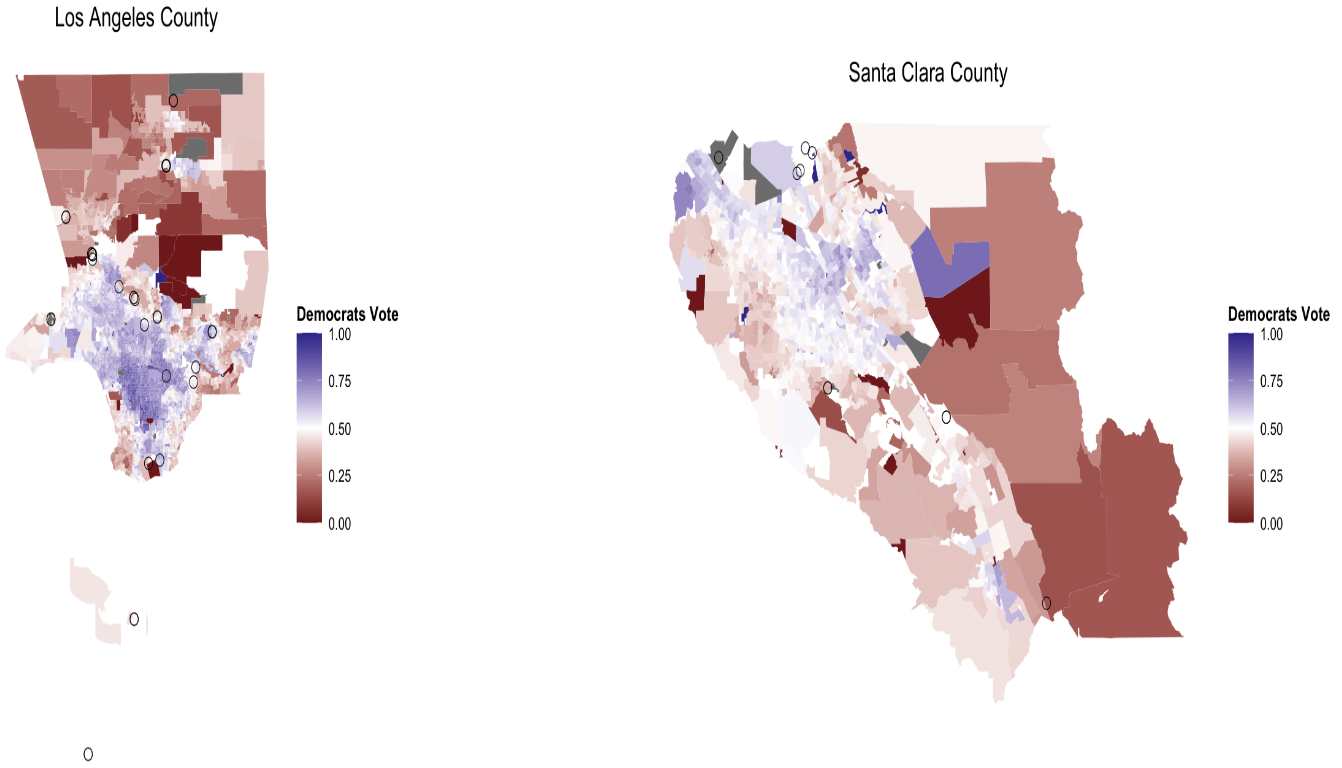


Fig.15 **Voting variation within the county**

Regression Result

OLS Regression

$$log(Y_{ijt}) = \alpha + \beta_1 P_j(Vjc) + \beta_2 GS_{post} * P_j(Vjc) + \beta_3 log(X_{jt})$$

$$\epsilon_o + \theta_d + \mu_{od} + \eta_t + \lambda_{odt}$$

	Overall	Republican	Democrats
Political Cost j	-0.144	-1.2584	0.59845
	(0.062)	(0.101)	(0.439)
Post * Political Cost j	0.726	1.113408	-3.32037
	(0.109)	(0.171)	(0.605)
Controls	Y	Y	Y
County d FE	Y	Y	Y
Year FE	Y	Y	Y
Quarter FE	Y	Y	Y
Two-way clustered SD	Y	Y	Y