If Not in My Backyard, Where?
The Distributional Effects of Restricting Interjurisdictional Waste Flows

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Motivation

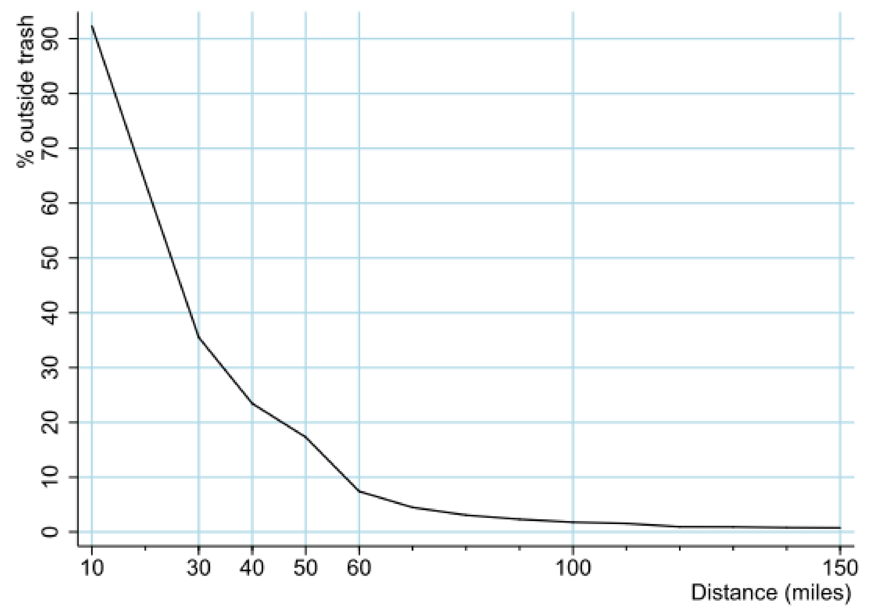
- Every year, the US generates more than 200 millon tons of waste. The long-running question is where to dispose of the trash.
- Several states and counties have attempted to limit out-of-jurisdiction waste imports, for example, New Jersey ban 1978, Alabama tax 1992, Wisconsin recycling standards 1999. However, these not-in-my-backyard (NIMBY) legislations have been overturned by Supreme Court due to their violations of Commerce Clause.
- The efforts of limiting interjurisdictional waste transport have spilled into Congress. In 2017—2018 session, Congress proposed Trash Act that allows states to regulate out-of-state waste imports and to provide community benefit fees to affected communities.
- Meanwhile, the environmental justice literature has documented uneven exposure to unwanted trash sites, which potentially magnifies the concern for environmental protection.

Objectives

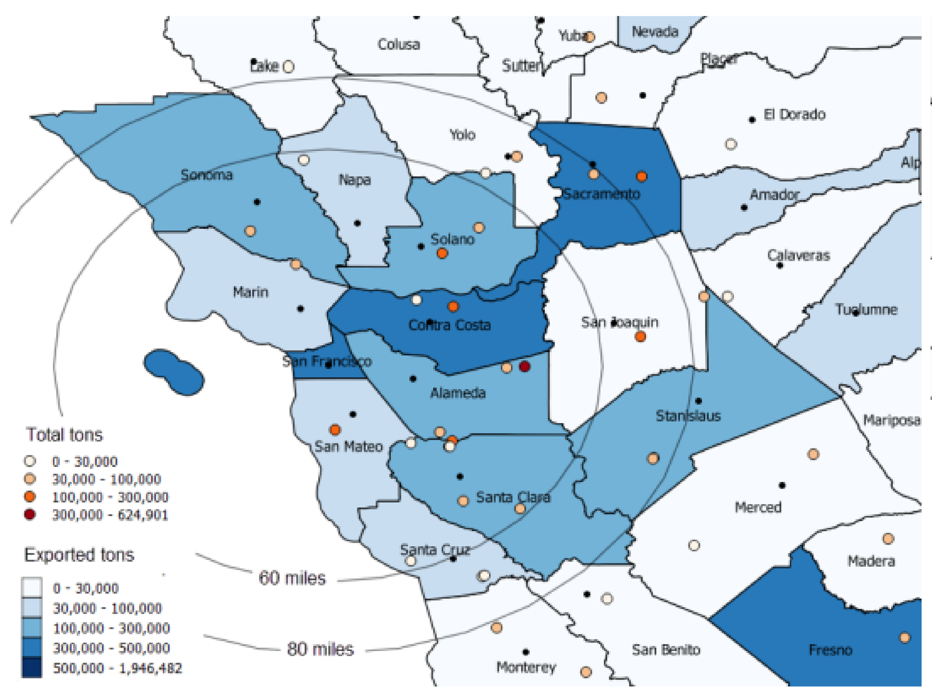
- What is the current demographic distribution of solid waste disposal?
- What are the effects of environmental protection policies on the spatial and demographic distribution of waste?
- ➢ NIMBY policies: bans on out-of-county imports, taxes on imports, universal trash tax where trash in all facilities are taxed.
- ➢ Fuel tax
- Since garbage transport is a commercial activity, I model the haulers' decisions about where to deposit waste. I consider how those decisions are affected by disposal prices, driving distances, and potential unobserved characteristics of destination facilities (facility fixed effects).

Data and Context

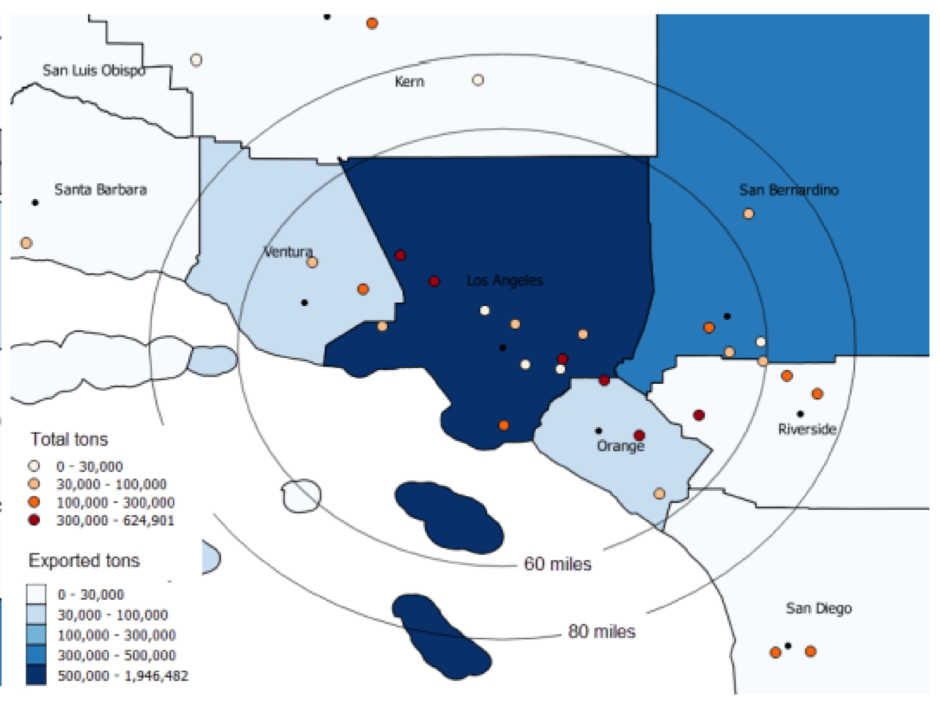
- The paper uses data on intercounty trash flows in California from 1995 to 2015, quarterly. Information includes the waste amount by origin county and destination facility, and the listed disposal prices at facilities.
- Driving distance is measured from population weighted centroid of origin county to facility location using Microsoft maps.
- Out-of-state exports occupy 1.16%. I do not observe the place of destination so assume the destination is the nearest out-of-state facility.
- Demographics data are collected from US 2010 Decennial Census.
- An important step in modeling the haulers' decisions is to define the hauler's choice set. Conversations with waste collection companies as well as to a representative in National Waste & Recycling Association reveal that trucks generally cart waste to a disposal facility that is less than about 30--45 miles from the place of collection. The figure on the right confirms that waste amounts decrease in transport distance. Consequently, I assume that haulers in a trash-generating county choose amongst all disposal facilities within 60 miles of the population-weighted centroid of the county when deciding where to dispose of waste.



Percent trash that goes beyond a given distance



The choice set of haulers in San Francisco. Black dots represent population centroids of counties. Counties are blue colorized by tons of exports. Facilities are red colorized by total tons.



The choice set of haulers in Los Angeles. Black dots represent population centroids of counties. Counties are blue colorized by tons of exports. Facilities are red colorized by total tons.

Current Demographics of Waste

- Demographic composition in neighborhoods of facilities

$$\%Race_j = \frac{\#\text{ people of the race in facility } j\text{'s community}}{\#\text{ people in facility } j\text{'s community}} \times 100$$

- When being weighted by the receiving waste amount, percent minorities become bigger while percent white becomes smaller → Facilities in high percent minorities receive more waste.
- I define an affected community as a neighborhood within 3 miles of the facility location.

	3-mile buffer		7-mile buffer		hosting county		California
	unweighted	weighted	unwd	weighted	unwd	weighted	level
% white	49.36	44.09	47.57	41.53	45.79	39.74	40.15
	(24.71)	(20.85)	(22.56)	(18.24)	(17.73)	(10.82)	
% black	2.73	3.73	3.62	4.20	4.26	5.80	5.81
	(3.62)	(3.92)	(3.78)	(3.47)	(3.52)	(3.42)	
% asian	8.11	13.01	8.45	13.75	8.74	12.67	12.82
	(11.98)	(12.02)	(10.52)	(9.73)	(8.31)	(6.90)	
% hispanic	35.33	35.72	36.31	36.94	37.29	38.21	37.62
	(25.53)	(22.32)	(21.99)	(18.56)	(17.03)	(11.19)	

- Consider the demographic distribution of waste flows in year 2010:

$$q_{cj} = \beta_0 + \beta_1 \%Race_j + \beta_2\, Income_j + \beta_3\, Price_j + \beta_4 Distance_{cj} + \beta_5 Nonlocal_{cj} + \epsilon_{cj}$$

- ➢ q_{cj}: waste amount generated by county c to be disposed at facility j
- ➢ $Income_j$: median household income at community 3 miles around j
- ➢ $Price_j$: disposal price at facility j
- ➢ $Distance_{cj}$: distance from population centroid of county c to facility j
- ➢ $Nonlocal_{cj} = 1$ if facility j is not located in county c, 0 otherwise.

	(1)	(2)	(3)	(4)
	q	q	q	q
% black (%)	1402.55	2786.28	3656.90	5449.69**
	(2813.79)	(2585.56)	(2425.35)	(2470.31)
% hispanic (%)	938.00*	1655.71**	1491.80**	1530.31**
	(537.69)	(688.77)	(649.82)	(660.53)
% asian (%)	813.77	-484.77	-621.28	66.95
	(1423.25)	(946.81)	(874.04)	(1058.19)
mdhhincome ($1000s)		2431.24**	2894.23***	3388.77***
		(947.02)	(1032.26)	(1003.12)
price			-624.28	-467.85
			(566.36)	(497.33)
distance			-13429.67***	2032.35
			(4174.16)	(6521.51)
distance^2			122.56**	-13.66
			(52.84)	(76.69)
nonlocal				-289332.09***
				(90559.80)
constant	41042.08**	-111653.19*	194059.71**	-2815.20
	(20248.58)	(59115.13)	(92610.28)	(118072.82)
N	374	374	374	374
R^2	0.008	0.033	0.133	0.239
adj. R^2	0.000	0.022	0.116	0.222

Key findings:

- The disparity disappears for Asian group after controlling for income.
- The disparities remain and are even larger for black group and Hispanic group after controlling for income, disposal prices, and distances.

Trash Site Choice Model

Every hauler picks up a waste amount in county c in quarter t. The hauler chooses facility j to maximize their utility

$$U_{ijct} = \beta X_{jct} + \epsilon_{ijct} \equiv \beta_p \text{price}_{jt} + \beta_d \text{distance}_{cj} * \text{fuel price}_t + \gamma_j + \epsilon_{ijct}$$

Assume ϵ follows type I extreme value distribution, then the probability that facility j is chosen in trip i is

$$P_{jct} = \frac{\exp(\beta X_{jct})}{\sum_{k \in C_{ct}} \exp(\beta X_{kct})}$$

- ➢ Facility fixed effects capture time-invariant characteristics of facility j.
- ➢ The ratio $^{-\beta_d}/_{\beta_p}$ captures hauler's willingness to pay for proximity to the disposal facility, the transportation cost.

Identification

- The estimate of price coefficient β_p may be biased because price is correlated with unobserved ϵ in the utility function. For example, haulers are willing to dump at expensive sites for good quality (high acceptance rates, operation flexibility). Another problem is that prices may have measurement errors because I observe listed prices instead of contracted prices.
- Correct for price endogeneity: facility fixed effects (γ_j)
- ➢ Rich variations of cross-sectional and time-series variations in the data allow me to identify facility fixed effects.
  - ➢ Facility fixed effects help alleviate the price endogeneity problem due to omitted variable bias, by controlling for time-invariant characteristics.
  - ➢ Facility fixed effects capture facility characteristics that are correlated with demographics of affected communities.
- Correct for price endogeneity and measurement error: using an instrument = sum of total waste in the other markets that include the facility in their choice sets (excluding the instrumented market).
  - ➢ This instrument is correlated with price because the facility is setting one common listed price for all markets, and operation costs of a facility depend on total receiving trash (e.g. diseconomies of scales).
  - ➢ This instrument is exogenous of the demand in the instrumented market because it excludes the demand factors of the instrumented market. It does not affect the *individual* hauler's choices in the instrumented market.
- In term of implementation, I apply control function approach, a method to estimate nonlinear models with instruments. Control function is estimated using polynomial of residuals obtained from the first stage in which price is regressed on exogenous variables and instruments. The polynomial terms enter the main model as extra explanatory variables (Petrin and Train, 2010). I estimate models with linear polynomial and quadratic polynomial of control terms.

Estimation Results

- The estimates imply that transportation costs $0.43 per ton-mile given diesel prices at the 2000 level ($1.672/gal).
- Miller and Osborne (2014) report the transportation costs $0.46 per ton-mile for shipping cement. The 20th edition of Transportation in American (2007) reports that revenues per ton mile for Class I general freight common carriers (basic truck transport) ranged from $0.29 to $0.35 over 1983—2003. Fischer et. al. (1993) report waste transportation in 1990 and 1992 costs from $0.16 to $0.36 per ton mile.

	(1)	(2)	(3)
Model	Facility	IV	IV
	fixed effects	linear control function	quadratic control function
price	−0.0011	−0.1592***	−0.1593***
	(0.0016)	(0.0238)	(0.0238)
distance∗fuel	−0.0442***	−0.0412***	−0.0411***
	(0.0010)	(0.0011)	(0.0011)
control term		15.9038e−2***	15.9199e−2***
		(0.0240)	(0.0241)
control term^2			−0.2507e−4
			(0.4580e−4)
price elasticity	−0.0277	−4.1983	−4.2007
transport elasticity	−1.7138	−1.5945	−1.5943

Counterfactual Policy Results

- Below table reports the change due to policies: county bans on imports, import taxes of 15%, fuel taxes of 15%, and waste tax of 15%.
- Metrics are calculated for every county market and then averaged over markets using market sizes (total trash generated) as weights to get the reported average levels. All measures use 2010 levels.
- Hauler surplus is implied from logit model, $1/\beta_{price} \log(\sum_{j \in J_c} \exp(\beta X_{jct})) + C$, where C is an unknown constant that represents the fact that the absolute level of utility cannot be measured; so, there is no reference for percent change in hauler surplus.
- % trash to white = $\frac{\sum_{j \in J_c} q_{cj} \times \#\text{whites in } j\text{'s buffer}/\text{population in } j\text{'s buffer}}{\sum_{j \in J_c} q_{cj}} \times 100$
- There are two baseline levels because five counties, Alpine, Amador, Del Norte, Nevada,, San Francisco, and Tuolumne do not have any local facilities. I drop these counties in calculating the metrics in the case of import bans. These account for 1.91% of waste in California in 2010.

Rate 15%	baseline 1	import ban	baseline 2	import tax	fuel tax	waste tax
exports	573,678	-573,678	568,381	-313,451	-115,927	-19,585
(tons)		(-100.0%)		(-55.15%)	(-20.40%)	(-3.45%)
tipping fees	145,000	-748	142,000	876	-1,579	14,500
(thousand $)		(-.52%)		(.62%)	(-1.11%)	(10.21%)
trash mileage	90,500	-10,300	88,700	-5,579	-4,976	-2,469
(kiloton-mile)		(-11.38%)		(-6.29%)	(-5.61%)	(-2.78%)
hauler surplus		-3,964		-993	-8,316	-20,900
(thousand $)						
% trash to white	42.27%	-1.08	42.56%	-.65	-.70	-.85
		(-2.55%)		(-1.54%)	(-1.64%)	(-1.99%)
% trash to black	3.40%	-.02	3.39%	.02	-.87e-3	-.05
		(-.58%)		(.62%)	(-.03%)	(-1.34%)
% trash to asian	13.52%	-.54	13.44%	-.36	.15	-.18
		(-4.01%)		(-2.65%)	(1.13%)	(-1.35%)
% trash to hispanic	37.46%	1.71	37.19%	1.02	.58	1.12
		(4.57%)		(2.75%)	(1.55%)	(3.01%)

Conclusion

- NIMBY policies and fuel tax would reduce intercounty trash flows but potentially exacerbate the uneven demographic distribution of trash.
- Policy implications:
- ➢ One-size policy does not fit all.
- ➢ Price-targeted and transport-targeted policies might not be appropriate. It might be important to ensure the compliance of environmental standards at facilities, especially if facilities in minority communities have low fees and are attractive for easy acceptance at gates and lenient rules.

References

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