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

Phuong Ho *

September 16, 2019

Download the most recent version here.

Abstract

In many recent U.S. Congress sessions, several state and local governments have attempted to legalize waste flow controls after their ordinances were overturned by Supreme Court. Using data on intercounty waste flows in California and a random utility model of haulers' decisions about where to deposit waste from each county, this paper studies the effects of not-in-my-backyard policies and fuel taxes on the spatial and demographic distribution of solid waste. I find that waste is currently more likely to be hauled to disposal facilities in communities with higher percentages of blacks and Hispanics, even after controlling for income, disposal fees, and transport distances. Counterfactual policy experiments show that policies that seek to limit waste flows would reduce intercounty waste transport. However, these policies tend to lead to substitution of waste away from facilities near white residents and toward facilities near Hispanic residents, potentially exacerbating distributional concerns.

Keywords: solid waste, NIMBY policy, distributional effects, environmental justice, discrete choice

JEL Classification: D04, L51, Q53, Q56

*Department of Economics, University of Arizona. Email: phuongho@email.arizona.edu. I am indebted to my advisors, Ashley Langer, and Mauricio Varela. I thank Price Fishback, Antonio Galvao, Gautam Gowrisankaran, Derek Lemoine, and Stanley Reynolds for helpful comments and discussions. I acknowledge financial support from the University of Arizona Graduate & Professional Student Council and Prof. Stanley Reynolds to acquire data.

1 Introduction

Every year the United States generates more than two hundred million tons of solid waste.[1] Where to dispose of this trash is a long-running question because of the externalities associated with the transport and disposal of solid waste. To avoid becoming a repository for waste from adjacent places, several state and local governments have attempted to restrict waste imports since the late 1970s. After those restrictions were overturned by the Supreme Court, legislative efforts have been placed into Congress. For example, a bill was presented in both the Senate and the House in the 2017-2018 Congress under the name Trash Act to give state and local governments permissions to restrict out-of-state waste. The bill did not pass, but it was controversial, amplifying the concern for environmental protection, especially if disadvantaged groups and/or minorities are disproportionately exposed to trash placement.

This paper studies the effects of those NIMBY policies and fuel taxes on the spatial and demographic distribution of waste disposal. NIMBY, an acronym for "not in my backyard," refers to laws designed to prevent waste disposal (or other undesirable activities) from occurring locally. In this paper I focus on the transboundary waste prohibition, transboundary waste tax, and the universal trash tax. I also explore the effects of a fuel tax because this is an important environmental regulation that aims to reduce pollution and the possibility of global warming. Although a fuel tax is not directly targeted at the solid waste industry, it is advocated to compensate for the externality of transporting an environmental nuisance, such as trash, along its route.

I use a novel data set on intercounty waste flows in California, which allows me to observe waste quantities by county of origin and by facility of destination. Although the Trash Act focused on interstate waste restrictions, waste flow controls across counties in a state was not rare. In fact, Solano county in California enacted Measure E that limited out-of-county imports in 1984. But it was prevented from enforcing the measure in 1992 due to the industry concern about its violation of the Commerce Clause (a legal ground for the Supreme Court to reject waste flow controls). In 2009 opponents of the Solano landfill expansion filed a lawsuit aiming to reinstate Measure E. To stop the controversy, California passed a bill in 2012 that prohibits local ordinances from restricting waste imports into a local privately owned disposal facility based on place of origin. The proposed interstate waste restrictions in Congress may set a precedent for interjurisdictional waste transportation within a state.

To study the effects of the NIMBY policies, I employ a structural econometric approach because I do not observe market outcomes where the trade barriers actually happened. I model the haulers' decisions about where to deposit their collected waste, considering their preferences for

[1] Short tons are referred unless specified. In 2015, U.S. Environmental Protection Agency (2016) reports that there are 262 million tons of solid waste generated.

disposal prices, transport distances, and facility quality (captured by facility fixed effects), to account for the fact that waste flows are the result of economic incentives in the trash collection market. Modeling the choice of haulers explains why there are waste flows from one trash generation county to multiple destination facilities.[2] The hauler may exploit the variation in disposal prices to cart waste to a distant disposal facility even though the facility is outside the county of waste origin. My model is an application of a multinomial logit discrete choice model using aggregate data at the market level (see McFadden (1974); Berry (1994); Berry et al. (1995)). However, to fit the features of the solid waste industry correctly, the model differs from the conventional model in two respects. First, I include observations of zero waste quantity to avoid selection bias from restricting observations to those with positive quantities. Second, my model does not have an outside option because picked-up trash must be disposed of at some disposal facility. The estimation shows that estimated transportation cost is $\$0.43$ per ton-mile given diesel prices at the 2000 level (\$1.672/gal). This agrees with the estimates from several publications, such as $\$0.46$ per ton mile for shipping cement in Miller and Osborne (2014), \$0.29–\$0.35 per ton mile over 1983–2003 for Class I general freight common carriers (basic truck transport) in Transportation in American (2007, and \$0.16–\$0.36 per ton mile for shipping waste in 1990 and 1992 in Fischer et al. (1993).

Given the estimated parameters underlying the haulers' decisions, I quantify how haulers' decisions about where to deposit waste would change in several counterfactual scenarios, holding facilities' characteristics constant. Results show that the NIMBY policies (import ban, proportional import tax, and proportional trash tax) and fuel tax would reduce the quantity of waste that flows across county lines, as would the distance that haulers transport waste from the population center of a county to a disposal facility. The import ban and fuel taxes would also reduce the tipping fees haulers pay for waste disposal. This implies that haulers carted waste to disposal facilities outside the waste-generating county for other benefits rather than tipping fees and distance. These might include high acceptance rates, flexible operation hours, capacity, loose regulation on nonlocal waste, etc. Forgoing these good quality facilities would result in a loss of economic surplus for haulers if the policies were implemented.

As mentioned above, I focus on not only the spatial distribution of waste flows but also how waste is distributed across facilities with different local demographics. Examining the demographic distribution of waste is important because the environmental justice literature has documented an uneven distribution of the location of environmental bads among race groups.[3] In addressing the matter of environmental justice, I first explore how many people live within three miles of a trash site as a share of the county population for each racial/ethnic group. I then examine

[2] Ley et al. (2000, 2002) model the social planner's problem.

[3] see U.S. General Accounting Office (1983); United Church of Christ's Commission on Racial Justice (1987); Mohai and Saha (2007)

the relationship between the demographic composition of the communities within three miles of a disposal facility and the waste flows that are sent to the facility. The results emerge two facts. First, there are fewer people of all racial groups near the facilities that receive more waste. Second, waste is more likely sent to facilities in high percent minority communities than white communities. The disparities for black communities and Hispanic communities persist once I control for income, disposal fees, and distance, suggesting unobserved characteristics of facilities and neighborhoods matter in haulers' decisions. It is hence important to include controls for those factors, such as facility fixed effects, when modeling the hauler's preference for dumping sites.

I find that the policies that limit waste flows would generally not lead to a more equitable distribution of waste. Waste that is sent to facilities near white residents would be rerouted toward facilities near Hispanic residents, potentially exacerbating distributional concerns. The reason is that these facilities in Hispanic communities have low tipping fees and are close to the population center of the waste-generating county. On the other hand, waste that is sent to facilities in black communities would remain fairly constant even though these facilities are expensive and distant. While it is beyond the scope of the paper to consider what are the exact reasons behind the attractiveness of the facilities in black areas, the results on counterfactual policies suggest that price-targeted and transport-targeted policies are not appropriate tools to reduce waste in minorities. Perhaps facilities in minority areas are attractive to haulers because they easily accept waste that is below regulated environmental standards. If this is the case, enforcing environmental regulations correctly in these facilities is a more effective policy.

This paper contributes to a growing number of studies on the waste industry. Greenstone and Gallagher (2008), Gamper-Rabindran and Timmins (2011) study the effects of Superfund-sponsored cleanups of hazardous waste sites on housing values. Currie et al. (2011) find that Superfund cleanups reduce the incidence of congenital anomalies by about 20–25%. A number of papers address industrial organization questions using solid waste data. Kamita (2001) analyzes the market structure consequences of merger. Salz (2017) studies the role of intermediaries between businesses and private institutions and private waste carters in New York trade waste collection market. Kawai (2011) studies auction design when sellers have incentive to invest for quality improvement in municipal plastic recycling auctions in Japan.

The paper also complements studies that address interstate waste flow controls. In the hazardous waste market, Levinson (1999a,b) find that interstate waste taxes decrease shipments of waste to states enacting high taxes, and provided an estimate of the magnitude of tax elasticities. In the solid waste market, Ley et al. (2000, 2002) find that limitations on the size of shipments can perversely increase interstate waste shipments since states export smaller volumes to more destinations. They use the aggregate data at the state level and consider state planners' problem assuming the demand for waste disposal services is linear and a competitive equilibrium. My model, however, considers the haulers' decisions about where to deposit waste from each county. This accounts for the fact that disposal landfills are differentiated in prices, distances, and quality, thereby explaining the impacts of environmental protection laws that aim to influence prices, transport costs, and the number of disposal options.

In the environmental justice literature, this paper departs from the literature by addressing the relation between demographics and waste *flows*. Previous studies have examined the disproportionate exposure pattern by focusing on total concentration of hazard at a site; see Baden and Coursey (2002); Depro et al. (2015). I, on the other hand, distinguish between multiple waste flows from different origins coming to the facility. This allows me to control for economic factors that determine flows such as disposal price and transport cost. By focusing on waste flows, I am also able to identify the exposure disparities among trash site neighborhoods within a certain distance (60 miles) from the population center of a county. This contrasts to the literature that has compared demographic composition between a trash site neighborhood and extended areas that are far away; see Baden and Coursey (2002); Mohai and Saha (2007).

The rest of the paper is structured as follows. Section 2 provides legislative background of NIMBY regulations. Section 3 shows general picture of waste disposals in California and the current distribution of waste flows by demographics. I emphasize that the inequitable distribution of waste flows by race and ethnicity is not fully explained by economic factors, namely, income, disposal prices, and transport distance to a facility. Hence, when modeling the waste flows to study distribution impacts by race, it is important to include facility fixed effects. Section 4 presents the structural model of haulers' decisions about where to deposit waste from each county. Section 5 reports results of counterfactual policy experiments. Section 6 concludes.

2 Background: NIMBY Legislation in Solid Waste Industry

The paper focuses on municipal solid waste: the every trash generated by households. Starting in 1976, the U.S. Congress sought reform of the waste management practices in the Resource Conservation and Recovery Act (RCRA). Subtitle D of RCRA aims to develop and encourage methods for solid waste disposal that are environmentally sound and maximize the utilization of recoverable energy and materials from solid waste. The subtitle D also places responsibility for solid waste management on states and local governments. However, the local waste management has been complicated by the escalation of interjurisdiction waste transport and contentious NIMBY legislation.

Several states became overwhelmed by the increasing waste imports from others and attempted to limit these flows by taxing out-of-state waste or even banning waste imports.[4] However, these

[4]They reasoned their restriction on the grounds of preventing environmental harm and preserving their own natural

attempts were overturned by the Supreme Court's decisions on the basis that they interfered with interstate commerce.[5] These cases, for example, include a New Jersey statute that prohibited out-of-state waste imports in *Philadelphia v. New Jersey (1978)*, an Alabama statute that imposed a special fee on out-of-state hazardous waste in *Chemical Waste Management Inc., v. Guy Hunt, Governor of Alabama (1992)*, an Oregon statute that imposed surcharge on out-of-state solid waste in *Oregon Waste Systems Inc. v. Department of Environmental Quality of the State of Oregon (1994)*, and a Wisconsin statute that required out-of-state communities to adopt Wisconsin recycling standards if exporting to Wisconsin facilities in *National Solid Waste Management Association v. Meyer (1999)*.

The legislative efforts to limit interstate waste transport have been put to a number of crafted bills in Congresses. In every Congress since 1990, legislation aiming to authorize states to control interstate waste flows has been introduced but have not been successfully enacted. In 1994, both the House and Senate passed the "State and Local Government Interstate Waste Control Act" that prohibit a landfill or incinerator from receiving out-of-state solid waste unless it obtains authorization from the affected local government to receive such waste. However, the bill was not enacted due to lack of agreement on common language in enactment.[6] In the most recent Congress, 2017-2018, a bill was introduced to both the Senate and the House under the name Trash Act. This bill aims to allow state and local governments to restrict out-of-state waste coming from states that have lower waste handling standards than the receiving state and to fee on out-of-state waste. I study the effects of transboundary waste controls on the short-run market outcomes in which disposal facilities would not change their pricing strategies and capacity investments.

I do not specify or estimate a supply for waste disposal, which would be necessary to allow some pass-through of taxes on disposal facility side. While this is clearly a restrictive simplification, the advantage is to give a transparent mechanism on key demand-side aspects of choice substitution and without misspecification implications. To some extent, disposal prices may remain the same for one or two years after a trash tax because haulers and disposal facilities may have had a contract.

3 Data

The paper uses three primary data sets. First, I collect data on the quantity of waste flows from California's Department of Resources Recycling and Recovery (CalRecycle) by county of origin

resources that are dwindling landfill spaces.

[5]The Supreme Court made it clear that under the "dormant" Commerce Clause of the Constitution, states may not erect barriers to interstate commerce unless Congress has explicitly allowed it.

[6]Another bill in later session (S. 534 in 1995) that authorizes states to prohibit out-of-state solid waste and to reinforce local waste flow control ever exercised before 1994 was passed in Senate but retained in the House.

and by facility of destination quarterly from January 1995 to December 2015. CalRecycle also reports the location of each facility. Second, I obtain disposal price (tipping fees) data quarterly from Jan 1992 to Dec 2015 from Waste Business Journal (WBJ), an industry research and analysis company. In the waste industry, tipping fee is known as the fee charged per ton to unload solid waste at a landfill or transfer station. Third, I use 2010 census data to reflect the most recent picture of the demographic distribution of waste. To depict demographic information most accurately, I use population and population by race at the block level, obtained from IPUMS. Since median household income is confidentially restricted at the block level, I use the information at the block group level. In addition to these three sources, I collect data from the Energy Information Agency on California diesel prices and calculate driving distance using Microsoft maps. For more details about the data and how it was formatted for the analysis, see appendix (A).

3.1 Waste Disposal In California

Figure (1) shows an overview of waste disposal in California from January 1995 to December 2015. While total waste amount generated by a county increased steadily in 1990s and early 2000s, it dropped dramatically from 2005. Though waste generation is correlated with the economy condition, the drop was mainly attributed to great efforts of recycling and zero waste policy in California in the late 2000s. The number of facilities decreases monotonically from nearly 200 facilities in 1995 to about 110 in 2015 where major decline happened in early 1990s due to the national enactment of the RCRA 1994. Average tipping fee (weighted by waste shipments) plunged to \$33/ton in 1997, which may be a short run consequence of the landfill closures after the 1994 RCRA, before escalating to \$42/ton from 2005.

Along with the drop in the number of disposal sites, the proportion of trash a county sends to other counties for disposal climbed from 15% to nearly 40% between 1995 and 2015. This climb was accompanied by an increase in shipping distance. Waste is traveling farther and farther to reach a disposal site, from 24 miles in 1995 to 31 miles in 2015. However, the shipping distance is still in a reasonable economic range. My conversations with waste collection companies as well as to a representative in National Waste & Recycling Association, a trade association for private sector haulers, recyclers, composters, and disposal companies, reveal that trucks generally cart waste to a disposal facility that is less than about 30–45 miles from the place of collection.

Figure (1f) confirms that the percentage of waste disposed beyond a given distance decreases in transport distance. The carted waste plummets quickly from 30 to 60 miles, following by a flat tail (until 700.17 miles in the California waste flow data). Consequently, when I move to my analysis of waste flows, I limit the analysis to waste flows within 60 miles between the population weighted centroid of the trash-generating county and the destination facility. I assume each county is an independent market in which households generate municipal solid waste that must be disposed of. Haulers in the market collect the waste and choose amongst all disposal facilities within 60 miles of the population-weighted centroid of the county to dispose of waste. Using the 60-mile market boundary, this paper aims to explain economic incentives underlying these disposal choices, which makes up more than 90% of the waste generated in California. In the next section, I test the assumption of the 60-mile market boundary. Specifically, I examine how trash flows respond to disposal price and driving distance from the population weighted centroid of an origin county to the destination facility.

3.2 Market Boundary of Waste Flows

To examine the economic incentives behind trash flows, I estimate the following regression:

$$q_{cjt} = \beta_d f_d(Distance_{cj}) + \beta_p f_p(Price_{jt}) + \gamma_{ct} + \eta_j + \epsilon_{cjt} \tag{1}$$

where c indicates origin county of waste, j indicates destination facility, and t indicates quarter. The dependent variable q_{cjt} is the waste amount generated in county c to be disposed at facility j in quarter t. Two key independent variables of interest are $Distance_{cj}$ and $Price_{jt}$. $Distance_{cj}$ is the driving distance from population weighted centroid of the trash-generating county to destination facility. $Price_{jt}$ is the disposal price (tipping fees, dollar per ton) charged for disposing every ton of waste in facility j in quarter t. The effects of distance and price are estimated using a piecewise linear function (linear splines) to explore their specific marginal effects in different intervals of traveling distance of the waste flows.

I present the results that adjust for different fixed effects. The first specification includes origin county by quarter fixed effects (γ_{ct}) and facility fixed effects (η_j). The second specification includes quarter fixed effects and origin county by facility fixed effects to further test for price response, because price is endogenous due to omitted variables. Of course the price endogeneity problem cannot be solved completely, but we will deal with it in the main model later. Here I emphasize the changes in price responses and distance responses among different knots of travel distances of waste flows.

Figure (2) shows the price response and distance response by distance travel knot using the samples of waste flows (including zero flows) within 120 miles and 150 miles. It plots the coefficients on knots of $Distance_{cj}$ and $Price_{jt}$ from the baseline specification (equation (1)). Table (1) presents the parameter estimates from the baseline specification (columns 1, 3, 5) and the specification with origin county by facility fixed effects (columns 2, 4, 6). Both the figure and table show that the negative effects of price and distance on trash flows are significantly in the first knots of distance, and decrease in distance in term of the magnitude. Beyond 80–90 miles, trash flows do not respond to price and distance any more. This confirms our assumption that there is a certain limit of distance under which trash flows economically respond to price and distance. If waste is transported farther than that limit, it must be a reporting error or an assignment beyond the economic reasons. I hence use 60 miles to define a market radius. Figure (1b) show the market boundaries for counties San Francisco and Los Angeles.

Table (2) shows summary statistics of the main sample that is used for my analysis, which includes all combination of flows within 60 miles. Panel A shows the characteristics of the waste flows, and contrasts the main sample with the raw data of positive flows. The unit of observation is the quarter $\times$ origin county $\times$ destination facility. Contrasting waste shipments, distance, tipping fee, total trash generated in a county, and out-of-county exports, the sample of waste flows within 60 miles remains typical features of the whole California picture of waste disposals. On average, a county sends 21 thousand tons of waste to a facility. The average distance is 24 miles and the average price is \$36/ton. Panel B shows the characteristics of the choice set. The unit of observation is the quarter $\times$ origin county. Compared to the unrestricted sample, the sample of 60-mile waste flows has fewer observations because a few counties sent all of their waste to facilities outside 60-mile boundary in certain quarters. Average size of a market (average trash amount a county generates) is about 175 thousand tons. On average a county exports 22% of their trash to other counties in the main sample. Haulers in a market have 8 options to transport their collected waste to.

3.3 The Relationship between Race and Waste Flows

As mentioned, we do not only care about spatial distribution of waste flows but also the demographic distribution. Previous studies have examined the contemporaneous and historical pattern of disproportionate exposure to environmental hazards of minorities by contrasting demographic composition between communities within facility's buffers and extended neighborhoods that are far away from hazards. I on the other hand focus on another aspect of environmental justice: Are minorities disproportionately exposed to waste *flows*? That is, if waste flows are resulted from the economic incentives of haulers, are the waste flows explained by factors associated with demographic composition in neighborhoods of trash sites? Before answering this question, I first examine the population in the affected communities, i.e. who lives near trash.

3.3.1 Who Lives Near Trash

How near is near? The choice of spatial unit to represent the hosting communities has been subject of considerable debate in the environmental justice literature. Previous studies have shown that the correlation between environmental hazards and demographics can be quite sensitive to community definitions; see Anderton et al. (1994); Sheppard et al. (1999); Mennis (2002). Data aggregated at higher levels such as a county have been documented to be less reliable as indicators of disproportionate burdens than data aggregated to smaller units such as census block groups. But the choice of whether to use blocks, block groups, or census tracts as community definition may be problematic either. They vary greatly in geographic size. For example, blocks in California range from $1/1,000,000$ of a square mile (1 square meter) to more than a thousand square miles (3 billion square meters). Hence, I use aggregate demographic data at available smallest census units, blocks, to construct demographic data for fixed circle communities centering disposal sites. A block is considered to be in the affected community, if its centroid location is in the fixed circle centering the facility. Population count at blocks are aggregated for counts in the community.[7]

Panel A in table (3) shows the percentage of population that live within a buffer (1, 2, 3 miles, and 7 miles) around a trash site, out of the population of the county that hosts the site for every racial and ethnic group.[8] This is the affected population level, affected population level $= \frac{\text{\#people of the race-group-of-interest in facility j's buffer}}{\text{\#people of the race-group-of-interest in facility j's county}} \times 100$. On average, only three percent of the population in a county lives within three miles of a waste disposal facility. However, it appears that minorities are more likely to live near a trash site than white people. In the 1-mile buffer zone, white residents occupy 0.50% while Hispanic people account for 0.61%. This pattern also persists in larger buffers, 2, 3, and 7 miles.

For the main analysis, I use 3-mile buffer zones to refer to affected communities nearby disposal facilities. I estimate the following regression to examine how the population for each racial/ethnic group, as a share of the hosting-county population, relates to their receiving waste quantity

$$\text{Affected population level}_j = \beta_0 + \beta_1 Waste_j + \beta_2 Income_j + \epsilon_j \qquad (2)$$

where j indicates a facility. Two key control variables are $Waste_j$, the total waste amount disposed at facility j in 2010, and $Income_j$, the median household income of people in the 3-mile community. Using the 2010 decennial census data, the regression is estimated separately for each of four race groups of concern, white, black, Asian, and Hispanic to explore the differences among race groups in exposure to the waste quantity of a nearby disposal facility.

The coefficient of primary interest is β_1. β_1 measures the change in the percentage of people of the race group of concern that live in 3-mile buffer around a trash site when there is an increase in the waste amount going to their backyard.

[7] Information that is not available at block level such as the number of households, is first assigned from block-group values to block based on population shares, then distributed to the communities. This is also used in **?**.

[8] There may be cases where a facility is near its county border that makes its nearby community include people in other counties. In such cases, I still use the population of the county that hosts the facility as the base group, and interpret the ratio of population as percentage of the hosting-county population.

Panel B in table (3) reports the estimates. Row 1 shows sharp differences in affected population levels across the four racial/ethnic groups at zero income and trash amount levels. Row 2 reveals that people in all race/ethnic groups are fleeing from waste repositories and the drop for white is largest. The percentage of white residents that live within 3 miles of a trash site would drop 2.38 percentage point if an additional million tons of waste is sent to the site, compared to 2.11 percentage points of black residents, 2.06 percentage points of Asians, and 1.79 percentage points of Hispanics. But the regression that stacks all four race samples shows that the disparities in affected population among race groups are not statistically significant.

Overall, we see that there are not many people living near trash, compared to the county population, and that there are fewer people living near a waste disposal site as the site receives more trash. Now let us consider the distribution of waste flows by race and ethnicity in the affected communities.

3.3.2 The Distribution of Waste Flows By Race in Affected Communities

Table (4) reports mean demographic composition in affected communities. The table also contrasts the demographic composition at county level in term of receiving trash with generating trash. In 3-mile affected communities, the average population is 26,000 persons of which 49.4% are white, 2.7% are black, 8.1% are Asian, and 35.3% are Hispanic. When weighted by trash amount at a facility, percentages of white, black, Asian, and Hispanic residents are 44.1%, 3.7%, 13.0%, and 35.7%, respectively. The differences between unweighted and trash weighted percentages by race imply that more waste is disposed in minority communities than in white communities. The disparity becomes more apparent when contrasting waste-weighted demographics in receiving community to generating county. While the percentage of white is higher in generating county than receiving community, the percentages of Asian and Hispanic people are lower.

Since waste flows are results of market activities, I now examine the distribution of waste flows after controlling for economic incentives of haulers such as disposal prices and transport costs (measured by the interaction between distance and fuel prices). I use decennial census data and waste flows by generating county and destination facility in 2010 for the analysis because this is the most recent demographic data available at block levels. The regression equation is:

$$s_{cjt} = \beta_1 \%Race_{j,2010} + \beta_2 Income_{j,2010} + \beta_3 Price_{jt} + \beta_4 Distance_{cj} * Fuel_t + \gamma_t + \delta_c + \epsilon_{cjt} \tag{3}$$

where c indicates the county origin of waste flow, j denotes the facility destination of the flow, and t is for quarters in 2010. The dependent variable, s_{cjt}, is the waste amount generated by county c to be disposed at facility j out of total waste generated by county c in quarter t in year 2010. The main explanatory variable is $\%Race_j = \frac{\text{\#people of the race in facility j's community}}{\text{\#people in facility j's community}} \times 100$. $Income_j$ is median household income at community around facility j. $Price_{jt}$ is average tipping fee of facility j in quarter t. $Distance_{cj}$ is the distance between population centroid of county c to location of facility j. $Fuel_t$ is diesel index in quarter t in California. I also include quarter fixed effects γ_t and market fixed effects δ_c. The regression is weighted by market size (total trash generated in a county).

Table (5) reports results. Column (1) shows that no significant differences are found in the receiving waste amount between minority communities and white community. However, controlling for income, waste is sent more to black and Hispanic communities. The positive coefficient of income implies that facilities in high income communities receives more trash than low income areas. This is potentially a reverse causality. On the one hand, facilities in low income communities are more attractive because of low resistance of the residents. On the other hand, waste disposal generates profits and improves income for those communities. Although the income coefficient estimate is upwardly biased, controlling for income in the estimation provides intuition for our interests in the coefficients of demographic composition variables. We see that the coefficients of black percentage and Hispanic percentage become bigger and statistically significant, implying that facilities in black and Hispanic communities receive more trash for other reasons rather than financial constraints.

Columns (3) and (4) show that disparities in receiving trash quantity between black, Hispanic communities and white community persist after controlling for prices and transport costs of disposing trash. One percentage point increase in the percentage of black population living nearby a trash site (on a mean of 3.34%) is associated with an one percentage point increase in the market share. The difference in market share between facility in Hispanic community and white community is smaller but statistically significant without controlling for transport costs. This implies that facilities in Hispanic community are attractive because they tend to be nearer to the population centers of trash generation.

While it is beyond the scope of this paper to show why exactly the disparities are happening, the reduced-form analysis suggests that there is something unobservable about waste facilities in black and Hispanic areas that makes them attractive to haulers above and beyond disposal prices and transport costs. This result motivates the question of whether NIMBY regulations, both bans and taxes on waste flows, could have environmental justice implications, especially when the regulations aim to provide collected fees to affected communities.

Of course the simple correlations between local demographics and waste disposal are not enough to understand the potential effects of these regulations on the demographic distribution of waste. I instead estimate a structural model of waste haulers' decisions about where to deposit waste from each county. Using a revealed preference approach, I uncover parameters underlying the economic choices of where to dump, identifying the demand parameters of haulers for disposal facilities. I then use estimated demand parameters to quantify the change in waste flows and distribution of waste flows under several counterfactual policy experiments that intervene choice sets, disposal prices, and transport costs. I currently consider only the demand side, assuming 100% of policy burden on haulers. While this simplicity is a clear limitation, this allows me to detect a key mechanism of the regulations on key demand factors. The results can be also considered as short-run impact because facilities may not adjust their pricing strategies immediately given the contract negotiation costs.

4 A Model of Waste Flows

4.1 Choices of Disposal Facilities

Assume every hauler i picks up a waste amount q_{ict} in county c in quarter t, he chooses a facility j to dump the trash to maximize his utility $U_{ijct}(X_{ijct}, \epsilon_{ijct})$. X_{ijct} are observables that include tipping fees and transport costs (measured by the interaction between distances and fuel prices). ϵ_{ijct} is the unobservable match quality for hauler i in county c carting trash to facility j in quarter t. The utility does not depend on waste amount q_{ict} for either of two reasons. First, picked up waste amount is exogenous to haulers. The hauler does not decide the trash quantity he picks up, nor does he decide the quantity he transports to a facility. Instead of quantity optimization, he decides an optimal route for collecting and carting waste to a facility. In this aspect, i is considered as an hauler×trip. Second, the hauler often use the same size of trucks to travel to all destinations. His utility then does not hold economy of scale.

Given the observed price and distance, I specify the utility specifically as

$$U_{ijct} = \beta X_{jct} + \epsilon_{ijct} \equiv \beta_p \text{price}_{jt} + \beta_d \text{distance}_{cj} * \text{fuel price}_t + \gamma_j + \epsilon_{ijct} \tag{4}$$

Assume ϵ_{ijct} follows type I extreme value distribution then the probability that facility j is chosen in hauler×trip i is

$$P_{ijct} = \frac{\exp(\beta X_{jct})}{\sum_{k \in C_{ct}} \exp(\beta X_{kct})} \equiv P_{jct} \tag{5}$$

This model share similarities with multinomial logit discrete choice models (see McFadden (1974); Berry (1994); Berry et al. (1995)) but has three distinct features. First, there is no outside option. A hauler must choose a facility to dump all of their trash. The hauler does not keep trash himself. This also means that there is no illegal dumping. Second, I observe market level data. Although the model describes individual hauler behaviors, data at individual haulers are not available. Such situation has been estimated using the method in Berry (1994); Berry et al. (1995). The contraction mapping result in Berry (1994) shows that there exists a unique mean utility vector to match the model implied choice probability to observed market shares. However, this result only applies to the case of positive market shares. In my model, zero market share may happen because a feasible facility that is within 60 miles of the population centroid of trash-generating county may be never chosen by any haulers in the county in a quarter. Estimation that ignores these zero shares would have bias selection. To deal with this situation, I propose the following maximum likelihood estimation. This approach assumes no heterogeneity in the choice probability of hauler/trip i, and in the waste amount of a trip, within a market.

4.2 Model Likelihood

The probability that hauler i chooses the facility j that he was actually observed to choose is

$$f(Y_{ict};\beta) = \prod_{j=1}^{J} P_{ijct}^{y_{ijct}} \tag{6}$$

where $y_{ijct} = 1$ if hauler i chose j and zero otherwise (in market ct). The log likelihood function of the model is

$$L(\beta) = \sum_{c,t}\sum_{i}\sum_{j} y_{ijct} \log P_{jct} \tag{7}$$

$$L(\beta) = \sum_{c,t}\sum_{j} \log P_{jct} \sum_{i} y_{ijct} \tag{8}$$

Assume picked-up waste amounts within a market at a time have the same size, i.e. $q_{ict} = q_{ct}$, then the market share of a county's waste that is dumped at facility j is

$$s_{jct} \equiv \frac{\sum_i q_{ict} y_{ijct}}{Q_{ct}} = \frac{q_{ct} \sum_i y_{ijct}}{Q_{ct}} \tag{9}$$

where Q_{ct} is the total waste generated by households in county c at time t. Then log likelihood becomes

$$L(\beta) = \sum_{c,t}\sum_{j} \log P_{jct} \cdot s_{jct} \cdot \underbrace{Q_{ct}/q_{ct}}_{N_{ct}} \tag{10}$$

It should be noticed that Q_{ct}/q_{ct} is the number of haulers N_{ct} in a market c at a time t. Now, there are two maximum likelihood estimators, depending on the assumptions we believe.

The first estimator assumes that the number of haulers across different markets is the same.

This implies that market sizes differ because the picked-up waste amounts vary across markets. The log likelihood function is

$$L(\beta) = \frac{1}{N} \sum_{c,t} \sum_{j} \log P_{jct} \cdot s_{jct} \tag{11}$$

The second estimator assumes that the picked-up waste amounts across different markets have the same size. This means that the trash collection trucks have the same size in the whole California. The log likelihood function becomes

$$L(\beta) = \frac{1}{q} \sum_{c,t} \sum_{j} \log P_{jct} \cdot s_{jct} \cdot Q_{ct} \tag{12}$$

The second estimator implies that market sizes differ across markets because the number of collection trips and the number of haulers vary across markets. Given this situation is more plausible, the main model will be estimated using the log likelihood function (12). I cannot identify the truck size, but I can identify the haulers' preference parameters.

4.3 Identification

I exploit cross-sectional and time-series variation in the data to identify the parameters. These rich variations allow me to control for facility fixed effects, which is important for two reasons. First, we have seen that after controlling for income, tipping fees, and distances, factors that are correlated with demographics of the residents living near the disposal facilities also matter in haulers' decisions. Hence, facility fixed effects capture the different influences of the demographics of communities living nearby facilities and time-invariant characteristics that are correlated with these demographics. Second, I can alleviate a part of the price endogeneity problem due to omitted variable bias. Facilities that have good quality (unobservable to an econometrician) in the sense that they have low hassle costs, high acceptance rates, or operation hour flexibility, etc. tend to have high disposal prices. Excluding the control for these qualities in the estimation would cause the price coefficient estimate to have upward bias.

The difficulty in consistently estimating price coefficient is also to overcome bias due to measurement error. This is because I observe listed prices rather than any deviations from these prices that haulers may pay if they were to sign contracts with individual waste facilities. Hence, to overcome both endogeneity and measurement error, I instrument for the price that a hauler coming from a given county would pay at any given facility with the quantity of waste generated by other counties that may consider this facility for depositing waste. Specifically, the instrument is the sum of market sizes of other markets that also consider the facility in their choice sets. This adds to the IO literature that has used cost shifters, BLP instruments, Hausman instruments, Nevo instruments; see Berry et al. (1995); Hausman (1996); Nevo (2001).

On the one hand, the market-size instrument is correlated with price because the disposal facility has economy of scale. Hence, if a hauler in a given county that is near other counties that generate a lot of waste, it will likely face lower prices at disposal facilities near those counties. On the other hand, this instrument is exogenous with the demand in the instrumented market because it excludes demand factors of the instrumented market. Even though market sizes of the other markets may be correlated with the waste amount in the instrumented market via common geographical shocks such as the growth of the state economy, they are not likely to affect the individual hauler's choices in the instrumented market.

To estimate price coefficients from exogenous variation in price using instrument in a nonlinear model, I apply control function approach. Following the literature, control function is estimated using polynomial of residuals obtained from the first stage in which price is regressed on exogenous variables and instruments. In the main model, the polynomial terms enter as extra explanatory variables; see Petrin and Train (2010). I estimate models with linear polynomial and quadratic polynomial of control terms.

The transport cost parameter is identified in part based on how waste flows vary by distance between the population center of a county and a disposal facility, and in part based on how these variations increase and decrease over time with diesel prices.

4.4 Model Results

Table (6) reports results of the model. Column (1), (2), and (3) show the estimates of facility fixed effect, linear control function, and quadratic control function specifications, respectively. As expected, the facility fixed effects specification does not resolve all bias in price coefficient estimate. Although its estimate of price coefficient has the correct sign, it is extremely small and statistically insignificant, and the resulted price elasticity is -0.03. Using market sizes of the other relevant markets to instrument price, the upward bias is mitigated. The magnitude of price coefficient becomes two order of magnitude bigger; price elasticity is -4.20. The positive sign of the first coefficient of control function confirms the upward bias is corrected.

The transport cost measured by the interaction between distance and diesel price is robustly estimated in all specification. The coefficient is negative and statistically significant, implying a distance elasticity of -1.59.

The ratio between transport cost coefficient and price coefficient captures hauler's willingness to pay for proximity to the disposal facility. This is the cost of transportation. The estimates imply that transportation costs $\$0.43$ per ton-mile given diesel prices at the 2000 level (\$$1.672$/gal).

This agrees with the estimates from several publications. First, Miller and Osborne (2014) report the transportation costs $\$0.46$ per ton mile for shipping cement. Second, 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 roughly \$0.29–\$0.35 over 1983–2003. Third, previous studies in waste transportation in 1990 and 1992 report transport costs from \$0.16 to \$0.36 per ton mile; see Fischer et al. (1993).

4.5 Model Fit

Figure (4) shows the scatter plots and correlation coefficients between observed values and fitted values of key variables. The key variables I consider are waste flows, waste-weighted average distance, and waste-weighted average price because it is important to match waste movements well to study the spatial and demographic distribution of waste flows. I also especially consider the goodness of fit in year 2010 because my analysis focuses on demographic distribution in 2010. Overall, the model successfully replicates the waste flows, waste-weighted average distance, and waste-weighted average price, especially in year 2010.

4.6 Sensitivity Checks

As mentioned above, there is an alternative estimator if the model assumes a fixed number of haulers across different markets. Intuitively, the alternative estimator aims to maximize the goodness of fit in all markets equally, instead of emphasizing the fitness in the big markets as does the current estimator. I re-estimate the model using that estimator to check the sensitivity.

Results in table (7) show that when weighting all markets equally, price coefficients becomes bigger while transport cost coefficient is similar to the case of market-weighted estimates. This reveals that big markets are less responsive to price.

5 Counterfactual Policies

Given the underlying primitives of the structural model (demand for waste disposal), I conduct several counterfactual policy experiments to evaluate the implications on spatial distribution (intercounty trash flows), hauler surplus, and demographic distribution of waste. Specifically, taking as given the baseline parameter estimates and the topology of the industry in year 2010, I compute the haulers' optimal choices of where to dump waste under policy interventions to examine the change in waste flows between a policy scenario and the baseline (the model-implied prediction in the absence of policy interventions).

I consider four counterfactual policies: import bans that outlaw intercounty waste flows, import taxes that tax waste flows that cross county lines, fuel taxes that tax diesel prices at a percent rate, and universal trash taxes that tax all trash disposal at an equal rate. These are NIMBY policies that aim to reduce waste flows occurring locally. I begin with the analysis on the change in intercounty waste flows and the economic impacts of the counterfactual policies. I then consider the implications of policies on demographic distribution of waste disposal.

5.1 Intercounty Waste Transport and Economic Impacts

Panel A in table (8) shows the economic impacts on hauler surplus of the policies, compared to the baseline level (prediction in the absence of policies). There are two baseline levels. One is used to quantify the effects of import bans. The other one is used for the comparison with import taxes, fuel taxes, and waste taxes. The reason why there are two baseline levels is that a few counties do not have any disposal facilities within their border lines, namely, Alpine, Amador, Del Norte, Nevada, San Francisco, and Tuolumne. I exclude those counties in calculating the change in economic factors and demographic distribution of waste flows for the import ban scenario (columns (1) and (2)).

Because an import ban that interdicts intercounty waste transport would restrict the choice set of a hauler in a waste generating county to only facilities within the county border line (local options), the policy would reduce exports completely. Specifically, the amount is about 570,000 tons in an average market (trash generating county) for year 2010 (row 1 in column 2). The distance to transport trash would also decrease unless most of trash is generated near the county border line rather than the county center. This is demonstrated by a reduction by 10,300 kiloton-mile in trash mileage, or equivalently around 3 miles in transporting trash from population center of generating county to a disposal facility.

Theoretically, the change in total tipping fees the hauler pays for disposal after an import ban is ambiguous because the model explains the hauler choice using three factors, price, transport cost, and facility fixed effects. If the hauler chose to dispose of trash at a nonlocal facility for cheaper prices despite distant location, they would pay higher tipping fees for being forced to dispose of trash at local facilities. On the other hand, the hauler may have chosen a nonlocal facility for good quality despite high tipping fees. In this case, the import ban would result in a decrease in tipping fees. Column (2) reveals that the overall effect of import bans on tipping fees is dominated by the second mechanism. Particularly, total tipping fees decrease by about \$750,000, or 12 cents per ton after imposing import bans. Although the import bans would save the hauler on tipping fees and transport costs, the hauler's surplus reduces by 4 million dollars, or equivalently \$1.25 per ton for forgoing good quality facilities outside the generating county borders.

An import tax would make disposal facilities outside the generating county borders (nonlocal facilities) become more expensive relative to local alternatives. As a result, the tax would reduce intercounty waste flows. Consider a tax of 15%, or $5.46/ton on average, which is 20% higher than the current fees imposed in Alameda (the top three waste importing counties in California).[9] Column (5) shows that the tax would reduce about 300,000 tons of exports, which is 55% of the current exports. Total tipping fees would increase by nearly $900,000, or 34 cents per ton because both options of switching to local facilities and staying at nonlocal facilities are more expensive than the current choice. Trash mileage falls by 5,500 kiloton-mile, or 1.6 miles for a transport journey from a population center of generating county to a disposal facility. Hauler surplus decreases by 2 million dollars, or 87 cents per ton.

A fuel tax that taxes diesel prices at a percent rate and hence, would make trash transportation more expensive. As a result, waste would be carted to nearer facilities, resulting in a reduction in trash travel mileage. Column (7) shows that a fuel tax at 15%, which is on average $30.6 cents per gallon or 65% of the 2019 fuel tax level, would reduce nearly 5,000 kiloton-miles in trash mileage, or equivalently 1.35 miles in a journey from population center of generating county to a disposal facility. Because out-of-county facilities are generally farther from waste-generating origin than local alternatives, the fuel tax would also reduce exports. At the tax of 15%, exports would fall by 116,000 tons, or 20%.

The change in total tipping fees in the case of fuel tax is theoretically ambiguous because of two opposite directions. First, switching to a nearer facility is costly because the nearer facility is expensive, which is the reason the hauler did not opt for. Second, switching to a nearer facility would save the hauler on paying tipping fees, but it did not offer other benefits rather than tipping fees and transport costs, such as high acceptance rates, operation hours, capacity, etc., which are captured by facility fixed effects in my model. Row 2 in columns (6) and (7) reveals that the second effect is dominant: haulers in a market would overall save 1.5 million dollars (a reduction by 1.11%) in paying tipping fees, or 21 cents per ton. However, forgoing good quality facilities would cost the haulers 8 million dollars, or equivalently $2.11 per ton.

The final policy of interest is a universal waste tax that taxes all trash disposal at an equal rate. This tax is motivated by the fact that everyone wants to protect themselves and justifies the tax as a mean to compensate for affected communities nearby a trash site. At an equal percent rate, the waste tax would penalize expensive facilities more than less expensive facilities. The policy impact on intercounty trash flows is theoretically ambiguous because of two opposite directions. First, if haulers carted trash to out-of-county options because of cheap tipping fees, the waste tax would exacerbate intercounty trash flows. Second, if out-of-county facilities are expensive but haulers opt

[9] Currently Alameda waste management department imposes a fee of $4.53/ton on all of the non-hazardous waste treated in Alameda.

for them for reasons other than prices and distances, the waste tax would mitigate intercounty trash transport. Columns (8) and (9) show that the second effect is dominant: Exports fall by 20,000 tons (3.45%) at the waste tax of 15%.[10] Total tipping fees haulers in a market would have to pay the facilities would increase 14 million dollars (10.21%), or $4.45 per ton. Trash mileage would decrease slightly by 2.78%, or 0.29 miles for a trip, revealing again that switching to less expensive facilities do not necessarily mean higher cost of transportation. Hauler surplus would fall by 20.9 million dollars, or $5.94 per ton.

5.2 Demographic Distribution Implications

Panel B in table (8) shows the impact of the four policies on the demographic distribution of waste disposal. The panel computes the percent trash in a market that ends up at disposal facilities by race and ethnicity of affected communities for the baseline estimates (before counterfactuals) and the percentage point changes after polices. Specifically, assuming that trash from a generating market c that is sent to disposal facility j affects all people living three miles of the facility location *equally*, the percent trash of the market c exposes on white community is

$$\%\text{ trash to white} = \frac{\sum_{j \in J_c} \overbrace{q_{cj}/\text{total population in j's buffer}_j}^{\text{trash per capita in community/facility j}} \times \#\text{whites in j's buffer}_j}{\underbrace{\sum_{j \in J_c} q_{cj}}_{\text{total trash generated in county c}}} \times 100 \quad (13)$$

Reports in panel B are average county levels after weighting these exposure percentages by market size (total trash generated in the origin county). The baseline level to compare the effects of import ban is column (1) and the baseline to compare the other policies is column (3). This separation arises because several counties do not have any disposal facilities within their borders.

Column (2) shows that after the import ban, while the percent waste that is out-of-county exported to Hispanic residents would fall, the total percent waste that is sent to Hispanic communities would increase. Meanwhile, waste sent to white communities would decrease. This implies that waste would substitute away from facilities in white areas toward Hispanic communities.

That substitution pattern persists in other policies, import tax, fuel tax, and trash tax. The fact that the trash tax would increase waste sent to Hispanic communities implies that facilities in these communities had low dumping fees in general. Similarly, the rises in waste in these communities after a fuel tax and an import tax imply that their backyard facilities were close to the population centers of trash generating origins. Hence, policies that target disposal prices and transport costs

[10]The trash tax of 15% is on average about $5.46 per ton, which is 20% higher than the current waste fee in Alameda.

would in fact exacerbate the unequal trash going to Hispanic communities.

These policies would not reduce waste sent to black communities either. Waste that is sent to black residents would generally remain the same or fall by a modest amount less than the reduction in white communities. This is because facilities in black neighborhoods are attractive despite their high dumping fees and distant locations. While explaining exactly what are the reasons for that attractiveness is beyond the scope of this paper, one potential reason is the hassle costs in disposing trash at these facilities. Specifically, these facilities might easily accept trash from the hauler because they do not maintain a right environmental standard. If this is the case, policies that aim to correctly enforce environmental standards in these facilities would be effective.

6 Conclusion

This paper documents the disproportionate distribution of waste disposal by race and ethnicity. Although there are not many people who live near (three miles) a trash site, there is a strong disparity between the amount of trash that is sent to facilities in highly present minority groups and that is sent to facilities in predominantly white communities. NIMBY policies that limit interjurisdictional waste flows would not generally lead to a more equitable distribution of trash. Making intercounty waste transport costlier by taxing gasoline prices, taxing out-of-county waste, or even banning interjurisdictional flows would generally not reduce waste that is sent to facilities near black residents. The reason is that haulers may switch from out-of-county facilities to other out-of-county facilities or within-waste-generating-county facilities near black communities. Additionally, the policies tend to substitute waste away from facilities near white residents toward facilities near Hispanic residents because the facilities in Hispanic communities are cheap and close to the population centers of the waste-generating counties. Hence, price-targeted and transport-targeted policies are not appropriate tools to reduce environmental injustice in disposal placements.

This paper is the first study that explores the demographic distribution of solid waste flows and how environmental protection policies affect the waste flows, taking into account of market factors of hauling decisions. While the explanation for exactly why minorities are disproportionately exposed to waste disposal is beyond the scope of this paper, future research on this matter is useful. What else in addition to tipping fees and transport distance that could explain the waste flows that go to minority communities? Is it because the minorities have lower political capability? Is it because the minorities come to nuisance for low housing costs? Most importantly, is it because they are seeking earning opportunity in the trash sites? Answering this question may reveal the direction on welfare changes in these minority communities.

References

Anderton, D. L., Anderson, A. B., Oakes, J. M., and Fraser, M. R. (1994). Environmental equity: the demographics of dumping. *Demography*, 31(2):229–248.

Baden, B. M. and Coursey, D. L. (2002). The locality of waste sites within the city of chicago: a demographic, social, and economic analysis. *Resource and Energy Economics*, 24(1-2):53–93.

Berry, S., Levinsohn, J., and Pakes, A. (1995). Automobile prices in market equilibrium. *Econometrica: Journal of the Econometric Society*, pages 841–890.

Berry, S. T. (1994). Estimating discrete-choice models of product differentiation. *The RAND Journal of Economics*, pages 242–262.

Currie, J., Greenstone, M., and Morettia, E. (2011). Superfund cleanups and infant health. *The American economic review*, 101(3):435–441.

Depro, B., Timmins, C., and O'Neil, M. (2015). White flight and coming to the nuisance: can residential mobility explain environmental injustice? *Journal of the Association of Environmental and resource Economists*, 2(3):439–468.

Fischer, W. R., Leistritz, F. L., Dooley, F. J., and Bangsund, D. A. (1993). Cost reductions for solid waste disposal in north dakota using regional landfills.

Gamper-Rabindran, S. and Timmins, C. (2011). Hazardous waste cleanup, neighborhood gentrification, and environmental justice: Evidence from restricted access census block data. *American Economic Review: Papers & Proceedings*, 101(3):620–24.

Greenstone, M. and Gallagher, J. (2008). Does hazardous waste matter? evidence from the housing market and the superfund program. *The Quarterly Journal of Economics*, 123(3):951–1003.

Hausman, J. A. (1996). Valuation of new goods under perfect and imperfect competition. In *The economics of new goods*, pages 207–248. University of Chicago Press.

Kamita, R. Y. (2001). Merger analysis in geographically differentiated industries with municipal and private competitors: The case of solid waste disposal.

Kawai, K. (2011). Auction design and the incentives to invest: Evidence from procurement auctions. *NYU Stern*.

Levinson, A. (1999a). Nimby taxes matter: the case of state hazardous waste disposal taxes. *Journal of Public Economics*, 74(1):31–51.

Levinson, A. (1999b). State taxes and interstate hazardous waste shipments. *The American Economic Review*, 89(3):666–677.

Ley, E., Macauley, M., and Salant, S. W. (2000). Restricting the trash trade. *The American Economic Review*, 90(2):243–246.

Ley, E., Macauley, M. K., and Salant, S. W. (2002). Spatially and intertemporally efficient waste management: the costs of interstate trade restrictions. *Journal of Environmental Economics and Management*, 43(2):188–218.

McFadden, D. (1974). Conditional logit analysis of qualitative choice behavior. *Frontiers in Econometrics*, pages 105–142.

Mennis, J. (2002). Using geographic information systems to create and analyze statistical surfaces of population and risk for environmental justice analysis. *Social science quarterly*, 83(1):281–297.

Miller, N. H. and Osborne, M. (2014). Spatial differentiation and price discrimination in the cement industry: evidence from a structural model. *The RAND Journal of Economics*, 45(2):221–247.

Mohai, P. and Saha, R. (2007). Racial inequality in the distribution of hazardous waste: A national-level reassessment. *Social problems*, 54(3):343–370.

Nevo, A. (2001). Measuring market power in the ready-to-eat cereal industry. *Econometrica*, 69(2):307–342.

Petrin, A. and Train, K. (2010). A control function approach to endogeneity in consumer choice models. *Journal of marketing research*, 47(1):3–13.

Salz, T. (2017). Intermediation and competition in search markets: An empirical case study.

Sheppard, E., Leitner, H., McMaster, R. B., and Tian, H. (1999). Gis-based measures of environmental equity: exploring their sensitivity and significance. *Journal of Exposure Science and Environmental Epidemiology*, 9(1):18.

United Church of Christ's Commission on Racial Justice (1987). *Toxic wastes and race in the United States: A national report on the racial and socio-economic characteristics of communities with hazardous waste sites*. Public Data Access.

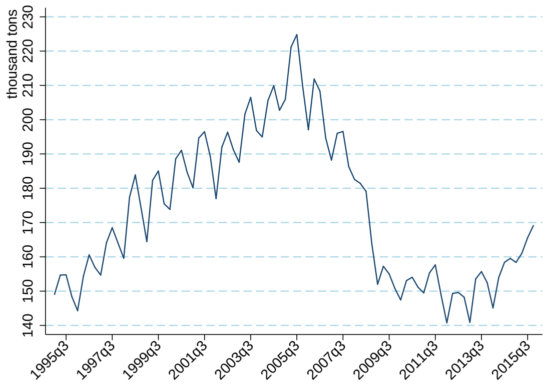
U.S. Environmental Protection Agency (2016). Advancing sustainable materials management: 2014 fact sheet. Technical report, US EPA.

U.S. General Accounting Office (1983). Siting of hazardous waste landfills and their correlation with racial and economic status of surrounding communities.

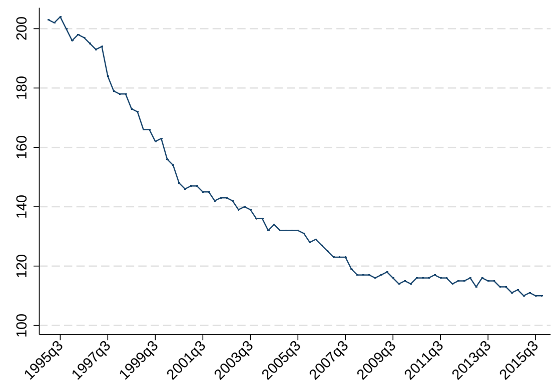
Figures

FIGURE 1: Overview of solid waste disposal in California from Jan 1995 to Dec 2015

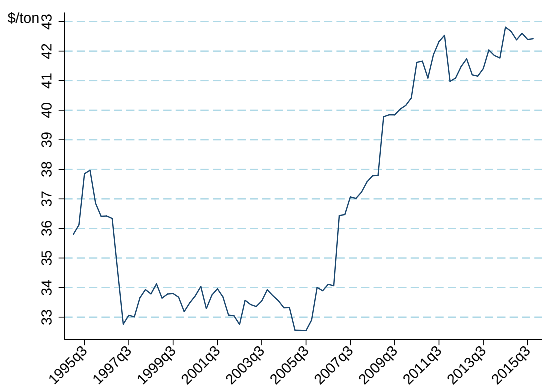
(A) Total waste amount generated by the average county



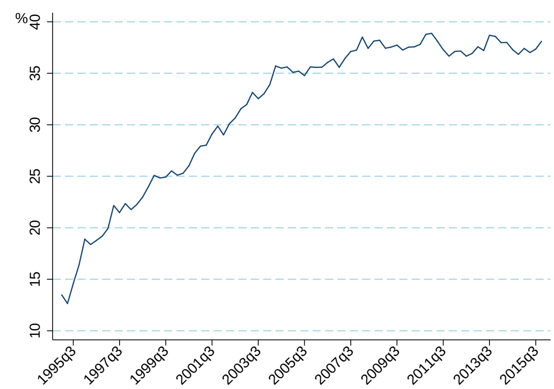
(B) Number of disposal facilities



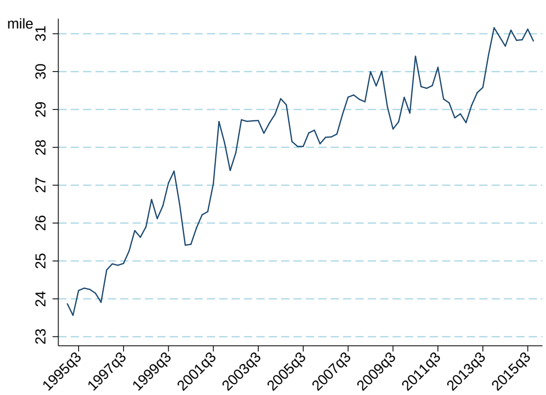
(C) (Waste weighted) average disposal price (in 2000 dollars) haulers in a county pay



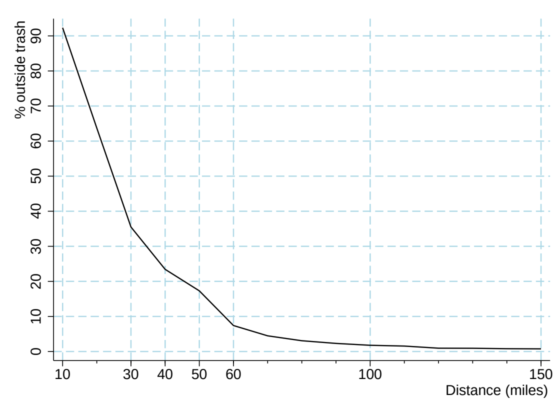
(D) Percentage of waste the average county sends to other counties



(E) (Waste weighted) average distance haulers in a county travel

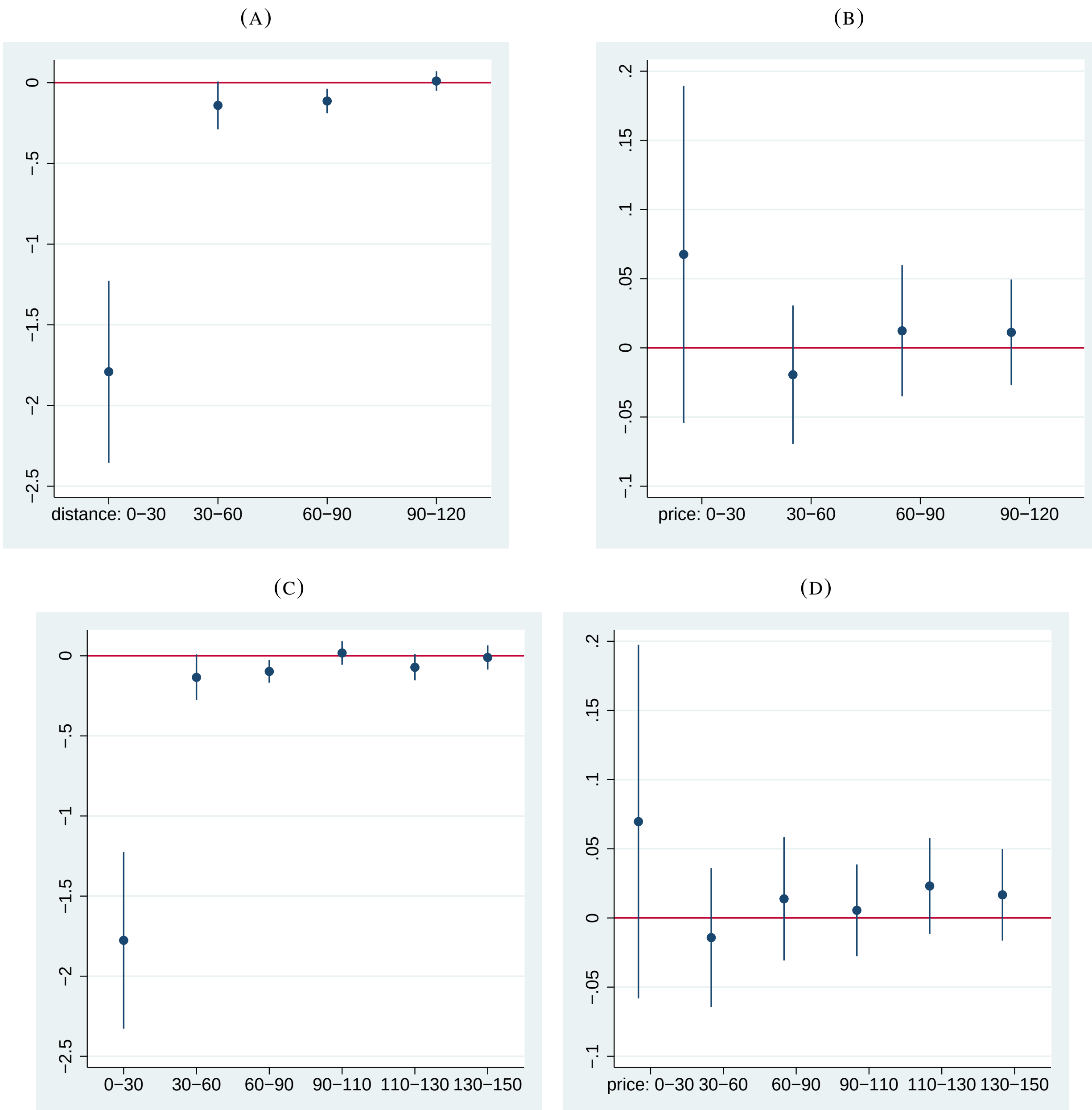


(F) Percentage of waste transported beyond a given distance



Note: The graph shows several features in California waste disposal industry over time. Distance is driving distance from population weighted coordinate of origin county to destination facility. Figure (1f) shows the percentage of waste that is transported beyond a given distance from the population weighted centroid of an origin county in 2015.

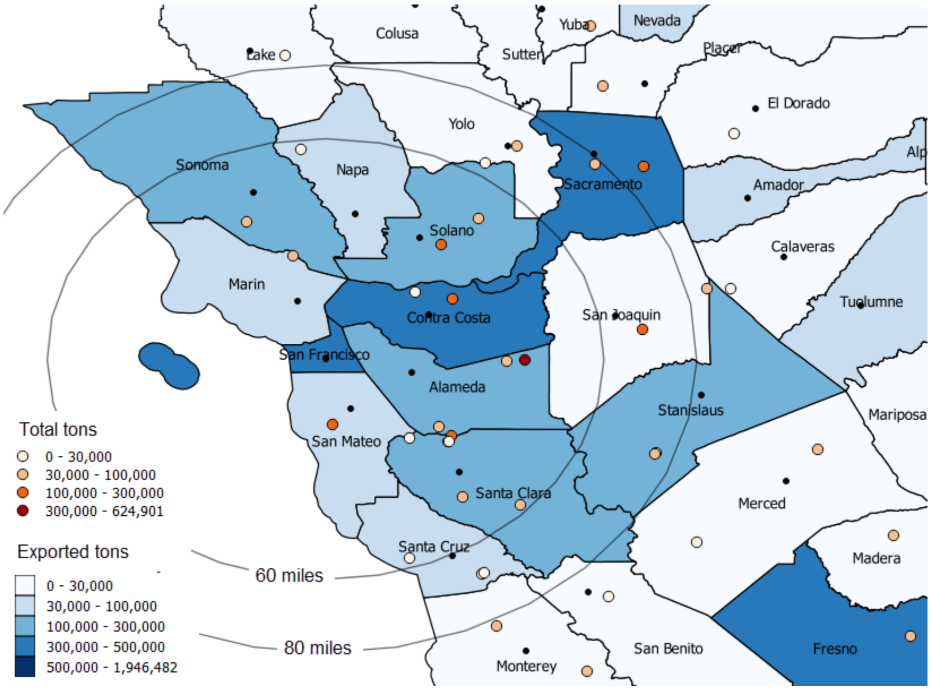
FIGURE 2: Price response and distance response by distance



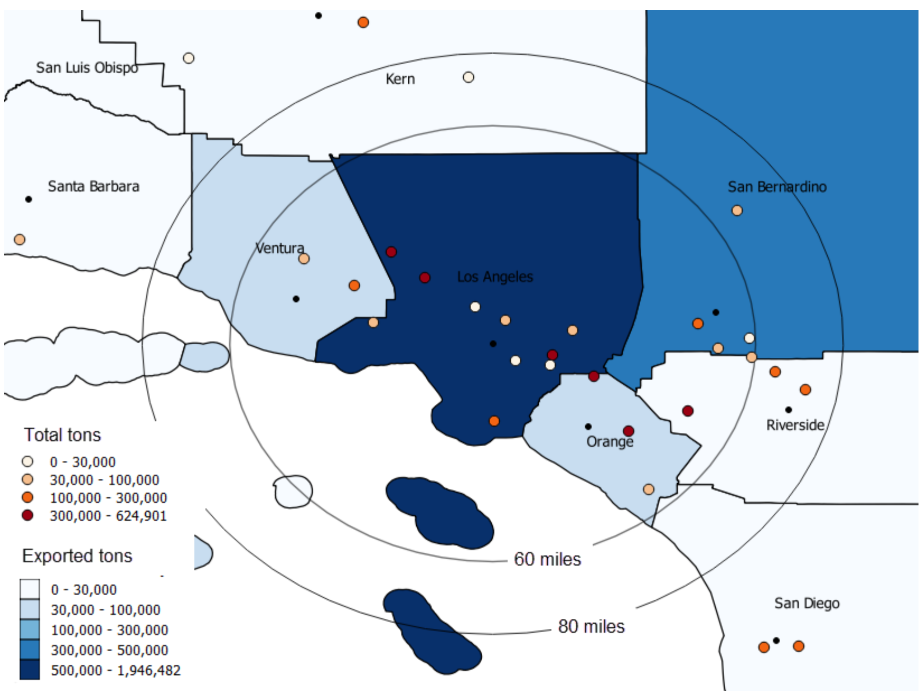
Note: Figure shows the coefficients on distance and price at different knots of distance(linear splines) from the quarter by origin county fixed effect regression, where dependent variable is trash amount from a county to a facility. Figures (2a) and (2b) use the sample of all combinations of flows by a county and a facility within 120 miles. Figures (2c) and (2d) use the sample of flows within 150 miles. 95% confidence intervals are displayed with the point estimates. Standard errors are clustered by origin county.

FIGURE 3: Sizes of Choice Sets

(A) Choice Set of San Francisco Market



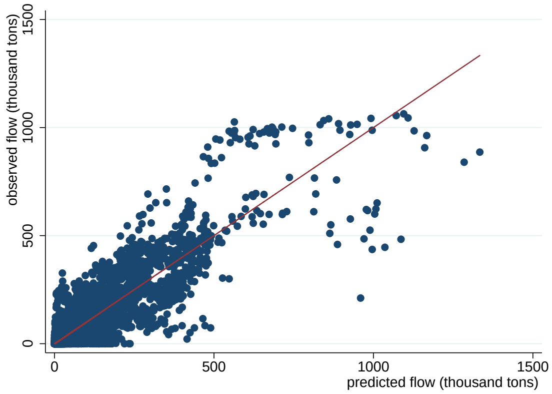
(B) Choice Set of Los Angeles Market



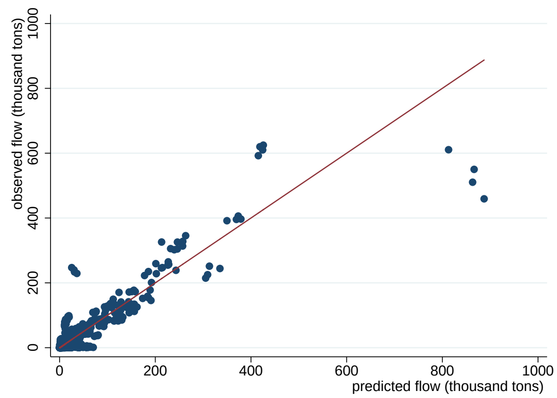
Note: The graph shows how wide 60-mile and 80-mile markets are from the population center of San Francisco and Los Angeles. Black dots represent population center coordinates of counties. Counties are blue colorized by out-of-county exports of waste. Facilities are red colorized by total waste amount.

FIGURE 4: Model fit

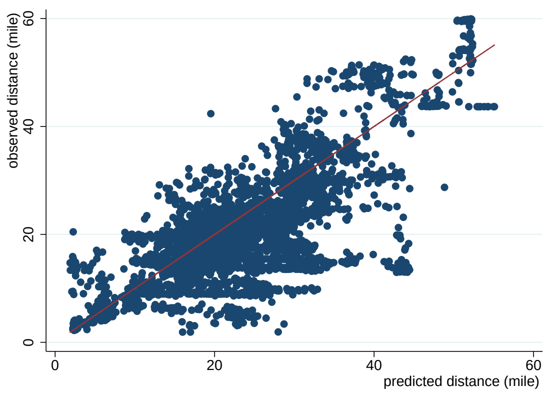
(A) Correlation in trash flows (= 0.8965)



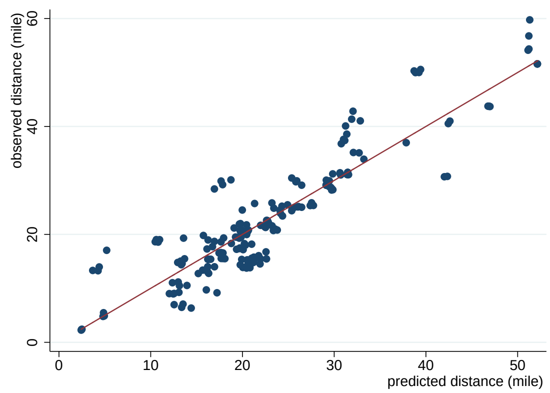
(B) Correlation in 2010 trash flows (= 0.9128)



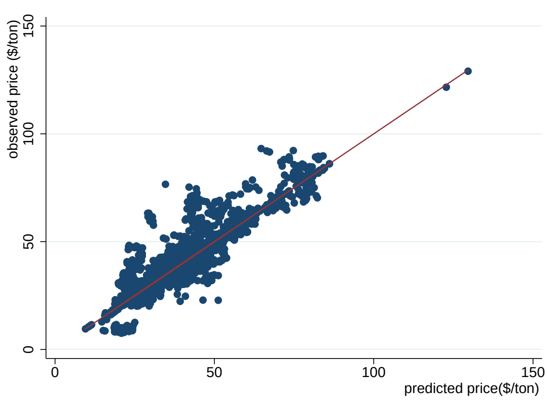
(C) Correlation in distance (= 0.8175)



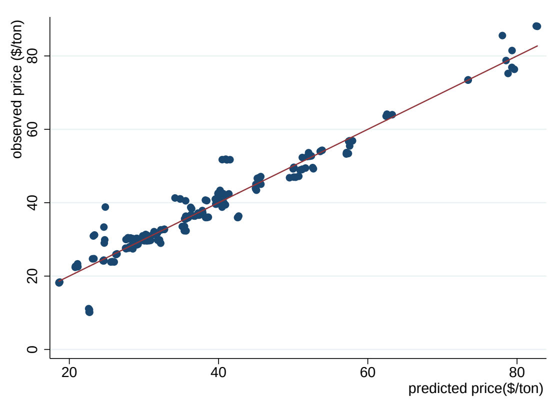
(D) Correlation in distance in 2010 (= 0.9205)



(E) Correlation in price (= 0.9268)



(F) Correlation in price in 2010 (= 0.9712)



Note: The graph shows the correlation coefficient between observed values and fitted values of key variables. Panels (4a) and (4b) show the correlation in trash flows (trash amount generated from a county to a facility in a quarter); panel (4b) shows the correlation in trash flows in year 2010. Panels (4c) and (4d) show the correlation in (waste weighted) average distance shipped by a county in a quarter; panel (4d) shows the correlation in average shipping distance in year 2010. Panels (4e) and (4f) show the correlation in (waste weighted) average tipping fee by a county in a quarter; panel (4f) shows the correlation in average tipping fee in year 2010.

Tables

TABLE 1: Regression analysis of trash flows in response to price and distance by distance

Dependent var.			Trash amount from an origin county to a facility in a quarter					
	(1)	(2)		(3)	(4)		(5)	(6)
price: 0–40	-0.0636	-0.0320	price: 0-30	0.0697	-0.0238	price: 0-30	0.0700	-0.0238
	(0.0463)	(0.0204)		(0.0652)	(0.0356)		(0.0653)	(0.0356)
price: 40–70	0.0528**	-0.0081	price: 30-60	-0.0142	-0.0134	price: 30-60	-0.0125	-0.0134
	(0.0252)	(0.0116)		(0.0256)	(0.0108)		(0.0255)	(0.0108)
price: 70–100	0.0156	-0.0052^{+}	price: 60-90	0.0138	-0.0118**	price: 60-80	0.0231	-0.0130
	(0.0206)	(0.0031)		(0.0227)	(0.0057)		(0.0265)	(0.0092)
price: 100–130	0.0212	-0.0034	price: 90-110	0.0055	-0.0038	price: 80-100	0.0167	-0.0066**
	(0.0152)	(0.0086)		(0.0169)	(0.0028)		(0.0263)	(0.0026)
price: 130+	0.0107	-0.0026	price: 110-130	0.0231	-0.0025	price: 100-125	0.0202	-0.0026
	(0.0157)	(0.0025)		(0.0177)	(0.0126)		(0.0159)	(0.0104)
price			price: 130-150	0.0167	-0.0027	price: 125+	0.0058	-0.0035
				(0.0169)	(0.0025)		(0.0148)	(0.0022)
distance: 0–40	-1.4723***		dist: 0-30	-1.7762***		dist:0-30	-1.7763***	
	(0.1709)			(0.2813)			(0.2811)	
distance: 40–70	0.0006		dist: 30-60	-0.1346^{+}		dist: 30-60	-0.1377^{+}	
	(0.0552)			(0.0730)			(0.0745)	
distance: 70–100	-0.0484		dist: 60-90	-0.0976***		dist: 60-80	-0.1213	
	(0.0341)			(0.0360)			(0.0767)	
distance: 100–130	-0.0169		dist: 90-110	0.0174		dist: 80-100	-0.0285	
	(0.0218)			(0.0373)			(0.0501)	
distance: 130+	-0.0216		dist: 110-130	-0.0719^{+}		dist: 100-125	-0.0018	
	(0.0392)			(0.0414)			(0.0294)	
distance			dist: 130+	-0.0104		dist: 125+	-0.0349	
				(0.0385)			(0.0277)	
facility FE	Y	Y		Y	Y		Y	Y
quarter FE	Y	Y		Y	Y		Y	Y
quarter $\times$ origin cnty FE	Y			Y			Y	
origin $\times$ des cnty FE		Y			Y			Y
Observations	151969	151969		151969	151969		151969	151969
Adjusted R^2	0.444	0.879		0.446	0.879		0.446	0.879

Note: This table shows the responses of all trash flows within 150 miles to price and distance by different knots of driving distance. Standard errors are clustered by origin county.

TABLE 2: Summary statistics of panels of waste flows

	count	mean	sd	min	max
Panel A: Flows characteristics (unit: quarter × origin county × destination facility)					
A1: Flows within 60 miles of the population-weighted centroid of a county					
quantity (ton)	36,186	21,453.27	70,161.38	0	1,063,515
distance (mile)	36,186	37.12	14.91	1.737	59.93
waste-weighted distance (mile)	36,186	23.52	12.90	1.73	59.93
waste-weighted price ($/ton)	36,186	36.40	12.10	1.50	181.00
A2: All positive flows in California, including shipments beyond 60 miles					
quantity (ton)	53,957	15,401.27	58,388.94	.01	1,063,515
waste-weighted distance (mile)	53,957	28.00	23.23	1.73	700.17
waste-weighted price ($/ton)	53,957	36.49	12.18	1.50	181.00
Panel B: Choice set characteristics (unit: quarter × origin county)					
B1: Within 60 miles					
market size (ton)	4,431	175,199.3	416,191	1.6	3,573,185
out-of-county exports (%)	4,431	21.68	33.34	0	100
number of options	4,431	8.17	5.24	1	30
B2: All choices in California					
market size (ton)	4,788	173,560.3	426,099.1	.37	3,881,458
out-of-county exports (%)	4,788	31.62	38.05	0	100

Note: Panel A shows summary statistics of the sample of trash flows, i.e. the unit of observation is quarter × origin county × destination facility. Panel A1 includes all waste flow pairs between an origin county and a destination facility in a quarter (36,186 observations) within 60 miles, of which there are 24,473 observations of positive waste flows. Panel A2 include only positive waste flows, but it covers all flows in California. Panel B1 shows summary characteristics of key indicators from the perspective of haulers in a market: total waste generated by a county (market size), the percentage of waste in the county that is exported to other counties (out-of-county exports), and the number of disposal facilities within 60 miles from population centroid of the county (number of options). Panel B2 is similar to panel B1, but covering all choices in California (including choices resulted from the waste flows beyond 60 miles).

TABLE 3: Descriptive analysis of the number of people who live near a trash site

Panel A: Descriptive statistics of the affected communities by distance

	1-mile buffer		2-mile buffer		3-mile buffer		7-mile buffer	
	mean	sd	mean	sd	mean	sd	mean	sd
% affected white	0.50	1.49	1.14	3.23	3.26	6.36	16.41	15.69
% affected black	0.39	1.63	1.46	6.69	3.69	8.33	17.47	18.42
% affected Asian	0.28	0.63	0.95	1.91	3.50	6.40	18.11	19.42
% affected Hispanic	0.61	2.23	1.58	5.49	3.95	8.62	18.19	19.05

Panel B: Descriptive regression of the 3-mile affected communities

	(1)	(2)	(3)	(4)
	% white	% Asian	% black	%Hhispanic
Constant	4.2310***	3.9226**	6.1367**	7.8969***
	(1.5182)	(1.6554)	(2.4411)	(2.2397)
trash (mil tons)	-2.3781***	-2.0630**	-2.1132**	-1.7931*
	(0.8737)	(0.8432)	(0.9835)	(0.9259)
median hh income($1000s)	-0.0046	0.0041	-0.0345	-0.0651**
	(0.0250)	(0.0285)	(0.0369)	(0.0296)
year	2010	2010	2010	2010
SE	robust	robust	robust	robust
Observations	103	103	103	103
R^2	0.035	0.022	0.030	0.046
Adjusted R^2	0.015	0.003	0.011	0.027

Note: Panel A shows summary statistics of the population who live near a trash site, relative to the hosting-county population, in 2010. % affected white is the percentage of white in the destination county who live near a trash site by a certain distance. Panel B reports how the affected population by race responds to trash amount in a nearby trash site. Dependent variable is Affected Level$_j = \frac{\#\text{people of the race in a facility's 3-mile buffer}_j}{\#\text{people of the race in a facility's county}_j} \times 100$. Separate regressions are done for different race groups. Significant level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE 4: Summary statistics of demographics at waste generating county vs. receiving community

	3-mile buffer		receiving county		generating county		California
	unweighted	weighted	unweighted	weighted	unweighted	weighted	level
population	25,938	36,085	1,689,346	3,550,303	724,375	1,278,399	37,253,956
	(43,949)	(40,852)	(2,808,017)	(3,539,681)	(1,493,933)	(1,649,397)	
white	8,359	11,339	569,291	1,181,551	288,631	520,299	14,956,253
	(12,600)	(11,466)	(794,328)	(946,047)	(468,834)	(550,838)	
black	1,027	1,416	116,516	248,290	42,373	76,759	2,163,804
	(2,256)	(2,515)	(236,562)	(313,591)	(119,996)	(129,642)	
asian	3,632	5,650	227,325	481,614	93,529	145,612	4,775,070
	(7,425)	(7,269)	(397,684)	(490,828)	(218,980)	(218,819)	
hispanic	12,095	16,596	723,394	1,530,798	273,970	489,225	14,013,719
	(31,336)	(28,459)	(1,343,598)	(1,753,682)	(686,709)	(762,695)	
% white	49.36	44.09	45.79	39.74	54.58	50.45	40.15
	(24.71)	(20.85)	(17.73)	(10.82)	(19.11)	(17.38)	
% black	2.73	3.73	4.26	5.80	3.31	4.27	5.81
	(3.62)	(3.92)	(3.52)	(3.42)	(3.28)	(2.93)	
% asian	8.11	13.01	8.74	12.67	7.06	9.76	12.82
	(11.98)	(12.02)	(8.31)	(6.90)	(7.86)	(8.28)	
% hispanic	35.33	35.72	37.29	38.21	30.46	31.51	37.62
	(25.53)	(22.32)	(17.03)	(11.19)	(17.36)	(15.03)	
median hh	66,071	82,062	45,670	49,402	45,187	49,711	48,072
income	(25,672)	(23,769)	(10,216)	(8,622)	(10,290)	(10,430)	

Note: This table shows summary statistics of population in waste receiving communities versus waste generating communities. Receiving communities are presented as receiving counties and nearby communities. A nearby community is defined by a 3-mile radius circle centering a trash site. Population counts for the nearby community are aggregated from 2010 census blocks that have their centroid location in the buffer. Median household income at a block is the one at its block group. The table contrasts unweighted average population level and average level weighted by waste amount.

TABLE 5: Current distribution of county waste share in 3-mile neighborhoods of facilities

	(1)	(2)	(3)	(4)
Dependent var.		market share ($\times 100$)		
% black	0.015	0.303	0.289	0.948***
	(0.255)	(0.299)	(0.294)	(0.264)
% Hispanic	-0.026	0.162**	0.154**	0.122
	(0.057)	(0.068)	(0.071)	(0.084)
% Asian	0.049	0.026	0.035	-0.084
	(0.095)	(0.079)	(0.078)	(0.083)
Income ($1000s)		0.345***	0.325***	0.417***
		(0.077)	(0.083)	(0.097)
price			0.059	0.078
			(0.078)	(0.087)
distance*fuel				-0.214***
				(0.038)
quarter FE	Y	Y	Y	Y
ori cnty FE	Y	Y	Y	Y
N	1478	1478	1478	1478
unclustered N	1114	1114	1114	1114

Note: This table reports coefficients of a Tobit model, weighted by market size (total waste generated by a county). Dependent variable is market shares, i.e. share of a generating county's waste to a facility. Demographic characteristics of facilities are characteristics of community within 3 miles of a facility. The sample only includes observations in 2010. The Tobit regression includes quarter fixed effects and waste-origin county fixed effects. Significant level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE 6: Results from logit demand, baseline model, using market-size-weighted estimator

Model	(1) Facility fixed effects	(2) IV linear control function	(3) IV 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)
facility FE	Y	Y	Y
First stage results		price	
total market sizes (hundred thousand tons)		−0.2205***	
		(0.0108)	
1(serve at least 2 markets)		−2.9998***	
		(0.9919)	
distance∗fuel		0.0200***	
		(0.0013)	
1st stage R^2		0.6685	
F test		212.62	
price elasticity	−0.0277	−4.1983	−4.2007
transport elasticity	−1.7138	−1.5945	−1.5943

Note: Specification (1) is facility fixed effect model. Specifications (2) and (3) use sum of other relevant market sizes as an instrument and control function approach with linear and quadratic forms, respectively. Specifically, price value of an observation cjt is instrumented by the sum of market sizes of other relevant market $M_{-c,jt}$. A market is relevant if that is not the instrumented market c but it contains facility j in its choice set. Standard errors are bootstrapped. Price elasticities are the average over all observations. All specifications include facility fixed effects. Significant level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE 7: Results from logit demand using market-equally-weighted estimator

Model	(1) Facility fixed effects	(2) IV linear control function	(3) IV quadratic control function
price	-0.0014	-0.3167***	-0.3183***
	(0.0014)	(0.0369)	(0.0376)
distance$*$fuel	-0.0539	-0.0476***	-0.0477***
	(0.0007)	(0.0011)	(0.0011)
control term		0.3157***	31.5187e$-$2***
		(0.0370)	(0.0378)
control term^2			-0.1605e-4
			(0.3207e-4)
facility FE	Y	Y	Y
price elasticity	-0.0370	-8.1787	-8.2218
transport elasticity	-2.0693	-1.8295	-1.8279

Note: Specification (1) is facility fixed effect model. Specifications (2) and (3) use sum of other relevant market sizes as an instrument and control function approach with linear and quadratic forms, respectively. Standard errors are bootstrapped. Price elasticities are the average over all observations. All specifications include facility fixed effects. Significant level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE 8: Change relative to baseline levels after counterfactual policies

	(1) baseline 1 (receiving counties)	(2) import ban	(3) baseline 2 (all counties)	(4) import tax 5%	(5) import tax 15%	(6) fuel tax 5%	(7) fuel tax 15%	(8) waste tax 5%	(9) waste tax 15%
exports	573,678	-573,678	568,381	-130,419	-313,451	-41,264	-115,927	-5,497	-19,585
(tons)		(-100.0%)		(-22.95%)	(-55.15%)	(-7.26%)	(-20.40%)	(-.97%)	(-3.45%)
total tipping fees	145,000	-748	142,000	582	876	-527	-1,579	4,971	14,500
(thousand $)		(-.52%)		(.41%)	(.62%)	(-.37%)	(-1.11%)	(3.50%)	(10.21%)
trash mileage	90,500	-10,300	88,700	-2,307	-5,579	-1,739	-4,976	-822	-2,469
(kiloton-mile)		(-11.38%)		(-2.60%)	(-6.29%)	(-1.96%)	(-5.61%)	(-.93%)	(-2.78%)
hauler surplus (thousand $)		-3,964		-993	-2,323	-2,826	-8,316	-7,059	-20,900
tipping fees	39.96	-.12	40.32	.19	.34	-.07	-.21	1.52	4.45
($/ton)		(-.29%)		(.46%)	(.83%)	(-.18%)	(-.53%)	(3.78%)	(11.03%)
trash mileage	22.22	-3.08	22.58	-.68	-1.64	-.48	-1.35	-.11	-.29
(mile)		(-13.88%)		(-2.99%)	(-7.26%)	(-2.12%)	(-5.98%)	(-.47%)	(-1.28%)
hauler surplus ($/ton)		-1.25		-.36	-.87	-.72	-2.11	-2.0	-5.94
% trash to white	42.27%	-1.08	42.56%	-.26	-.65	-.24	-.70	-.28	-.85
		(-2.55%)		(-.62%)	(-1.54%)	(-.57%)	(-1.64%)	(-.66%)	(-1.99%)
% trash to black	3.40%	-.02	3.39%	.01	.02	-1.19e-3	-.87e-3	-.01	-.05
		(-.58%)		(.35%)	(.62%)	(-.04%)	(-.03%)	(-.44%)	(-1.34%)
% trash to asian	13.52%	-.54	13.44%	-.16	-.36	.05	.15	-.06	-.18
		(-4.01%)		(-1.21%)	(-2.65%)	(.40%)	(1.13%)	(-.45%)	(-1.35%)
% trash to hispanic	37.46%	1.71	37.19%	.43	1.02	.20	.58	.37	1.12
		(4.57%)		(1.15%)	(2.75%)	(.53%)	(1.55%)	(1.0%)	(3.01%)
% export to white	8.19%	-8.19	9.13%	-1.77	-4.27	-.57	-1.58	-.07	-.16
		(-100.0%)		(-19.42%)	(-46.74%)	(-6.22%)	(-17.35%)	(-.75%)	(-1.71%)
% export to black	.60%	-.60	.65%	-.12	-.29	-.04	-.12	.01	.03
		(-100.0%)		(-17.91%)	(-44.49%)	(-6.61%)	(-18.29%)	(1.28%)	(4.40%)
% export to asian	2.70%	-2.70	2.83%	-.65	-1.53	-.14	-.41	-.05	-.13
		(-100.0%)		(-23.07%)	(-54.19%)	(-5.06%)	(-14.35%)	(-1.69%)	(-4.58%)
% export to hispanic	4.93%	-4.93	5.28%	-.98	-2.39	-.35	-.98	.05	.21
		(-100.0%)		(-18.49%)	(-45.28%)	(-6.69%)	(-18.56%)	(1.03%)	(4.02%)

Note: Metrics are calculated for every county market and then averaged over markets using market sizes (total trash generated) as weights to get the above reported average. All measures use 2010 levels. Hauler surplus is implied from logit model, $\frac{1}{-\beta_{price}} \log\left(\sum_j^{J_m} \exp(\beta X_{jct})\right) + C$, 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. The measure "% trash to white" is the percent share of market trash that is sent to white, i.e. $= \frac{\sum_{j \in J_c} q_{cj} \times \#\text{ whites in j's buffer}_j/\text{total population in j's buffer}_j}{\sum_{j \in J_c} q_{cj}} \times 100$. The measure "% export to white" is the percent portion of exports that is sent to white to total trash generated in the origin county market, i.e.$= \frac{\sum_{j \in J_c} \mathbf{1}(\text{j is not located in c}) \cdot q_{cj} \times \#\text{ whites in j's buffer}_j/\text{total population in j's buffer}_j}{\sum_{j \in J_c} q_{cj}} \times 100$. In the case of import bans, five counties, Alpine, Amador, Del Norte, Nevada, San Francisco, and Tuolumne do not have any local facilities. Hence, I drop those counties in calculating the above averages. These account for 1.91% of waste in California in 2010.

APPENDIX

A Data Handling and Format

Waste amount data are merged with price data for the period from January 1995 to December 2015. 0.52% of California waste is sent to disposal facilities that are not found in the price dataset. I drop those observations to keep only matching observations. I continue to filter the matching data in three important aspects. First, some time-facility observations in the price dataset have zero price. Since zero prices may be recorded due to missing values, I drop those observations. They represent 0.41% of the total waste amount. Second, three facilities in California are located on Santa Catalina island and San Clemente island. Since these facilities are built for local needs and the waste management in islands is isolated from other areas in mainland due to geographical and transportation constraints, I drop those observations. They account for 0.01% of the total waste amount. Third, some disposal facilities in California share the same facility code in the price dataset. This arises from the shutting down and opening of a new facility or expanding a sub-unit in the same area but requiring a new permit number registration from the state. I combine waste amounts at different permitted number facilities that share the same price-data identifier to consider them as one disposal facility.

For out-of-state exports in California solid waste, I observe the export amount, but I do not observe the place of destination.[11] I construct an out-of-state disposal option for haulers in California by assuming a hauler would export to a nearest out-of-state facility, if export is considered.

I also construct a hypothetical out-of-state option for haulers in a specific county by the following procedure. A group of out-of-state facilities within a radius from the centroid location of the county is taken. A characteristic (e.g. price and driving distance) of the hypothetical out-of-state option is the average of the corresponding characteristic of all facilities in that group weighted by either trash volume of those facilities or inverse driving distance. Waste volume and inverse traveling distance of a facility are considered as weights because they highlight the importance of the facility's presence in the market. The analysis results using this alternative process does not change the main results. Overall, out-of-state exports make up a very small amount of California solid waste, 1.16% during this whole period.

[11] Since 2006, the state of destination has been observed but the out-of-state facility of destination has still not been available.

B Test of Market Boundaries Using 2SLS Models

TABLE 1: Price responses and distance responses in different-boundary markets

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Market radius	50	50	60	60	80	80	100	100	120	120
price	-0.0136	-0.0152	0.0087	-0.0105	0.0190	-0.0184	0.0280	-0.0156**	0.0080	-0.0106**
	(0.0407)	(0.0270)	(0.0285)	(0.0193)	(0.0269)	(0.0116)	(0.0277)	(0.0071)	(0.0186)	(0.0054)
distance*fuel	-0.5805***		-0.4190***		-0.2276***		-0.1512***		-0.1012***	
	(0.0589)		(0.0437)		(0.0183)		(0.0108)		(0.0064)	
ori-des FE		Y		Y		Y		Y		Y
time-ori FE	Y		Y		Y		Y		Y	
Radius	50	50	60	60	80	80	100	100	120	120
Observations	27515	27515	36186	36186	57005	57005	81206	81206	109596	109596
Adjusted R^2	0.600	0.919	0.478	0.905	0.404	0.896	0.335	0.894	0.288	0.881

Note: The table present how trash flows respond to price and distance by using 2SLS models and different defined market sizes. The sample of analysis includes all combinations of waste flows from an origin county to a destination facility within the defined radius. Price value of an observation cjt is instrumented by the sum of market sizes of other relevant market $M_{-c,jt}$. A market is relevant if that is not the instrumented market c but it contains facility j in its choice set.

C Examine the Percentage of Affected People By Different Ranges of Neighborhood

TABLE 2: People of 1-mile exposure to facility relative to facility's county levels

	(1)	(2)	(3)	(4)
	% white	% Asian	% black	%Hispanic
trash (mil tons)	-0.4463**	-0.0996	-0.2618**	-0.3007
	(0.1727)	(0.0896)	(0.1312)	(0.2297)
median hh income($1000s)	-0.0033	0.0011	-0.0036	-0.0110*
	(0.0039)	(0.0018)	(0.0066)	(0.0066)
Constant	0.8092**	0.2512*	0.6507	1.2577**
	(0.3454)	(0.1268)	(0.4938)	(0.5518)
year	2010	2010	2010	2010
SE	robust	robust	robust	robust
Observations	103	103	103	103
R^2	0.029	0.006	0.012	0.025
Adjusted R^2	0.010	-0.014	-0.008	0.005

Note: This table reports how the affected population by race responds to trash amount in a nearby trash site within 1 mile. Dependent variable is Affected Level$_j = \frac{\#\text{people of the race in a facility's 1-mile buffer}_j}{\#\text{people of the race in a facility's county}_j} \times 100$. Separate regressions are done for different race groups. Significant level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE 3: People of 2-mile exposure to facility relative to facility's county levels

	(1) % white	(2) % Asian	(3) % black	(4) %Hispanic
trash (mil tons)	-0.9313**	-0.4388**	-1.0489	-0.8499
	(0.3722)	(0.2117)	(0.6937)	(0.5741)
median hh income($1000s)	-0.0086	-0.0058	-0.0218	-0.0319*
	(0.0098)	(0.0079)	(0.0211)	(0.0169)
Constant	1.8758**	1.3847**	2.9139	3.4890**
	(0.8007)	(0.5556)	(1.7612)	(1.4155)
year	2010	2010	2010	2010
SE	robust	robust	robust	robust
Observations	103	103	103	103
R^2	0.029	0.022	0.015	0.030
Adjusted R^2	0.009	0.003	-0.005	0.010

Note: This table reports how the affected population by race responds to trash amount in a nearby trash site within 2 miles. Dependent variable is Affected Level$_j = \frac{\text{\#people of the race in a facility's 2-mile buffer}_j}{\text{\#people of the race in a facility's county}_j} \times 100$. Separate regressions are done for different race groups. Significant level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE 4: People of 5-mile exposure to facility relative to facility's county levels

	(1) % white	(2) % Asian	(3) % black	(4) %Hispanic
trash (mil tons)	-5.0165***	-4.4788**	-4.0808**	-4.0361**
	(1.5473)	(1.9285)	(1.7174)	(1.7077)
median hh income($1000s)	0.0317	0.0310	-0.1074	-0.1153*
	(0.0497)	(0.0639)	(0.0872)	(0.0658)
Constant	8.9063***	10.1468***	16.9322***	17.7059***
	(2.6939)	(3.3091)	(5.0122)	(4.2066)
year	2010	2010	2010	2010
SE	robust	robust	robust	robust
Observations	103	103	103	103
R^2	0.037	0.020	0.049	0.048
Adjusted R^2	0.018	0.000	0.030	0.029

Note: This table reports how the affected population by race responds to trash amount in a nearby trash site within 5 miles. Dependent variable is Affected Level$_j = \frac{\text{\#people of the race in a facility's 5-mile buffer}_j}{\text{\#people of the race in a facility's county}_j} \times 100$. Separate regressions are done for different race groups. Significant level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

D Examine the Demographic Distribution of Waste by Different Ranges of Neighborhood

TABLE 5: Current distribution of county waste share in 1-mile neighborhoods of facilities

	(1)	(2)	(3)	(4)	(5)
Dependent			market share		
Zero population	-0.499	2.943	1.393	-0.004	-4.303
	(7.767)	(8.622)	(8.411)	(8.686)	(7.776)
% black	-0.035	-0.002	0.030	0.223	0.155
	(0.136)	(0.149)	(0.157)	(0.201)	(0.192)
% Hispanic	-0.021	-0.004	-0.010	-0.042	-0.019
	(0.046)	(0.047)	(0.047)	(0.059)	(0.057)
% Asian	0.047	0.037	0.040	-0.007	0.072
	(0.066)	(0.066)	(0.062)	(0.073)	(0.083)
Income ($1000s)		0.055	0.030	0.023	0.011
		(0.060)	(0.057)	(0.071)	(0.074)
price			0.142*	0.208**	0.185**
			(0.083)	(0.105)	(0.093)
distance*fuel				-0.182***	0.013
				(0.043)	(0.044)
nonlocal					-20.572***
					(3.043)
quarter FE	Y	Y	Y	Y	Y
ori cnty FE	Y	Y	Y	Y	Y
N	1478	1478	1478	1478	1478
unclustered N	1114	1114	1114	1114	1114

Note: This table reports coefficients of a Tobit model. Dependent variable is market shares, i.e. share of a generating county's waste to a facility. Dependent variable is weighted by market size, i.e. total waste generated by a county. Demographic characteristics of facilities are characteristics of community within 1 miles of a facility. The sample only includes observations in 2010. The Tobit regression includes quarter fixed effects and waste-origin county fixed effects. Significant level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE 6: Current distribution of county waste share in 2-mile neighborhoods of facilities

	(1)	(2)	(3)	(4)	(5)
Dependent			market share		
Zero population	0.637	17.591	15.357	16.316	5.746
	(9.383)	(11.669)	(11.807)	(11.618)	(10.090)
% black	0.065	0.133	0.128	0.699***	0.527***
	(0.225)	(0.235)	(0.236)	(0.205)	(0.192)
% Hispanic	-0.003	0.110*	0.098	0.032	0.051
	(0.053)	(0.064)	(0.067)	(0.081)	(0.076)
% Asian	0.090	0.087	0.088	-0.035	0.099
	(0.091)	(0.089)	(0.086)	(0.112)	(0.116)
Income ($1000s)		0.236***	0.209**	0.228**	0.184*
		(0.085)	(0.089)	(0.104)	(0.105)
price			0.077	0.126	0.124
			(0.076)	(0.092)	(0.085)
distance*fuel				-0.207***	-0.010
				(0.037)	(0.041)
nonlocal					-19.951***
					(3.005)
quarter FE	Y	Y	Y	Y	Y
ori cnty FE	Y	Y	Y	Y	Y
N	1478	1478	1478	1478	1478
unclustered N	1114	1114	1114	1114	1114

Note: This table reports coefficients of a Tobit model. Dependent variable is market shares, i.e. share of a generating county's waste to a facility. Dependent variable is weighted by market size, i.e. total waste generated by a county. Demographic characteristics of facilities are characteristics of community within 2 miles of a facility. The sample only includes observations in 2010. The Tobit regression includes quarter fixed effects and waste-origin county fixed effects. Significant level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE 7: Current distribution of county waste share in 5-mile neighborhoods of facilities

	(1)	(2)	(3)	(4)	(5)
Dependent			market share		
% black	0.019	0.372	0.340	0.928***	0.653**
	(0.236)	(0.258)	(0.256)	(0.252)	(0.278)
% Hispanic	-0.026	0.163**	0.152*	0.170*	0.171*
	(0.059)	(0.080)	(0.081)	(0.099)	(0.099)
% Asian	0.089	0.084	0.103	-0.038	0.091
	(0.087)	(0.086)	(0.082)	(0.094)	(0.116)
Income ($1000s)		0.315***	0.286***	0.422***	0.354***
		(0.083)	(0.086)	(0.119)	(0.126)
price			0.115	0.132	0.136
			(0.078)	(0.095)	(0.087)
distance*fuel				-0.208***	-0.018
				(0.036)	(0.040)
nonlocal					-19.027***
					(3.284)
quarter FE	Y	Y	Y	Y	Y
ori cnty FE	Y	Y	Y	Y	Y
N	1478	1478	1478	1478	1478
adj. R^2					
N_unc	1114.000	1114.000	1114.000	1114.000	1114.000
ll	-1.402e+09	-1.395e+09	-1.394e+09	-1.351e+09	-1.321e+09

Note: This table reports coefficients of a Tobit model. Dependent variable is market shares, i.e. share of a generating county's waste to a facility. Dependent variable is weighted by market size, i.e. total waste generated by a county. Demographic characteristics of facilities are characteristics of community within 5 miles of a facility. The sample only includes observations in 2010. The Tobit regression includes quarter fixed effects and waste-origin county fixed effects. Significant level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$