When Does "Not in My Backyard" Make Matters Worse? Environmental Justice Concerns in Solid Waste Disposal *

Phuong Ho †

September 23, 2020

Download the most recent version here.

Abstract

In many recent U.S. Congress sessions, several state and local governments have attempted to legalize transboundary waste flow controls. 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 hauling costs and the perspective of environmental justice of not-in-my-backyard (NIMBY) policies. 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 NIMBY regulations would reduce intercounty waste transport. However, they tend to lead to substitution of waste away from facilities near white residents and toward facilities near Hispanic residents, potentially exacerbating distributional concerns.

Keywords: Distributional effects; Environmental justice; Intercounty trash flows; NIMBY; Solid waste

JEL Classification: D63; L90; L98; Q52; Q53; Q58

*This paper is based on chapter two of my Ph.D. dissertation at the University of Arizona (UA). Earlier version was circulated under the title "If Not in My Backyard, Where? The Distributional Effects of Restricting Interjurisdictional Waste Flows." I am indebted to Ashley Langer and Mauricio Varela for their help. I thank Price Fishback, Antonio Galvao, Soheil Ghili, Gautam Gowrisankaran, Corbett Grainger, Derek Lemoine, Mateusz Mysliwski, Linda Nøstbakken, Stanley Reynolds, and the seminar participants at the UA, Kobe University, Norwegian School of Economics, the 2019 European Association for Research in Industrial Economics meetings, and the 2020 Economics of Inequality and the Environment (EAERE post-conference) workshop for valuable comments and discussions. I acknowledge financial support from the UA Graduate & Professional Student Council (RSRCH-105FY18) and Dr. Stanley Reynolds.

†SNF – Centre for Applied Research at NHH, Helleveien 30, NO-5045 Bergen, Norway. Email: phuong.ho@snf.no.

1 Introduction

Every year, the U.S. generates more than 200 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. In the 115th Congress (2018–2019), the TRASH Act was proposed to authorize states to limit interstate waste flows.[2] Using the data on intercounty waste flows in California, this paper studies the economic inefficiency costs of NIMBY policies in terms of haulers' costs and the implications of NIMBY regulations on environmental justice.

In contrast to other nuisance issues, municipal solid waste is distinct because generating sources can differ from receiving places. People may get rid of the trash they generate by depositing it in a different place. This escapability creates political hotbeds and protests when one's backyard becomes a dumping ground for others, especially if the disposal is not environmentally sound. However, the court considers waste to be an ordinary commodity (*Philadelphia v. New Jersey*, 1978). The industry reasons that its choices of disposal facilities are economically efficient, because wide differences in disposal fees justify incurring transportation costs.

Therefore, I consider the economic tradeoff underlying the choice of where to dump to address the costs of restricting transboundary waste flows. I model the haulers' decisions about where to deposit their collected waste, considering their preferences for disposal fees, 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 disposal market. The hauler may exploit the variation in disposal fees to cart waste to a distant disposal facility even though the facility is outside the county of waste origin.

My model follows a revealed preference approach and 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)). To overcome price endogeneity and measurement error issues in estimating price coefficient, I instrument for a facility's price in a county by total waste (market sizes) of other nearby counties. This instrument variable is correlated with the facility's price in a specific county due to the (dis)economy of scale of the facility. For example, suppose the landfill currently has an economy of scale. Then, the landfill is likely to charge low disposal fees when receiving a lot of waste from its surrounding markets. Hence, if a hauler is in a county that is near other counties that generates a lot of waste, the hauler will likely face lower prices at a landfill that serves all these counties. This

[1] I refer to short tons unless specified otherwise. The U.S. Environmental Protection Agency (2017) reports that 268 million tons of solid waste were generated in 2017.

[2] Interjurisdictional waste flow controls have been overturned by the Supreme Court on the grounds of violating commerce clause. Legislative efforts have been put into a number of crafted bills in Congresses, but none of the bills have been enacted.

instrument variable has variation across time and does not suffer measurement error when observed prices are listed prices rather than differentiated-by-market contracted prices, adding to the literature on industrial organization that has employed direct cost shifters (input prices), BLP instruments, or Hausman instruments (see Berry et al. (1995); Hausman (1996); Nevo (2001)).

Given the estimated parameters underlying the haulers' decisions, I quantify how these decisions about where to deposit waste would change in several counterfactual scenarios, holding facilities' characteristics constant. I consider four counterfactual NIMBY policies: transboundary waste prohibition, transboundary waste tax, trash tax (regardless of its origin), and fuel tax.[3] Results show NIMBY policies would reduce the waste amount that crosses county lines. However, import bans and fuel taxes would reduce the disposal fees haulers pay for waste disposal, implying that haulers cart waste to disposal facilities outside the waste-generating county for benefits besides disposal fees. These benefits are associated with facility features such as high capacity, flexible operation hours, high acceptance rates in terms of low hassle costs of intermediary diversion before disposal, and so on. In all cases, NIMBY would impose economic costs on haulers, by rerouting disposal to expensive facilities or giving up other benefits at previously preferred facilities. For example, an intercounty waste transport ban in California would stop 17% of the generated waste that one county ships to other counties in 2010, but would cost haulers in the shipment-origin county $3.86 million on average.

These results add to previous studies that address interstate waste flow controls. In the hazardous waste market, Levinson (1999a,b) show interstate waste taxes decrease shipments of waste to states with high taxes, and provide an estimate of the tax elasticities. In the solid waste market, Ley et al. (2000, 2002) find limitations on the size of shipments can increase interstate waste shipments, because states would export smaller volumes to more destinations. They use the aggregate data at the state level and characterize the state planner's intertemporal allocation of waste disposal, assuming the demand for waste disposal services is linear and a competitive equilibrium.[4] My model, however, considers the haulers' decision about which disposal facility to uncover the effects of interjurisdictional trade barriers on the distribution of products in the presence of market power in the industry. The model accounts that disposal landfills have market power because waste disposal is a differentiated service in price and in distance between a generating place and a disposal facility. This accountability helps evaluate and explain the impact of NIMBY regulations in the way they interfere with the hauling decision.

This paper also contributes to the literature on environmental justice by being the first to address the racial distribution of waste *flows* and the implications of NIMBY regulations on this distribution.

[3] 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 along its route. A fuel tax tends to penalize long-haul transportation and can be considered an implicit NIMBY restriction on transboundary waste transport.

[4] Ley et al. (2000) follows the approach of Nordhaus et al. (1973) to model the use over time of spatially differentiated resources. Ley et al. (2002) applies the model of Gaudet et al. (2001) to determine the solution for the intertemporal planning problem.

Previous studies have examined the disproportionate exposure to undesirable materials by focusing on the total concentration of a hazard at a facility and comparing the demographic composition between a nearby exposed neighborhood and areas that are far away, for example, Baden and Coursey (2002); Mohai and Saha (2007); Depro et al. (2015). I, on the other hand, consider the variation in waste shipments coming from a county to different disposal facilities. Considering all available disposal facilities within 60 miles in driving distance of the population center of the waste-generating county, does the demographic feature of the neighborhood surrounding the facility explain the facility choice?

The analysis of the status quo correlation between race and waste flows in California in 2010 shows waste is more likely to be sent to facilities in communities with a high percentage of minorities than to facilities in white communities. The disparities for black communities and Hispanic communities persist once I control for income, disposal fees, and distance. The analysis reveals facilities in Hispanic communities may have low disposal fees and be mostly close to the population center of the waste-generating counties. However, there are other unobserved characteristics of the neighborhoods that matter in haulers' decisions for facilities in black communities.

Although establishing a causal effect or showing exactly the causes of environmental injustice is beyond the scope of this paper, the results highlight NIMBY regulations would generally not lead to a more equitable distribution of waste. Waste that is sent to facilities near white residents would be rerouted to facilities near Hispanic residents, potentially exacerbating distributional concerns. The reason is that facilities in Hispanic communities have low disposal fees and are close to the waste-generating places. Meanwhile, waste that is sent to facilities in black communities would remain fairly constant. As expected from the status-quo analysis, the reason is that facilities in black communities offer other benefits beyond disposal fees and transport distance that capture haulers' preferences. Although the exact reasons are not examined, the results suggest policies that target disposal prices and transport costs would not significantly affect the trash percentage going to these facilities. For example, if haulers prefer facilities in black areas because these facilities do not follow the environmental standards and easily accept all of the trash the haulers transfer to, frequent inspections and strict enforcement of the standards will provide a better scope in waste management than price-target or transport-cost-target policies.

The rest of the paper is structured as follows. Section 2 provides background on the solid waste disposal industry and NIMBY legislation, as well as the environmental justice literature. Section 3 shows a general picture of waste disposals in California, where the data are focused. Section 4 presents the model of haulers' decisions about where to deposit waste from each county and the estimation results. Section 5 reports the impacts of counterfactual NIMBY regulations on intercounty waste flows and the costs of haulers. Section 6 discusses the unintended consequences of NIMBY on environmental justice. Section 7 concludes with a summary and suggested extensions.

2 Background

2.1 The solid waste disposal industry and NIMBY legislation

Municipal solid waste (MSW), commonly known as "trash" or "garbage," is the every-day waste type generated by residential, municipal, and commercial establishments. It does not include special-handling waste, such as waste from manufacturing processes, regulated medical waste, sewage, or hazardous waste. A waste collection firm, or "hauler," collects MSW from households and commercial establishments. After collecting a truckload of trash, the hauler transports the trash to a disposal site, a landfill or an incinerator. If no landfills or incinerators are nearby, he may unload the trash at a transfer station. The transfer station consolidates waste into a larger vehicle and transports it to a landfill or incinerator. The transfer station also often removes hazardous materials and diverts waste for recycling or reuse prior to final disposal. Of the 268 million tons of MSW in 2017, 52% was landfilled, 35% was recycled, and 12% was incinerated.

Historically, disposal of MSW took place at local town dumps but was then transported to regional and large scale facilities. In the 1990s, stricter government regulation to protect human health and the environment led to major changes in the scale and scope of waste-handling technologies.[5] Many landfills that did not meet the standards were forced to closed. The town dumps were replaced by state-of-the-art and large scale facilities.[6] The amount of MSW transported across states and counties also increased dramatically. Between 1989 and 1999, the interstate waste transport rose by 300%, from 10 million tons to 30 million tons (Repa (2005)).

Several states became overwhelmed by the increasing waste imports and attempted to limit the flows. Many citizen groups, environmental organizations, and state legislators expressed concern about being a dumping ground, the impact of landfill growth on local property values, the limited capacity of local landfills, and the interference with local recycling efforts (if waste was imported from places with poor handling standards). The opposition led to several ordinances that taxed out-of-state waste, restricted imports to waste of equivalent handling standards, or even banned the imports. However, the Supreme Court's decisions overturned these attempts on the basis that they discriminated against interstate commerce. The court found waste to be "ordinary commodity" and restriction on interstate shipments of the ordinary commodity to be "protectionist" (*Philadelphia v. New Jersey*, 1978). The Supreme Court also made clear that under the "dormant" Commerce Clause of the Constitution, states may not erect barriers to interstate commerce unless Congress explicitly allows

[5] The Congress sought a reform of MSW management in subtitle D of the 1976 Resource Conservation and Resource Recovery Act (RCRA). The U.S. EPA established final rules and implemented the practices from 1991 to 1997. These rules set criteria for location restrictions and standards for the design, operation, groundwater monitoring, financial assurance, closure and post-closure care for MSW landfills.

[6] Kinnaman and Fullterton (1999) note that prior to the RCRA, almost every town in the U.S. had a local dump. Macauley (2009) reports that the number of landfills in 1988 was nearly 8,000 but fell to 2,300 in 1998. Repa (2000) notes that while the number of public landfills decreased, the number of private landfills increased substantially, from 17% in 1984 to 36% in 1998.

it.[7]

Hence, 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 has not been successfully enacted.[8] 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 charge a fee for out-of-state waste.

This paper studies the effects of NIMBY policies in terms of taxing or banning interstate waste flows and seemingly nondiscriminatory policies such as waste tax (regardless of the waste's origin) and fuel tax. I focus on the cost argument against NIMBY that interstate waste transport is efficient. Private haulers in the court cases against the flow control ordinance of a municipality argued the control prevented them from accessing economic landfills. Ley et al. (2002) and Macauley (2009) comment long-haul waste shipments became popular to exploit the wide differences among disposal fees that justified incurring transportation costs.[9] Therefore, I focus on how NIMBY policies, by altering disposal fees, fuel costs, or alternative options of facilities, affect the waste flows and the efficiency in terms of the haulers' costs.

A growing amount of recent research has also explored the waste industry. Greenstone and Gallagher (2008), and Gamper-Rabindran and Timmins (2011) study the effects of Superfund-sponsored cleanups of hazardous waste sites on housing values. Currie et al. (2011) find Superfund cleanups reduce the incidence of congenital anomalies by about 20%–25%. Kamita (2001) considers the final disposal stage and analyzes the market structure consequences of mergers between two disposal firms. Kawai (2011) explores the recycling stage and studies auction design when sellers have incentives to invest in quality improvement in municipal plastic recycling auctions in Japan. Salz (2017) focuses

[7] Some examples include a New Jersey statute that prohibited out-of-state waste imports in *Philadelphia v. New Jersey* (1978), an Alabama statute that imposed a fee on out-of-state hazardous waste in *Chemical Waste Management Inc., v. Guy Hunt, Governor of Alabama* (1992), an Oregon statute that imposed a 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).

[8] In 1994, both the House and Senate passed the "State and Local Government Interstate Waste Control Act" that prohibits 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 a lack of agreement on common language in the enactment. Another bill in a later session (S. 534 in 1995) that authorizes states to prohibit out-of-state solid waste and to reinforce local waste flow control exercised before 1994 was passed in the Senate but retained in the House.

[9] Of course, the long-haul shipments are also a means to access large-scale facilities, and especially the results of closing many landfills and opposition to expanding capacity at existing facilities or building new ones. But these factors are reflected in differences in disposal fees. Ley et al. (2002) provide an example in which the trend in interstate waste from Northeast to Midwest during the early 1990s was due to the closing of many landfills in New York and New Jersey. These closures caused a sharp increase in disposal fees at the remaining facilities: The fee at Fresh Kills landfill rose from \$80 to \$150 per ton. By contrast, the average fee in midwestern states is significantly lower, about \$25-\$30 per ton. Thus, even with the transportation costs, exporting waste to the Midwest can remain cheaper.

on the collection stage and studies the role of intermediaries between commercial establishments and private waste haulers in New York trade waste collection market. Ho (2019) considers changes in neighborhood demographics in response to openings and closings of solid waste facilities to test the residential mobility hypothesis in environmental justice analysis.

2.2 Environmental justice

In addition to the economic inefficiency costs, I consider the environmental justice evaluation of NIMBY policies. Addressing the environmental justice perspective of a regulation is important because the U.S. EPA has recently integrated environmental justice in their programs and policies. Following President Clinton's issuance of a 1994 executive order and federal actions to address environmental justice in minority populations and low-income populations, Plan EJ 2014 was issued to lay a foundation for integrating environmental justice in EPA activities. The EJ 2020 Action Agenda then provides strategic plans for advancing environmental justice. This paper is the first to address the environmental justice perspective of (counterfactual) NIMBY policies.

The environmental justice movement started from the illegal dumping of 31,000 gallons of PCB-contaminated oil along 240 miles of North Carolina highways. The state collected contaminated soil and identified a landfill site for the waste. Contention was heated when a Warren County site, which was predominantly low income and black, was chosen. Protests that followed led to the first two influential studies by the U.S. General Accounting Office (1983) and the United Church of Christ's Commission on Racial Justice (1987) that showed poor and minority groups were unevenly exposed to hazardous waste sites in many parts of the U.S.

The literature has been gathering evidence and providing alternative explanations for the observed correlations between race, income, and undesired environmental risks. A recent review by Banzhaf et al. (2019) classifies possible mechanisms into four categories: disproportionate siting by firms, "coming to the nuisance" on the household side, market-like coordination between the two sides in a Coasean bargaining process, and discriminatory politics and enforcement. For example, Anderton et al. (1994), Baden and Coursey (2002), and Mohai and Saha (2007) revisit racial disparities around hazardous waste treatment facilities using several methods to better control for proximity between hazardous sites and nearby residential populations. They find the disparities persist even when controlling for economic and sociopolitical factors, suggesting that factors uniquely associated with race, such as racial targeting, housing discrimination, and so on are associated with the location of hazardous waste facilities. Wolverton (2009) models firm location as a decision variable and finds the disproportionate siting seems to arise from economic factors such as land cost, labor, and access to transportation, rather than directly from local demographics. Banzhaf and Walsh (2008), Banzhaf and Walsh (2013), Gamper-Rabindran and Timmins (2011), Depro et al. (2015), and Ho (2019) consider changes in demographic composition over time and suggest environmental injustice is explained by nuisance-driven residential mobility. Timmins and Vissing (2017) examine the content of leases between shale gas operators and households in Tarrant County, Texas, and find race and speaking in English are correlated with lease terms and royalty compensation. Gray and Shadbegian (2004) and Shadbegian and Gray (2012) examine the determinants of regulatory stringency in terms of penalties and inspection frequencies in communities near polluting facilities, and find mixed results.

This paper focuses on environmental justice in terms of the distribution of waste *flows*. Previous studies have studied the disproportionate exposure patterns by focusing on the total concentration of undesirable materials at a site. They compare a neighborhood that is exposed to the materials with places that are far away from the site. I, on the other hand, exploit the variation in waste shipments that originate from a county but end up at different disposal facilities. These waste shipments arise as a result of haulers' optimization choices for disposal facilities, which may correlate with the racial composition of the surrounding neighborhoods, leading to unintended consequences of NIMBY regulations.

3 Data: Solid waste disposal in California

To illustrate the effects of NIMBY on interjurisdictional waste flows, I use the data on intercounty waste in California. This data restriction is due to not many states in the U.S. reporting waste flows. Whereas microdata about the amount of solid waste by place of origin and by disposal facility (landfills and incinerators) in California are available for a long-time frame, it is not the case in all other states. The amount of out-of-state exports from California is also very modest, 1.16% during 1995–2015, which allows the focus on intercounty waste transport.

Studying the effects of NIMBY on intercounty waste flows in California is not only a narrow illustration for interjurisdictional waste restriction at a bigger scope, but is also interesting by itself. In 1984, Solano county in California enacted Measure E, which limited imported quantities. The measure was then prevented from being enforced in 1992 due to the concern about violating the Commerce Clause. In 2009, opponents of the landfill expansion in Solano filed a lawsuit aimed at reinstating Measure E. In 2012, however, California passed a bill prohibiting local ordinances from restricting the importation of solid waste into a local privately-owned disposal facility based on place of origin.[10] The legislation on interstate waste restrictions by Congress may set a new precedent on intercounty flow controls.

I collect data on intercounty waste flows from the California's Department of Resources Recycling and Recovery (CalRecycle). The data show trash quantity by county of origin and by facility of destination quarterly from January 1995 to December 2015. This quantity dataset is then combined with the data on quarterly disposal price (tipping fees) from Waste Business Journal, an industry

[10]South Carolina also prepared a similar Senate Bill 203 in 2013, but the bill currently resides in the state Senate.

research and analysis company. In the waste industry, the tipping fee is known as the fee charged per ton to unload solid waste at a landfill or transfer station. To represent the driving cost, I use the interaction between quarterly diesel price and driving distance. I obtain California diesel prices from the Energy Information Agency and calculate driving distance from a population-weighted centroid of a county to a facility location using HERE maps.[11] For more details about the data and how they were processed for the analysis, see appendix A.

The data show the trends in waste disposal in California mirror the national trends. Figure 1a shows the total waste amount generated by a county increased steadily in the 1990s and early 2000s but dropped dramatically from 2005. The drop may be correlated with the economy recession in 2008, but it may be mainly attributed to great efforts of recycling and zero waste policies in California in the late 2000s. For example, in 2002, San Francisco set a goal of 75% diversion by 2010 and zero waste by 2020. The number of disposal facilities in fact has been decreasing since 1995; see Figure 1b. Mirroring the national trends in the 1990s due to the enforcement of the RCRA, a large number of disposal facilities were closed. California had more than 200 facilities in 1995, but the number fell to 170 in 1998.

Figure 1c shows average tipping fee (weighted by waste shipments) plunged from $38 per ton in 1995 to $33 per ton in 1997 but then escalated to $42 per ton beginning in 2005. The short-run drop in the 1990s may be attributed to the expansion of many state-of-the-art landfills and new builds of a few but large-scale facilities after the RCRA. Gradually, the mass of disposed trash and opposition to the expansion of existing landfills and construction of new landfills may dwindle existing disposal capacity, resulting in the jump in disposal fees.

Therefore, the increase in long-haul shipments of trash is not surprising. Figure 1d shows that, along with the drop in the number of local 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; see Figure 1e.

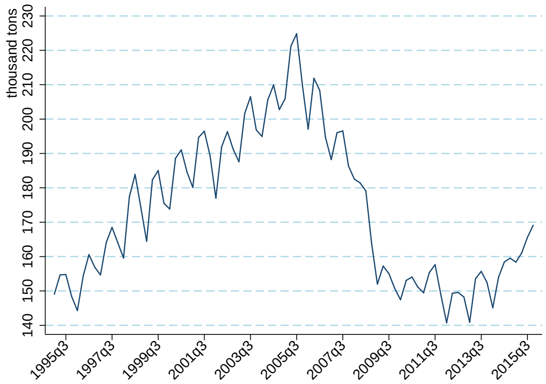
However, note the shipping distance is still in a reasonable economic range. My conversations with waste collection companies as well as with a representative in the National Waste & Recycling Association, a trade association for the private waste management sector, reveal that trucks generally cart waste to a disposal facility that is less than about 30–45 miles from the place of collection. Figure 1f plots the percentage of waste transported beyond a given distance. It shows less and less trash is shipped to a facility if the transport distance increases. The amount of trash carted plummets quickly for the distance ranging from 30 to 60 miles, followed by a flat tail for distances beyond 60 miles (up until 613.56 miles according to the 1995–2015 data).

The reason for the focus on the reasonable economic range of shipping distance is to define the

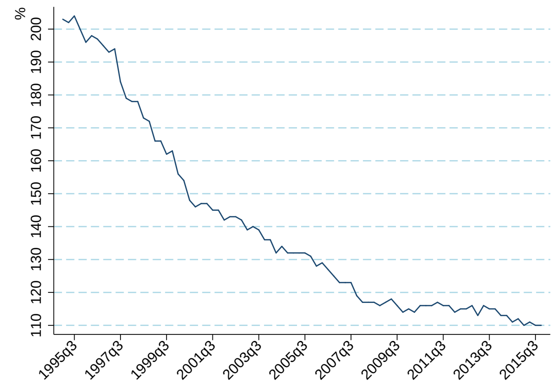
[11] HERE is a company working on digitizing mapping and in-car navigation systems, `https://www.here.com/company`.

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

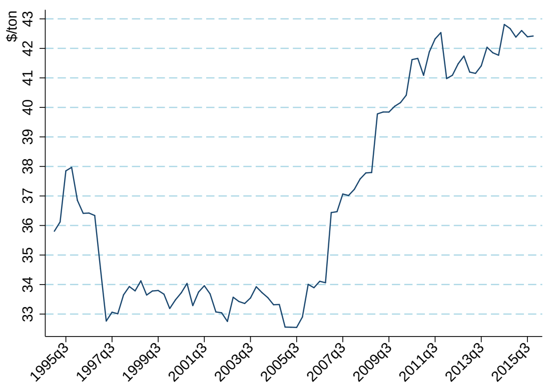
(A) Total waste amount generated by one county



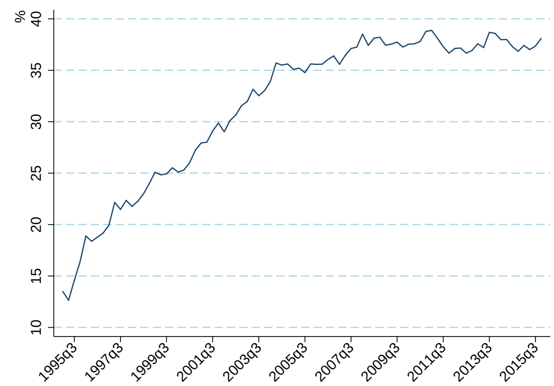
(B) Number of disposal facilities in California



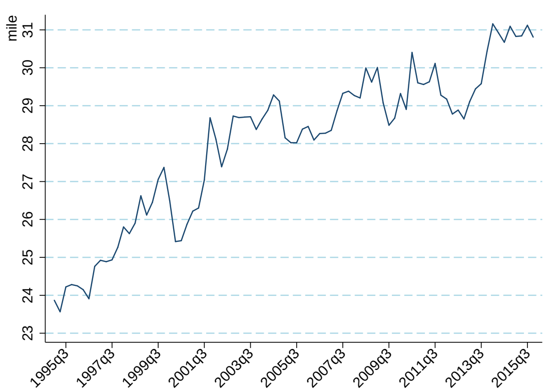
(C) (Waste weighted) average disposal price (in 2000 dollars) paid by haulers in one county



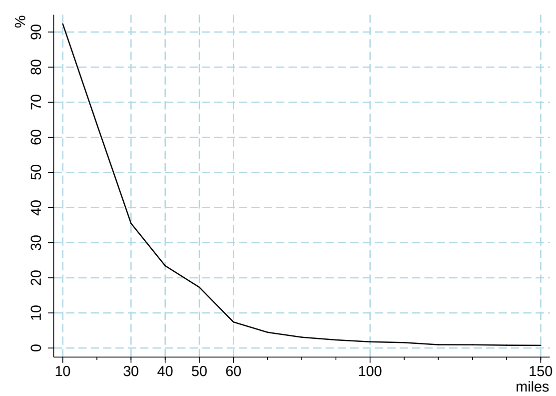
(D) Percentage of waste one county sends to other counties



(E) (Waste weighted) average distance of waste shipments from one county to a disposal facility



(F) Percentage of waste transported beyond a given distance



Note: The graph shows a general picture of waste flows in California from quarter 1, 1995 to quarter 4, 2015. Distance is driving distance from population-weighted coordinate of the waste-generating county to a disposal facility. Panel 1f shows the percentage of waste that is transported beyond a given distance in 2015.

economic choice set of disposal facilities for a hauler that I describe in detail in the next section. When I move to the analysis of waste flows, I limit the analysis to flows within 60 miles. This restriction is reasonable because we have seen that most of the waste transported within 60 miles and the trash beyond 60 miles composes a very flat tail on the distribution of waste by distance. Sixty miles is also a plausible limit compared to the 30–45 miles suggested by the industry, because I measure the distance between the population-weighted centroid of the trash-generating county and the destination facility rather than an exact location of the pickup. In short, this paper aims to explain the economic incentives underlying the 60-mile waste flows, which makes up more than 90% of the waste generated in California.

4 Modelling waste flows

In the MSW industry, activities in the collection stage result from both exclusive contracts between a local government and a hauler, and nonexclusive services between market participants. Waste generated by residential customers is often collected either by local governments or by private haulers pursuant to contracts bid on by, or franchises granted by municipalities. These contracts and franchise agreements grant exclusive rights for the hauler to collect waste in a defined residential area. However, private waste haulers can contract directly with businesses and multi-family establishments for the collection of waste generated by commercial accounts.

In the disposal stage, a municipality has more difficulty controlling waste flows. The disposal market has both public landfills (owned by municipality) and private facilities. Trash collected by haulers is disposed of at a facility governed by economic incentives such as tradeoff between transport costs and disposal fees rather than directed by a flow control. In fact, several flow controls by a local government trying to designate a facility to be used by haulers were challenged by Courts for violating the Commerce Clause. Exceptions of successful flow controls are cases in which the local government acts as a market participant, choosing a disposal facility for themselves after collecting the trash.[12]

The MSW industry has several cases of vertical integration but keeps certain degree of competition. In responding to stricter regulations on operation standards in the 1990s (the RCRA), some private firms, such as Waste Management Inc. and Republic Services Inc., found vertical integration is a means to consolidate economy of scale and ensure large volumes of waste could be taken to large-scale facilities. As McCarthy (2004) notices, consolidated firms often ship waste to their own disposal facility across a border, rather than to an in-state facility owned by a rival. However, Kamita (2001) suggests the disposal market has room for competition. In fact, many merger and acquisitions cases have been challenged by the U.S. Department of Justice.[13]

[12] Macauley (2009) reviews many cases for successful and unsuccessful flow controls by a municipality.

[13] For example, *U.S. v. Waste Management, Inc., et al.* (1988), U.S., *New York Pennsylvania and Florida v. Waste Management, Inc., et al.* (1998), *U.S. v. Allied Waste Industries, Inc. and Republic Services, Inc.* (2000), *U.S. v. Waste*

In this paper, I consider the final places of waste disposal with an emphasis on the trade-off between transport costs and disposal fees. I abstract from the details of contracts and vertical integration in the industry to focus on how a final place for waste disposal is chosen to balance the transport costs of long-haul shipments with the opportunity to arbitrage differences in disposal fees.

4.1 The model

Assuming hauler i picks up waste amount q_{ict} in county c in quarter t, he chooses facility j to dump the trash to maximize his utility $U_{ijct}(X_{ijct}, \epsilon_{ijct})$, which is a function of X_{ijct} and ϵ_{ijct}. X_{ijct} are observables that include tipping fees and transport costs. Transportation costs are measured by the interaction between driving distances from a population-weighted centroid of a waste-generating county to a landing facility location and fuel prices.[14] ϵ_{ijct} is the unobservable match quality for hauler i. Given the observed price and distance, the utility is

$$U_{ijct} = \beta X_{jct} + \epsilon_{ijct} \equiv \beta_p \text{price}_{jt} + \beta_d \text{distance}_{cj} * \text{fuel price}_t + \gamma_j + \epsilon_{ijct}. \tag{1}$$

Several notices are marked. First, haulers i are hypothetical agents because I do not observe data at the hauler level. I instead observe the data at the market level, the waste amount from county c to facility j. Hence, the hauler in this model includes several cases. He can be a private hauler, a waste service firm that owns both the landfill and the collection service, or the municipality that later contracts with the private landfill's owner or owns the landfill themselves. In all cases, the justification between transport costs and disposal fees should be sensible and is the one I focus on.

Second, as a result, utility is the cost of disposal in terms of the surplus of waste collectors. The observed waste flows, without policy intervention, reflect efficiency in which the choice of a disposal facility currently maximizes the utility that takes account of transport costs from generation to final disposal, and tipping fees that reflect disposal costs on the landfill side.

Third, utility does not depend on waste amount q_{ict}. One reason is that the amount of waste collected is exogenous to haulers. The hauler does not decide the trash quantity he picks up, neither 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 respect, i is considered as a hauler$\times$trip. Another reason is that the hauler often uses trucks of similar sizes to travel to all destinations. His utility then does not hold an economy of scale.

Fourth, I control for facility fixed effects γ_j. As described, vertical integration and public versus private ownership may be a reason why waste is carried to a distant facility instead of a local dump. The facility fixed effects aim to control these time-invariant features of disposal facilities during 1995–2015. Although the fixed effects do not capture the vertical integration completely, they absorb parts

Industries USA, Inc. (2005), *U.S. v. Waste Management, Inc. and Deffenbaugh Disposal, Inc.* (2015), etc.

[14] Fuel price is the diesel index in quarter t in California, obtained from the U.S. Energy Information Administration.

of the variation in which consolidated firms are big firms with high-capacity landfills.

Assuming ϵ_{ijct} follows type I extreme value distribution, the probability that the facility j, of available options in the choice set C_{ct}, is chosen in decision i is

$$P_{ijct} = \frac{\exp(\beta X_{jct})}{\sum_{k \in C_{ct}} \exp(\beta X_{kct})} \equiv P_{jct}. \tag{2}$$

With this assumption of the unobservable (to an econometrician), the model is a familiar multinomial logit discrete choice models (see McFadden (1974); Berry (1994); Berry et al. (1995)), except no outside option exists. A hauler must choose a facility to dump all of his trash. The hauler does not keep the trash himself. Thus, no illegal dumping occurs either.

From the perspective of industrial organization, this model is the demand for disposal facilities. I do not model the supply side that characterizes how disposal facilities compete with each other. In other words, I do not endogenize the decisions of disposal facilities about disposal fee settings, capacity adjustments, or location choices. This is clearly a limitation of the model because it does not allow pass-through of NIMBY policies on the disposal facility side. However, the advantage is to give a transparent mechanism on key demand-side aspects of choice substitution and without misspecification implications. To some extent, given the rigidity of contracts between haulers and disposal facilities, disposal fees may remain the same for a few years after a NIMBY policy. This model, hence, sheds light on the short-run effects of NIMBY policies.

4.2 Defining choice sets

As mentioned in section 3, the analysis will cover waste flows within 60 miles of the population-weighted centroid of a county that generates trash. Therefore, the choice set for a hauler in county c in quarter t is the set of facilities within a 60-mile driving distance. As a further examination of economic incentives underlying these trash flows, I estimate the following regression:

$$s_{cjt} = \beta_d f_d(\text{distance}_{cj}) + \beta_p f_p(\text{price}_{jt}) + \gamma_{ct} + \eta_j + \epsilon_{cjt}. \tag{3}$$

The dependent variable s_{cjt} is the share of waste amount generated in county c to be disposed of at 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 deal with it in the estimation for the main model in the next section. Here, I emphasize the changes in price responses and distance responses among different knots of transport 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 $distance_{cj}$ from the baseline specification (regression equation (3)) and the coefficients on knots of $price_{jt}$ from the specification that inclues waste-origin county×facility fixed effects. Exact estimates are reported in Table B1 in the appendix. Results show significant negative effects of price and distance on trash flows in the first few knots of distance (from 0 to 90 miles). The effects dwindle in distance. Beyond 80–90 miles, trash flows no longer respond to price and distance, which confirms our assumption that a certain distance limit exists under which trash flows economically respond to price and distance. If waste is transported farther than that limit, it must haven been a reporting error or a designation beyond the economic reasons.

As said, I use 60 miles to define the market radius, which aims to explain at least 93% of waste disposal in California. A market is a county that generates trash. Decision makers are haulers (either private or public) in the county and face a choice set of alternative options that consists of all disposal facilities within 60 miles in driving distance of the population-weighted centroid of the county. Figure E1 in the appendix illustrates alternative options for different choice sets in the counties San Francisco and Los Angeles (the figure uses air distances instead of driving distances, however).

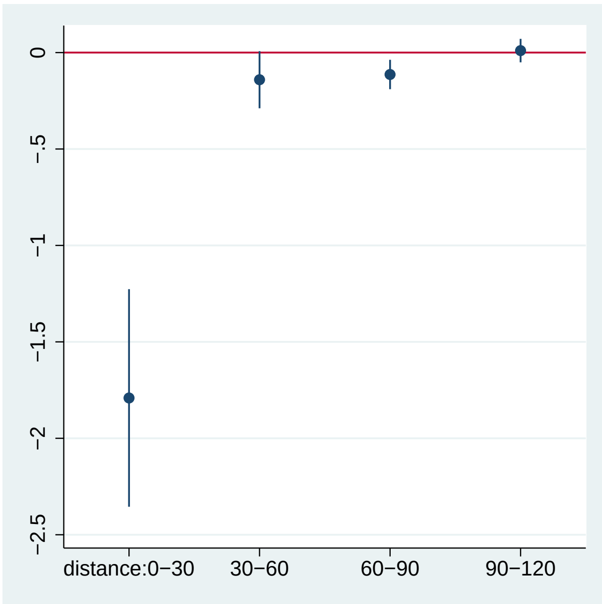
Table 1 shows summary statistics of this sample, that is, all combinations of flows within 60 miles. Panel A contrasts the waste-flow characteristics of the sample with the raw data of positive flows (without being restricted to 60 miles). The unit of observation is quarter × waste-origin county × waste-destination 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 21,000 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 of 60-mile options. The unit of observation is quarter × origin county. Compared to the unrestricted sample, the sample of 60-mile waste flows has fewer observations because in certain quarters, a few counties sent their waste to only facilities beyond 60 miles. The average market size (average trash amount a county generates) is about 175,000 tons. A county exports about 22% of its trash to other counties in the main sample. Haulers in a market have an average of eight options to dispose of their collected waste.

4.3 Estimation

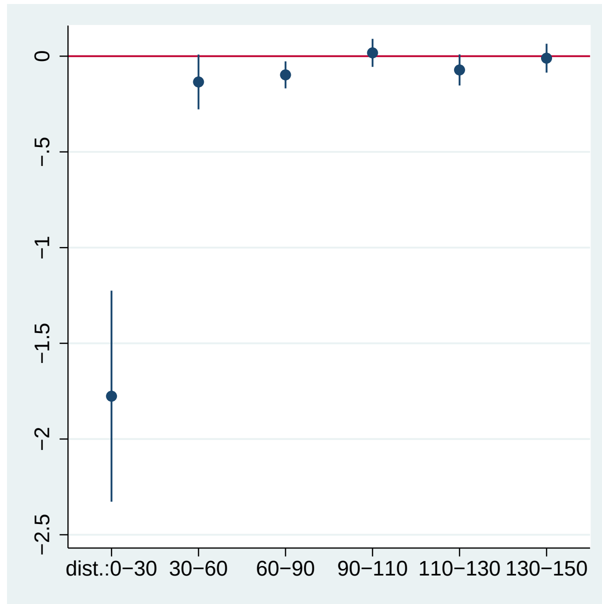
Estimating multinomial logit discrete choice models with data at the market level has been well documented in Berry (1994); Berry et al. (1995). The contraction mapping result in Berry (1994)

FIGURE 2: Price response and distance response by distance

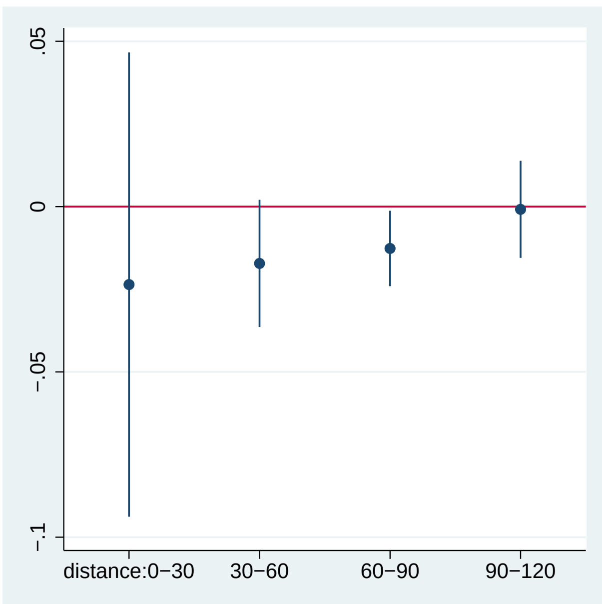
(A) Distance response in 120-mile waste flows



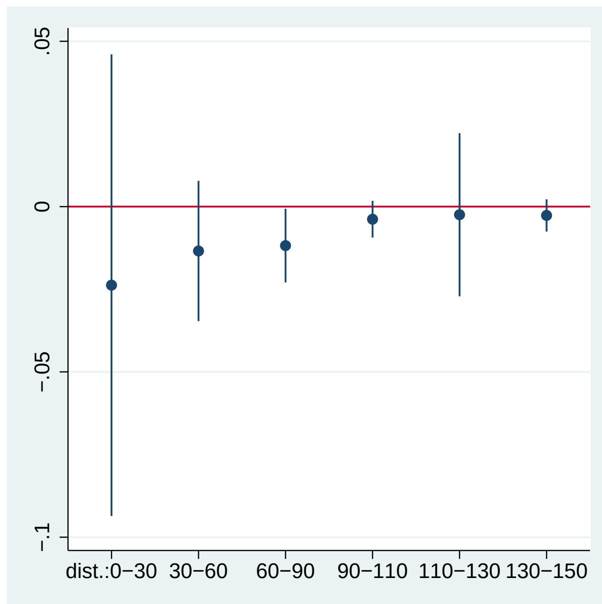
(B) Distance response in 150-miles waste flows



(C) Price response in 120-mile waste flows



(D) Price response in 150-mile waste flows



Note: Figure shows the coefficients of distance and price at different knots of distance (linear splines) of waste transportation, i.e., regression $s_{cjt} = \beta_d f_d(\text{distance}_{cj}) + \beta_p f_p(\text{price}_{jt}) + \text{fixed effects} + \epsilon_{cjt}$. Figures 2a and 2b show distance response after controlling county-by-quarter fixed effects and facility fixed effects, using the sample of all combinations of flows by a county and a facility within 120 miles and within 150 miles, respectively. Figures 2c and 2d show price response after controlling quarter fixed effects and origin-county-by-facility fixed effects, using the sample of flows within 120 and 150 miles, respectively. Point estimates are displayed with 95% confidence intervals. Standard errors are clustered by waste-origin county.

TABLE 1: Summary statistics of panels of waste flows

	count	mean	sd	min	max
Panel A: Flows characteristics (unit: quarter $\times$ origin county $\times$ 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	1.73	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 $\times$ 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; the unit of observation is quarter $\times$ origin county $\times$ 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 we have 24,473 observations of positive waste flows. Panel A2 includes 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 of the population-weighted centroid of the county (the number of options). Panel B2 is similar to panel B1, but covers all choices in California (including choices observed in waste flows beyond 60 miles).

shows a unique mean utility vector exists that matches the model-implied choice probability to observed market shares. Hence, given observed shares, we can solve for the choice probabilities and estimate preference parameters. However, this result only applies to the case of positive market shares. In my model, zero market shares may happen because a feasible facility in the choice set 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 use the following maximum likelihood estimation, which is similar to the work by Martin (2008) (cited in chapter 13 in Train (2009)).[15] The limitation is that

[15] Martin (2008) studies consumers' choice between incandescent and compact fluorescent light bulbs, where advertising and promotions occurred weekly and varied over stores, but stores commonly did not sell any fluorescent light bulbs

it does not measure individual heterogeneity in the choice probability of hauler/trip i within a market.

To obtain the model likelihood, start with the probability that hauler i chooses the facility j that he was actually observed choosing:

$$f(Y_{ict};\beta) = \prod_{j=1}^{J} P_{ijct}^{y_{ijct}}, \tag{4}$$

where $y_{ijct} = 1$ if hauler i chose j, and 0 otherwise (in market ct). The log-likelihood function of the model is

$$L(\beta) = \sum_{c,t}\sum_{i}\sum_{j} y_{ijct}\log P_{jct} \tag{5}$$

$$\Leftrightarrow L(\beta) = \sum_{c,t}\sum_{j}\log P_{jct}\sum_{i} y_{ijct}. \tag{6}$$

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

$$s_{jct} \equiv \frac{\sum_i q_{ict}y_{ijct}}{Q_{ct}} = \frac{q_{ct}\sum_i y_{ijct}}{Q_{ct}}, \tag{7}$$

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

$$L(\beta) = \sum_{c,t}\sum_{j}\log P_{jct}\cdot s_{jct}\cdot \underbrace{Q_{ct}/q_{ct}}_{N_{ct}}. \tag{8}$$

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

The first estimator assumes the number of haulers across different markets is the same, namely, $N_{ct} = N\ \forall c,t$, which implies that market sizes differ because the picked-up waste amounts vary across markets. The log-likelihood function is

$$L(\beta) = \frac{1}{N}\sum_{c,t}\sum_{j}\log P_{jct}\cdot s_{jct}. \tag{9}$$

The second estimator assumes the picked-up waste amounts across different markets have the same size, namely, $q_{ct} = q\ \forall c,t$, which means the trash collection trucks have the same size in the

in a given week.

whole California. The log-likelihood function becomes

$$L(\beta) = \frac{1}{q} \sum_{c,t} \sum_{j} \log P_{jct} \cdot s_{jct} \cdot Q_{ct}. \tag{10}$$

The second estimator implies that market sizes differ across markets because the number of collection trips and the number of haulers varies across markets. Given that this situation is more plausible, we use the second estimator for the main results. Appendix C shows the results of the first estimator.

4.4 Identification

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. Transport cost explains both the variation in trash shares to a facility from different counties and the variation in shares from a same county to different facilities.

Of course, the variation in trash shares within a county to different facilities is also explained by disposal prices and other factors. The panel data allow me to exploit cross-sectional and time-series variation to control for facility fixed effects. Including facility fixed effects helps identify the price preference and control other factors that explain the choice of a facility. Without facility fixed effects, estimates for the price parameter are upward biased because price is endogenous in which price positively correlates with omitted variables that positively affect the likelihood of choosing a disposal facility. For example, haulers that face the costs of diverting materials for different types of trash will prefer facilities that do not strictly check the coming trash and turn away their trucks. Haulers will also prefer facilities with flexible operation hours or those on easily accessible highways. Such factors likely contribute to the operation costs of facilities and add up to high disposal fees.

In addition to reducing upward bias in estimating the price parameter, facility fixed effects explain variation in trash shares beyond the explanation from transport costs and disposal fees. For example, vertically integrated firms likely ship waste to their own disposal facility across a border rather than dispose of it at a rival's local facility. Some municipalities successfully designate waste flows to a local public landfill without challenge by the Court, because they are acting as a market participant. Facility fixed effects take account of such nearly time-invariant factors (consolidated firms, public vs. private ownership, large-scale firms with high capacity) to explain variation in trash shares. Later, we see the fixed effects also capture the factors, other than transport costs and disposal price, that are correlated with the demographics of a community near a facility.

When taking a closer look at the price-parameter estimate, the difficulty in getting a consistent estimate is also to overcome bias due to measurement error. The reason is that I observe listed prices rather than deviations from these prices that haulers may pay if they were to sign contracts with individual waste facilities. 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 instrument construction adds to the literature on industrial organization that has used direct cost shifters, BLP instruments, and Hausman instruments; see Berry et al. (1995); Hausman (1996); Nevo (2001). Cost shifters such as prices of inputs that shift the supply but not the demand are rarely observed. Berry et al. (1995, 1999) use measures of isolation in characteristic space other than prices, such as own characteristics, sum of characteristics of other products produced by the own firm, or sum of characteristics of competitors' products. However, these instruments have little variation over time. Hausman (1996); Nevo (2001) suggest prices of own firm in different cities within a region are valid instruments due to common regional marginal cost shocks. Similar instruments that can be developed in my context are prices of (indirect) competitors that compete with the facility in other markets rather than the instrumented market. However, these instruments may suffer measurement error because listed prices are observed rather than transaction prices.

The market-size instrument in this paper is compelling because it is correlated with price even though deviations may exist between observed listed prices and actual contracted prices. The reason is that the disposal facility has strictly nonlinear costs with an economy of scale or a diseconomy of scale on certain ranges of the amount of trash. For example, suppose the landfill currently has an economy of scale. Its incurred cost of landfilling trash is lower than other landfills, creating an opportunity for the landfill to charge lower tipping fees to attract dumping from haulers without cutting the markup. Such a landfill has been receiving a lot of waste from its surrounding markets (to reach an economy of scale). Hence, if a hauler is in a county that is near other counties that generates a lot of waste, the hauler will likely face lower prices at a disposal facility that serves all these counties.

A simple but useful mathematical illustration is to consider a landfill that charges haulers in county c a fee p_c. These prices have to maximize the landfill's total revenue net of the cost $C(\cdot)$:

$$\Pi = \left(\sum_{c \in C_{jt}} p_c s_c(p_c) Q_c \right) - C \left(\sum_{c \in C_{jt}} s(p_c) Q_c \right), \tag{11}$$

where C_{jt} is the set of all counties with population-weighted centroid within 60 miles in driving distance of the landfill location. $s_c(p_c)$ is county c's share of trash if the landfill charges county c a fee p_c, a result from the demand side. Q_c is the market size, that is, total waste generated by county c. Hence, $s_c(p_c)Q_c$ is the waste amount the landfill receives from county c. Given that the nonlinear cost $C(\cdot)$ depends on the total waste amount the landfill receives from all possible counties within 60 miles, the optimal price in an instrumented market p_c satisfying the first-order condition of the above maximization problem must depend on market sizes of other markets too.

The second feature of the instrument is that it is likely exogenous to the demand in the instrumented market. By construction, the instrument takes account of the market sizes of other markets while excluding the market size of the instrumented market. Hence, the instrument excludes demand factors of the instrumented market. One may be concerned that the market sizes of other markets may be correlated with the waste amount in the instrumented market due to common geographical shocks such as the growth of the region's economy. In that case, however, note that the model is considering the choice of disposal facilities and explains the variation in market shares rather than the waste amount.

To estimate the price coefficient from exogenous variation in price using instruments in a nonlinear model, I apply the control function approach. Following the literature, the control function is estimated using the 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 the linear polynomial and quadratic polynomial of control terms.

4.5 Estimation results

TABLE 2: Results of the structural model

Structural model	(1) Facility fixed effects	(2) IV linear control function	(3) IV quadratic control function
price	−0.0011	−0.1590***	−0.1602***
	(0.0016)	(0.0238)	(0.0238)
distance∗fuel	−0.0442***	−0.0412***	−0.0411***
	(0.0010)	(0.0011)	(0.0011)
control term		0.1588	0.1603
		(0.0240)	(0.0241)
control term^2			−25.103e−6
			(0.4580e−4)
facility FE	Y	Y	Y
First stage results		price	
total market sizes (hundred thousand tons)		−0.2205**	
		(0.1047)	
1(serve at least 2 markets)		41.5998***	
		(1.2710)	
distance∗fuel		0.0200***	
		(0.0069)	
1st stage adjusted R^2		0.6684	
F test		1997.65	
price elasticity	−0.0280	−4.1932	−4.2255
transport elasticity	−1.7139	−1.5950	−1.5940

Note: Specification (1) is facility fixed-effects model. Specifications (2) and (3) use the sum of other relevant market sizes as an instrument and control-function approach with linear and quadratic forms, respectively. Specifically, the price value of an observation cjt is instrumented by the sum of market sizes of other relevant markets excluding the instrumented market, $M_{-c,jt}$. A market is relevant if 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. Significance level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2 reports results of the model. Columns (1), (2), and (3) show the estimates of facility fixed effects, the linear control function, and quadratic control function specifications, respectively. As expected, the facility-fixed-effects specification does not resolve all bias in the price-coefficient estimate. Although its estimate of the price coefficient has the correct sign, it is extremely small and statistically insignificant, and the resulting price elasticity is -0.03. Using the market sizes of the other relevant markets to instrument for price, the upward bias is mitigated. The magnitude of the price coefficient becomes two orders of magnitude bigger; price elasticity is -4.20. The positive sign of the first coefficient of the control function confirms the upward bias is corrected. The first-stage result confirms the market-size instrument variable is strongly correlated with disposal prices. The negative sign of the correlation reveals that the industry is exhibiting economy of scale: Haulers tend to be charged a low disposal fee at a facility that is surrounded by counties that generate a lot of trash.

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.

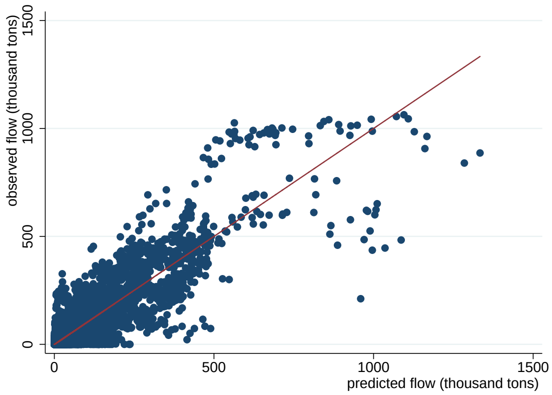
The ratio between the transport-cost coefficient and the price coefficient captures the hauler's willingness to pay for proximity to the disposal facility. This ratio is the cost of transportation. The estimates imply transportation costs $\$0.43$ per ton-mile given diesel prices at the 2000 level ($\$1.672$/gal). 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) (cited in Miller and Osborne (2014)) 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).

4.6 Fitness

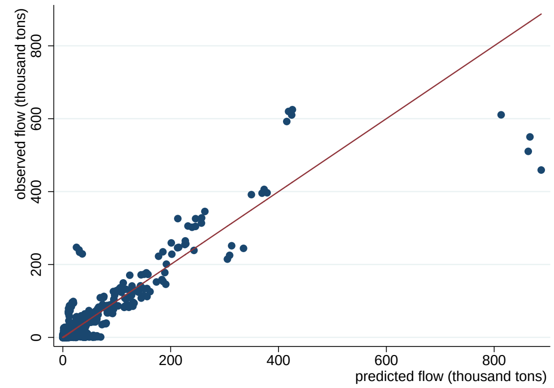
Figure 3 shows the scatter plots and correlation coefficients between observed values and fitted values of key variables. The key variables I consider are waste flows, waste-weighted average distance, and waste-weighted average price because matching waste movements well to study the spatial and demographic distribution of waste flows is important. I also especially consider the goodness of fit in year 2010 because my analysis focuses on the demographic distribution in 2010. Overall, the model successfully replicates the waste flows, waste-weighted average distance, and waste-weighted average price, especially in 2010.

FIGURE 3: Model fit

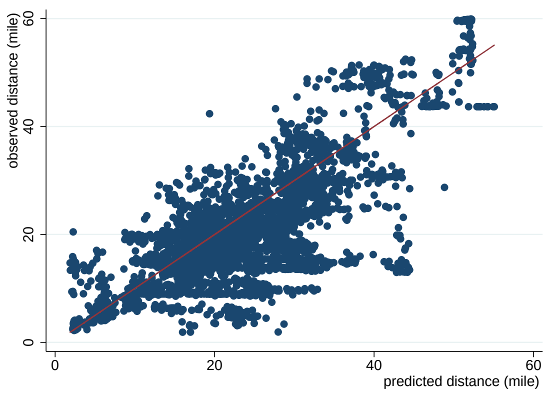
(A) Correlation in trash flows (= 0.8965)



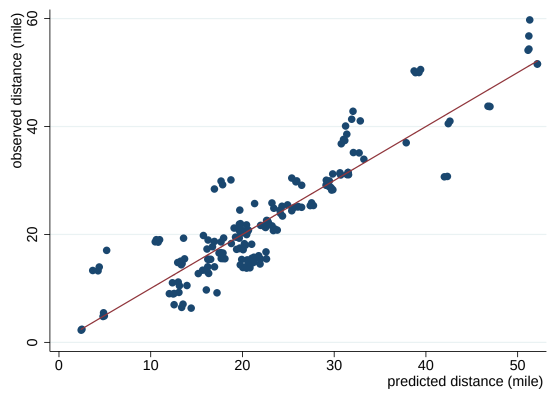
(B) Correlation in 2010 trash flows (= 0.9128)



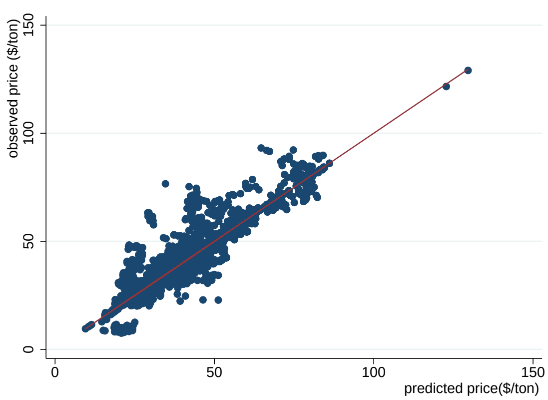
(C) Correlation in distance (= 0.8175)



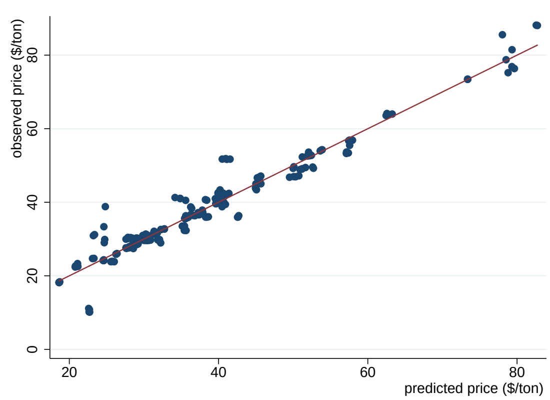
(D) Correlation in distance in 2010 (= 0.9204)



(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 for several key variables. Panels 3a and 3b show the correlation in trash flows (trash amount generated from a county to a facility in a quarter); panel 3b shows the correlation in trash flows in year 2010. Panels 3c and 3d show the correlation in (waste weighted) average distance shipped by a county in a quarter; panel 3d shows the correlation in average shipping distance in year 2010. Panels 3e and 3f show the correlation in (waste weighted) average tipping fee by a county in a quarter; panel 3f shows the correlation in average tipping fee in year 2010.

5 The economic costs of NIMBY on intercounty waste

Given the underlying primitives of the structural model, I conduct several counterfactual policy experiments to evaluate the implications of NIMBY policies on the spatial distribution of waste disposal (intercounty trash flows) and their economic inefficiency in terms of haulers' costs. Specifically, taking as given the baseline parameter estimates and the topology of the industry in year 2010, I compute the status-quo market shares as model-implied choice probabilities.[16] I then evaluate the change in trash shares and haulers' costs when disposal fees, diesel prices, or choice sets change due to trash taxes, fuel taxes, or import bans. Haulers' costs are calculated according to the familiar log-sum formula:

$$-EU_{ct} = \frac{1}{-\beta_p} \ln \left(\sum_{j \in \mathcal{C}_{ct}} \exp(V_{jct}) \right), \tag{12}$$

where $V_{jct} = \beta_p \text{price} + \beta_d \text{distance}_{cj} * \text{fuel price}_t + \gamma_j$.

Four counterfactual policies are considered. Import bans outlaw intercounty waste flows. Import taxes tax waste flows that cross county lines. Fuel taxes that tax diesel prices at percent rates. Trash taxes tax *all* waste disposal at equal rates no matter where the trash is from.

TABLE 3: Change in intercounty waste flows after counterfactual policies

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
		exports (tons)	tipping fees (thousand \$)	trash mileage (kiloton-mile)	hauler cost (thousand \$)	tipping fees (\$/ton)	trash mileage (mile)	hauler cost (\$/ton)
(1)	baseline	572,429	145,000	90,200		40.11	22.22	
(2)	import ban	−572,429	−810	−10,300	3,859	−0.13	−3.12	1.21
		(−100%)	(−0.56%)	(−11.42%)		(−0.32%)	(−14.04%)	
(3)	import tax 5%	−133,657	583	−2,363	992	0.17	−0.69	0.32
		(−23.35%)	(0.4%)	(−2.62%)		(0.42%)	(−3.11%)	
(4)	import tax 15%	−320,813	859	−5,706	2,306	0.27	−1.67	0.74
		(−56.04%)	(0.59%)	(−6.33%)		(0.67%)	(−7.52%)	
(5)	fuel tax 5%	−42,056	−536	−1,769	2,855	−0.07	−0.48	0.7
		(−7.35%)	(−0.37%)	(−1.96%)		(−0.17%)	(−2.16%)	
(6)	fuel tax 15%	−118,156	−1,607	−5,063	8,401	−0.21	−1.35	2.06
		(−20.64%)	(−1.11%)	(−5.61%)		(−0.52%)	(−6.08%)	
(7)	trash tax 5%	−5,640	5,047	−842	7,177	1.53	−0.11	1.99
		(−0.99%)	(3.48%)	(−0.93%)		(3.81%)	(−0.5%)	
(8)	trash tax 15%	−20,107	14,700	−2,528	21,200	4.45	−0.28	5.91
		(−3.51%)	(10.14%)	(−2.8%)		(11.09%)	(−1.26%)	

Note: The table reports changes and percentage changes (in brackets) from a baseline level to a new level due to counterfactual polices. Each metric is 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.

Table 3 presents the results. The reported numbers are averages over 45 counties (markets), although California has 58 counties. The reason is six counties have all of their waste transported beyond 60 miles and are excluded from the main sample of analysis. These counties, Humboldt,

[16] I evaluate the change in 2010 because I consider the effects of NIMBY on the racial distribution of waste in 2010, when the demographic data by the U.S. Census Bureau are most recently available.

Mendocino, Modoc, Plumas, Siskiyou, and Trinity, generate 0.58% of total waste in California in 2010. Additionally, five counties, Alpine, Amador, Del Norte, Nevada, San Francisco, and Tuolumne, export all of their waste to other counties. These five counties account for 1.91% of 60-mile waste (or 1.89% of total waste) in California in 2010. Two counties, Sutter and Yuba, has a joint waste management system and are considered to be one unit of the analysis.[17]

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, one county on average would reduce exports by about 572,000 tons, or 17% of its generated trash amount, in 2010.[18] The transportation distance would also decrease, by 10.3 million ton-miles in total mileage, or, equivalently, around 3 miles in hauling from the population center of the generating place 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 the distant location, they would pay higher tipping fees for being forced to dispose of trash at local facilities. On the other hand, the hauler might choose a nonlocal facility for other benefits despite high tipping fees. In this case, the import ban would result in a decrease in tipping fees. Row 2 and column 2 reveal the overall effect of import bans on tipping fees is dominated by the second mechanism. Particularly, haulers in one county would pay $810,000, or 13 cents per ton less if being forced to dump at local places. However, haulers' costs in one county would increase by $3.86 million, or $1.21 per ton, for the costs of forgoing other benefits beyond tipping fees and transportation costs.

The second policy, import tax, would make disposal facilities outside the generating county borders (nonlocal facilities) more expensive than 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 (one of the top three waste-importing counties in California).[19] Row 4 and column 1 show the 15% tax would reduce one-county exports by about 320,000 tons, which is 56% of the current exports. Total tipping fees would increase by nearly $860,000, or 27 cents per ton, because both options—switching to local facilities and staying at nonlocal facilities—would become more expensive than before. Trash mileage would fall by 5.7 million ton-miles, or 1.7 miles for a transport journey from a population center of generating county to a disposal facility. Overall, the costs for haulers in one county would increase by $2.3 million, or 74 cents per ton.

[17]We can present two baseline levels. One is the averages over 45 counties and used to evaluate the effects of import bans. The other is averages over 50 counties and used for the comparison with import taxes, fuel taxes, and trash taxes. The results do not change much. An advantage of using one baseline level is to contrast all policies at a time.

[18]This number is lower than the 37% in Figure 1d for two reasons. First, reports in the Figure includes waste flows beyond 60 miles. Second, the 17% in the baseline excludes counties that export 100% of their waste such as San Francisco.

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

The third policy, fuel tax, that taxes diesel prices at a percent rate would make long-haul waste transportation more expensive. As a result, waste would be carted to nearer facilities, resulting in a reduction in trash travel mileage. Row 6 shows a fuel tax at 15%, which is, on average, $30.6 cents per gallon or 65% of the 2019 fuel tax level, would lead to a reduction of nearly 5 million ton-miles in trash mileage, or, equivalently, 1.35 miles in a journey from a population center of a generating county to a disposal facility. Because out-of-county facilities are generally farther from the waste-generating origin than local alternatives, the fuel tax would also reduce exports. At the tax of 15%, exports would fall by 118,000 tons, or 21%.

The change in total tipping fees in the case of fuel tax is theoretically ambiguous for two reasons. First, switching to a closer facility is costly because the closer facility is expensive, which is why the hauler did not opt for it. Second, switching to a closer facility would save the hauler on paying tipping fees, but it would not offer any benefits beyond tipping fees and transport costs, such as high acceptance rates, operation hours, capacity, and so on, which are captured by facility fixed effects in my model. Row 7 and column 2 reveal the second effect is dominant: Haulers in one county would overall save $1.6 million (an 1.11% reduction), or 21 cents per ton, in tipping fees. However, forgoing "good" facilities would cost the haulers $8.4 million, or $2.06 per ton.

The final policy of interest is the trash 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 means to compensate for affected communities near a trash site. Imposed at an equal percent rate, the trash tax would penalize expensive facilities more than less expensive facilities. The impact on intercounty waste flows is theoretically ambiguous because of two opposite direction effects. First, if haulers carted waste to out-of-county options because of cheap tipping fees, the trash tax would exacerbate intercounty trash flows. Second, if out-of-county facilities were expensive but haulers opted for them for reasons other than price and distance, the trash tax would mitigate intercounty waste transport. Column 1 and row 8 show the second effect is dominant: Exports would fall by 20,000 tons (3.51%) at the waste tax of 15%.[20] Total tipping fees that haulers in a county would have to pay the disposal facilities would increase $14.7 million (10.14%), or $4.45 per ton. Trash mileage would decrease slightly by 2.8%, or 0.28 miles for a trip, revealing again that switching to less expensive facilities does not necessarily mean a higher cost of transportation. Overall, costs would jump by $21.2 million, or $5.91 per ton.

6 NIMBY and the distribution of waste disposal by race

As mentioned, this paper also focuses on the environmental justice perspective of NIMBY policies, by considering the distribution of waste flows by race. First, I explore the current distribution of

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

waste shipments by race in California. I use the census data in 2010 to reflect the most recent picture of the demographic distribution. The data come with population by race at the census block level, and household income at the block group level.[21]

Following the literature, I define the community unit at disposal facilities for my analysis. Previous studies showed that correlation between environmental hazards and demographics can be quite sensitive to the definitions of community; see Anderton et al. (1994); Sheppard et al. (1999); Mennis (2002). Data aggregated at high 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 or blocks. However, the choice of whether to use blocks, block groups, or census tracts as communities may also be problematic, because these units vary considerably in geographic size. For example, blocks in California range from 1/1,000,000 of a square mile to more than 1,000 square miles. Hence, I use aggregate demographic data at the smallest census units available, namely blocks, to construct demographic data for fixed-circle communities surrounding disposal sites. A block is considered to be in the affected community if its centroid location is in the fixed circle surrounding the facility. Population counts at blocks are aggregated for counts in the community.[22]

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

	3-mile buffer		receiving county		generating county	
	unweighted	weighted	unweighted	weighted	unweighted	weighted
population	26,573	41,144	798,131	3,550,303	753,333	3,993,731
	(44,459)	(43,580)	(1,574,105)	(3,539,681)	(1,517,561)	(3,791,670)
white	8,657	13,716	315,605	1,181,551	300,017	1,289,182
	(13,063)	(14,353)	(491,569)	(946,047)	(474,959)	(999,398)
black	1,050	1,598	46,908	248,290	44,083	290,452
	(2,268)	(2,565)	(127,057)	(313,591)	(122,159)	(336,261)
Asian	3,727	6,408	100,029	481,614	97,328	544,765
	(7,486)	(7,508)	(229,767)	(490,828)	(222,654)	(520,212)
Hispanic	12,295	18,189	307,254	1,530,798	285,047	1,749,941
	(31,392)	(28,649)	(725,248)	(1,753,682)	(698,587)	(1,887,725)
% white	49.64	44.27	52.36	39.74	54	39.35
	(24.74)	(20.88)	(18.5)	(10.82)	(19.26)	(11.61)
% black	2.73	3.73	3.44	5.8	3.38	5.92
	(3.62)	(3.92)	(3.4)	(3.42)	(3.31)	(3.31)
% Asian	8.13	13.16	7.11	12.67	7.27	13
	(11.99)	(12.02)	(7.16)	(6.9)	(7.95)	(7.12)
% Hispanic	35.04	35.38	32.93	38.21	31.19	38.2
	(25.41)	(22.3)	(16.96)	(11.19)	(17.28)	(11.72)
median hh	52,184	64,920	45,417	49,402	45,426	48,870
income	(20,286)	(18,820)	(10,447)	(8,622)	(10,195)	(8,510)

Note: This table shows summary statistics of the 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 centered around 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 the unweighted average population level and the average level weighted by waste amount.

[21]Median household income at census blocks is confidentially restricted. Public data are available at block group level as the smallest unit.

[22]Information that is not available at blocks 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 approach is also used in Banzhaf and Walsh (2008).

For the main analysis, I use 3-mile buffer zones to refer to affected communities near disposal facilities. Appendix D shows the results for 1-mile buffers, 2-mile buffers, 4-mile buffers, and 5-mile buffers. Table 4 reports mean demographic composition in 3-mile affected communities. The table also contrasts the demographic composition at the county level in terms of receiving trash versus generating trash. In 3-mile affected communities, the average population is 26,000, of which 49.6% are white, 2.7% are black, 8.1% are Asian, and 35.3% are Hispanic. When weighted by the trash amount at a facility, percentages of white, black, Asian, and Hispanic residents are 44.1%, 3.7%, 13.0%, and 35.0%, respectively. The differences between unweighted and trash-weighted percentages by race imply more waste is disposed of in minority communities than in white communities. The disparity is also evident when comparing unweighted and receiving-trash-weighted percentages by race at county level. One apparent reason is that minority groups live near or in urban areas that generate a lot of waste. This argument is supported by the fact that percentages of minority groups in counties become bigger after being weighted by generating-waste quantity, compared to unweighted levels. Therefore, considering the correlation between race and trash share conditional on each given county (market) rather than waste quantity is more compelling. Another interpretation of the correlation between trash share and race is whether race is a factor that affects the probability that a disposal facility is chosen.[23]

Because waste flows are the result of market activities, I now examine the correlation between trash share and race after controlling for the economic incentives of haulers (disposal prices and transport costs). The specification is a (type 2) Tobit model:

$$s^*_{cjt} = \beta_1 \% Race_j + \beta_2 \text{income}_j + \beta_3 \text{price}_{jt} + \beta_4 \text{distance}_{cj} * \text{fuel price}_t + \gamma_t + \delta_c + \epsilon_{cjt}, \tag{13}$$

where s^*_{cjt} is a latent variable. The observed dependent variable s_{jct} is the waste amount generated by county c to be disposed of at facility j out of total waste generated by county c in quarter t in year 2010. The observed trash share s_{jct} equals the latent variable for positive values of the latent variable, and 0 otherwise ($s_{jct} = s^*_{jct}\mathbf{1}(s^*_{jct} > 0)$). The main explanatory variable of interest is $\% Race_j = \frac{\text{\#people of the race in facility j's community}}{\text{\#people in facility j's community}} \times 100$, which is the population of the race of interest as a percentage of the population in the affected community. Control variable income$_j$ is the median household income in the community surrounding facility j. 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) and uses observations in year 2010.

Table 5 reports results. Column 1 shows that no significant differences are found in the receiving waste amount between minority communities and white communities. However, controlling for in-

[23] Note that we are considering horizontal environmental justice. That is, is there a place that receives more trash than others? One can think of vertical environmental justice: Do majority areas send trash to minority areas? This paper focuses on horizontal environmental justice rather than vertical relation. The racial composition in counties after being weighted by waste-generating amount and the level after being weighted by waste-receiving amount are very similar, implying no inequity in the vertical relation.

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	0.017	0.299	0.285	0.942***
	(0.254)	(0.297)	(0.292)	(0.264)
% Hispanic	-0.027	0.155**	0.148**	0.113
	(0.057)	(0.066)	(0.069)	(0.082)
% Asian	0.056	0.030	0.039	-0.081
	(0.095)	(0.079)	(0.079)	(0.083)
income ($1000s)		0.339***	0.318***	0.407***
		(0.075)	(0.081)	(0.095)
price			0.061	0.080
			(0.078)	(0.087)
distance*fuel				-0.214***
				(0.039)
quarter FE	Y	Y	Y	Y
ori cnty FE	Y	Y	Y	Y
observations	1478	1478	1478	1478
non-zero observations	1114	1114	1114	1114

Note: This table reports coefficients of a Tobit model, weighted by market size (total waste generated by a county). The dependent variable is market shares, that is, the share of a generating county's waste to a facility. Demographic characteristics of facilities are characteristics of the 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. Significance level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

come, more waste is sent to black and Hispanic communities (column 2). We see that the coefficients of the black percentage and Hispanic percentage become bigger and statistically significant, implying facilities in black and Hispanic communities receive more trash for reasons unrelated to income.

The finding that the coefficient of income is positive may be surprising. However, note that we are considering the correlation between income and waste *flows*. The correlation is hence already conditional on facility location. Because we are looking at the correlation in 2010, this correlation is also implied by the variation in income *among* affected communities near disposal facilities. This comparison differs from the literature that compares places that are exposed to undesired activites with places that are not. The correlation between income and waste flows in my case arises because income happens to be correlated with factors that induce waste flows. As a result, theoretically, the income coefficient can be either positive or negative. On the one hand, facilities in communities with higher incomes than the neighborhoods of other facilities may be less attractive (to haulers) because these higher-income communities have higher resistance to incoming waste shipments, either because of a higher willingness to move out or higher political resistance. On the other hand, facilities in communities with higher incomes than communities surrounding other facilities may be large-scale and high-capacity facilities. We have seen that carrying waste for a very long journey is not efficient. Hence, the large-scale facilities are still likely located reasonably near counties that generate a lot of trash, where the median income is also potentially higher than in remote areas. Because haulers prefer large-scale facilities, they may happen to ship more trash to facilities in areas with higher incomes than facilities in areas with lower incomes. The empirical result of a positive sign in this paper implies the second story. However, one should note that the estimate may suffer measurement error because

I use median household income at block groups to infer income at blocks and to construct income in affected communities. For this reason, I do not focus on the correlation between waste shipments and income, but rather on the relation between waste shipments and race.

Columns 3 and 4 show that disparities in the quantity of trash received between black, Hispanic communities and white community persist after controlling for prices and transport costs of disposing of trash. The coefficient of the Hispanic percentage is statistically significant after controlling for prices but becomes insignificant after controlling for transport costs. This change suggests facilities in predominantly Hispanic communities are near the population center of waste-generating counties.

Surprisingly, the coefficient of the black percentage becomes statistically and economically significant after controlling prices and transport costs. A one-percentage-point increase in the percentage of the black population living near a trash site (on a mean of 3.34%) is associated with a one-percentage-point increase in the market share. This finding implies that facilities in predominantly black communities offer some factors beyond prices and transport costs that benefit haulers. One factor is that large-scale facilities may be located in areas that have a lot of black residents living nearby, a similar story that happens in the case of the above positive correlation between income and waste flows. Furthermore, facilities in these areas may offer benefits such as flexible operation hours, easily accessible highways, high acceptance rates due to low hassle costs that require haulers to divert collected trash before disposing of it at landfills, and so on.

In summary, my evidence of the disproportionate distribution of waste flow holds after controlling for waste-shipment distances and disposal fees. This evidence, given the controls of distance, disposal fees, income, may not be enough to establish environmental injustice. However, "one could still argue that there is an injustice when there are inequities in the simple correlations [...] simply because the inequity is mediated through some mechanism does not mean it isn't there" (Banzhaf et al. (2019)).

I do not aim to provide an exhaustive list of explanations for the uneven racial distribution of waste flows. Neither do I emphasize a causal effect of race on waste shipments in this paper. The current analysis uses only cross-sectional variation in waste flows in 2010 to provide a picture of the correlation between race and waste flows in the absence of NIMBY policies. Although it is beyond the scope of this paper to show why exactly the disparities are happening, this analysis suggests that something unobservable about waste facilities in black areas makes them attractive to haulers, above and beyond disposal prices and transport costs, and that facilities in Hispanic areas tend to be near to centers of waste-generating counties. This result motivates the question of whether NIMBY regulations, by affecting the cost preferences of haulers, could have environmental justice implications, especially when the regulations aim to provide collected taxes for affected communities.

Table 6 shows the impacts of the four counterfactual policies on the demographic distribution of waste disposal. The table computes the percent of trash in a county 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 trash from a generating county c

TABLE 6: Change in percentages of waste going to affected communities after NIMBY policies

	% trash to white	% trash to black	% trash to Asian	% trash to Hispanic	% exported to white	% exported to black	% exported to Asian	% exported to Hispanic
baseline	42.47	3.4	13.63	37.14	8.25	0.6	2.7	4.85
import ban	−1.13	−0.02	−0.52	1.74	−8.25	−0.6	−2.7	−4.85
	(−2.66%)	(−0.59%)	(−3.82%)	(4.68%)	(−100%)	(−100%)	(−100%)	(−100%)
import tax 5%	−0.27	0.01	−0.16	0.43	−1.82	−0.12	−0.67	−1
	(−0.64%)	(0.29%)	(−1.17%)	(1.16%)	(−22.06%)	(−20%)	(−24.81%)	(−20.62%)
import tax 15%	−0.66	0.02	−0.34	1.03	−4.37	−0.3	−1.56	−2.45
	(−1.55%)	(0.59%)	(−2.49%)	(2.77%)	(−52.97%)	(−50%)	(−57.78%)	(−50.52%)
fuel tax 5%	−0.26	0	0.06	0.21	−0.59	−0.04	−0.14	−0.35
	(−0.61%)	(0%)	(0.44%)	(0.57%)	(−7.15%)	(−6.67%)	(−5.19%)	(−7.22%)
fuel tax 15%	−0.74	0	0.16	0.61	−1.64	−0.12	−0.41	−0.98
	(−1.74%)	(0%)	(1.17%)	(1.64%)	(−19.88%)	(−20%)	(−15.19%)	(−20.21%)
trash tax 5%	−0.29	−0.02	−0.07	0.39	−0.06	0.01	−0.04	0.05
	(−0.68%)	(−0.59%)	(−0.51%)	(1.05%)	(−0.73%)	(1.67%)	(−1.48%)	(1.03%)
trash tax 15%	−0.88	−0.05	−0.21	1.19	−0.14	0.02	−0.12	0.2
	(−2.07%)	(−1.47%)	(−1.54%)	(3.2%)	(−1.7%)	(3.33%)	(−4.44%)	(4.12%)

Note: The table presents changes in percentage point of percentage of trash sent to specific demographic groups. Numbers in brackets show the percentage-point changes in percentage. 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.

that is sent to disposal facility j equally affects all people living within three miles of the facility location, the percent of trash that market c imposes on white communities is

$$\%\text{ trash to white} = \frac{\sum_{j \in J_c} \overbrace{q_{cj}/\text{total population in j's buffer}_j}^{\text{trash per capita in communities near facility j}} \times \#\text{whites in j's buffer}_j}{\underbrace{\sum_{j \in J_c} q_{cj}}_{\text{total trash generated in county c}}} \times 100. \quad (14)$$

This percentage is calculated for every waste-generating county and then weighted by market size (total trash generated in a county). I use two baselines because a few counties do not have disposal facilities within their borders. The baseline for the import bans excludes trash in these counties.

Results show that after the import ban, the percentage of waste that crosses county borders to export to Hispanic residents would fall. However, the total percentage of waste that is sent to Hispanic communities would increase, whereas the waste sent to white communities would decrease. This finding implies waste would substitute away from facilities in white areas toward Hispanic communities.

This substitution pattern persists in other policies, import tax, fuel tax, and trash tax. This is as expected from the analysis of the status quo: Facilities in predominantly Hispanic communities tend to be near the population centers of waste-generating counties. For this reason, the NIMBY policies that would reduce long-haul shipments of waste by diverting the trash to closer facilities would increase shipments to facilities in Hispanic areas.

Note the fact that the trash tax would increase waste to facilities in Hispanic areas implies these facilities tend to have low tipping fees. The reason is that the trash tax, with an equal percent rate on all trash, would penalize expensive facilities more than less expensive facilities. This result also corroborates the analysis of the status quo that shows the coefficient of the Hispanic percentage becomes smaller after controlling for price, though it is still significant.

Whereas NIMBY policies would increase waste to Hispanic communities, the policies would produce almost no changes on waste sent to black areas. Waste that is sent to black residents would generally remain the same or decrease by a modest amount less than the reduction in white communities (under the trash tax). The reason is that facilities in black neighborhoods are attractive despite their high dumping fees and distant locations. The analysis of the status quo also predicts this result. Potential reasons are factors strongly correlated with facility fixed effects, flexible operation hours, acceptance rates, hassle costs to haulers, and so on. Although explaining the exact reasons for that attractiveness is beyond the scope of this paper, the finding suggests policies that target disposal fees and transport costs do not effectively reduce waste to black communities. For example, if facilities in black communities easily accepted trash from haulers because the facilities do not properly follow the environmental standard, policies that aim to strictly inspect and/or enforce the standards in these facilities would be more effective than market-based instruments.

7 Conclusion

This paper studies the inefficiency costs of NIMBY regulations in terms of the costs for haulers in a short run, when disposal facilities do not adjust disposal fees and capacity in response to the regulations. The paper also considers the environmental justice perspective of NIMBY. I find NIMBY would reduce intercounty waste flows but with significant costs, and would potentially exacerbate the disproportionate distribution of waste flows by race in California. The reason is that reducing long-haul shipments of waste means increasing waste to Hispanic communities, because facilities in Hispanic communities tend to be near waste-generating counties.

The paper has several limitations that suggest avenues for future research. First, considering how disposal facilities set disposal fees and/or set capacity adjustment is helpful for exploring the passthrough of policies on the landfill side. Second, identifying what underlies the attractiveness of facilities in black communities will help in the creation of more appropriate "protection" policies. For example, several states that advocate NIMBY argue on the grounds of the protection of public health and safety. However, if disposal facilities in some areas are preferred because they intentionally do not maintain the proper environmental standards, enforcing those standards will be more effective than NIMBY taxes and import bans. Third, studying the welfare change in the affected communities is definitely interesting and important. Have the affected communities been compensated for the jobs and profits the disposal facilities offer? Do minorities move to these areas for these opportunities and are better off than previously?

Despite limitations, the findings in this paper suggest unintended effects of NIMBY. Unintended consequence happens when the regulations work against the direction of what causes the injustice: Hispanic facilities are ones near population center with low transport costs of hauling. Unintended implication also happens when the regulations do not target the right aspects: Black facilities are attractive for other reasons rather than disposal fees and transport costs. Ultimately, as Banzhaf et al. (2019) note, "key to policy discussion is that any specific prescription is contingent upon *how* inequities arise." Yet, the unintended effects of NIMBY are understandable because NIMBY initially intended to address environmental justice at the beginning.

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.

Banzhaf, H. S. and Walsh, R. P. (2008). Do people vote with their feet? An empirical test of Tiebout. *American Economic Review*, 98(3):843–63.

Banzhaf, H. S. and Walsh, R. P. (2013). Segregation and Tiebout sorting: The link between place-based investments and neighborhood tipping. *Journal of Urban Economics*, 74:83–98.

Banzhaf, S., Ma, L., and Timmins, C. (2019). Environmental justice: The economics of race, place, and pollution. *Journal of Economic Perspectives*, 33(1):185–208.

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

Berry, S., Levinsohn, J., and Pakes, A. (1999). Voluntary export restraints on automobiles: Evaluating a trade policy. *American Economic Review*, pages 400–430.

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. *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.

Gaudet, G., Moreaux, M., and Salant, S. W. (2001). Intertemporal depletion of resource sites by spatially distributed users. *American Economic Review*, 91(4):1149–1159.

Gray, W. B. and Shadbegian, R. J. (2004). 'Optimal' pollution abatement—whose benefits matter, and how much? *Journal of Environmental Economics and management*, 47(3):510–534.

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.

Ho, P. (2019). Living near trash: Testing residential mobility in the context of solid waste disposal. Working paper. August 29.

Kamita, R. Y. (2001). Merger analysis in geographically differentiated industries with municipal and private competitors: The case of solid waste disposal. Working paper. ssrn 292344.

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

Kinnaman, T. C. and Fullterton, D. (1999). The economics of residential solid waste management. Working paper, National Bureau of Economic Research.

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. *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.

Macauley, M. K. (2009). Waste Not, Want Not: Economic and Legal Challenges of Regulation-Induced Changes in Waste Technology and Management. Discussion paper, Resource for the Future.

Martin, L. A. (2008). Consumer demand for compact flourescent light bulbs. Working paper, Department of Agricultural and Resource Economics, University of California, Berkeley.

McCarthy, J. E. (2004). Interstate shipment of municipal solid waste: 2004 update.

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.

Nordhaus, W. D., Houthakker, H., and Solow, R. (1973). The allocation of energy resources. *Brookings Papers on Economic Activity*, 1973(3):529–576.

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

Repa, E. W. (2000). Solid waste disposal trends. *Waste Age*, 31:262–65.

Repa, E. W. (2005). Interstate movement of municipal solid waste. Bulletin report.

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

Shadbegian, R. J. and Gray, W. B. (2012). Spatial patterns in regulatory enforcement: Local tests of environmental justice. *Chapter 9 in The Political Economy of Environmental Justice*.

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.

Timmins, C. and Vissing, A. (2017). Environmental Justice and Coasian Bargaining: The role of race and income in lease negotiations for shale gas. Working paper.

Train, K. E. (2009). *Discrete choice methods with simulation*. Cambridge university press.

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 (2017). Facts and figures about materials, waste and recycling. Online retrieval, US EPA.

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

Wolverton, A. (2009). Effects of socio-economic and input-related factors on polluting plants' location decisions. *The BE Journal of Economic Analysis & Policy*, 9(1).

APPENDICES: FOR ONLINE PUBLICATION

A Data handling and processing

Waste-disposal data are combined from three sources. First, the waste-quantity data by county of origin and by facility of destination is obtained from California Department of Resources and Recycling and Recovery (CalRecycle). The data are available quarterly from January 1995 to December 2015. Second, the database of waste disposal facility profile (solid waste information system, or SWIS) describing the state identification (SWIS id), location coordinates, operating status, and so on is obtained from CalRecycle. This database is not time series and is updated every Friday on CalRecyle website. I use this database as of September 2017 to obtain information on state identification and location of disposal facilities. Third, information on disposal prices at facilities is purchased from Waste Business Journal (WBJ).

I merge waste-flow-quantity data with SWIS-and-location data by matching facility name. The two data are from CalRecycle and hence, exact facility names are match completely. This quantity data set includes 244 disposal facilities and is merged with WBJ price data by manually matching SWIS id, facility names, and location. The final data set for the analysis drops several observations for three reasons. First, observations of facilities that are in the waste flow data but not found in WBJ data, representing 0.52% of California waste. Second, observations with zero prices. Since zero prices may be recorded due to missing values, I drop those observations. They represent 0.41% of the total waste amount. Third, three facilities in California are located on Santa Catalina island and San Clemente island. Because these facilities are built for local needs and the waste management on islands is isolated from other areas on mainland due to geographical and transportation constraints, I drop those observations. They account for 0.01% of the total waste amount.

Using the information on facility location, I calculate car-driving distance using HERE maps from a facility coordinate to the population center coordinate of a county. The population center coordinate of the county is the average centroid weighted by population of all blocks in the county. For out-of-state exports in California solid waste, I observe the export amount, but I do not observe the destination.[24] I construct an out-of-state disposal option for haulers in the county by assuming a hauler would export to the nearest out-of-state facility (among facilities in Oregon, Nevada, or Arizona). Overall, out-of-state exports make up a very small amount of California solid waste, that is, 1.16% during this whole period.

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

B Price responses and distance responses by choice set radius

TABLE B1: Regression analysis of trash flows in response to price and distance by distance

s_{cjt}: Trash share from a county of origin to a facility of destination in a quarter											
Trash flows within 120 miles			Trash flows within 150 miles								
	(1)	(2)		(3)	(4)		(5)	(6)		(7)	(8)
price: 0–30	0.0676	−0.0236	price: 0–40	−0.0636	−0.0320	price: 0-30	0.0697	−0.0238	price: 0-30	0.0700	−0.0238
	(0.0622)	(0.0358)		(0.0463)	(0.0204)		(0.0652)	(0.0356)		(0.0653)	(0.0356)
price: 30–60	−0.0194	−0.0172*	price: 40–70	0.0527**	−0.0081	price: 30-60	−0.0142	−0.0134	price: 30-60	−0.0125	−0.0134
	(0.0255)	(0.0098)		(0.0252)	(0.0116)		(0.0256)	(0.0108)		(0.0255)	(0.0108)
price: 60–90	0.0123	−0.0127**	price: 70–100	0.0156	−0.0052*	price: 60-90	0.0138	−0.0118**	price: 60-80	0.0231	−0.0130
	(0.0242)	(0.0058)		(0.0206)	(0.0031)		(0.0227)	(0.0057)		(0.0265)	(0.0092)
price: 90–120	0.0112	−0.0008	price: 100–130	0.0212	−0.0033	price: 90-110	0.0055	−0.0038	price: 80-100	0.0167	−0.0066**
	(0.0195)	(0.0075)		(0.0152)	(0.0086)		(0.0169)	(0.0028)		(0.0263)	(0.0026)
			price: 130–150	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: 130-150	0.0167	−0.0027	price: 125–150	0.0058	−0.0035
							(0.0169)	(0.0025)		(0.0148)	(0.0022)
distance: 0–30	−1.7908***		dist.: 0–40	−1.4723***		dist: 0-30	−1.7762***		dist:0-30	−1.7763***	
	(0.2878)			(0.1709)			(0.2812)			(0.2811)	
distance: 30–60	−0.1407*		dist.: 40–70	0.0006		dist: 30-60	−0.1346*		dist: 30-60	−0.1377*	
	(0.0756)			(0.0552)			(0.0730)			(0.0745)	
distance: 60–90	−0.1137***		dist.: 70–100	−0.0484		dist: 60-90	−0.0976***		dist: 60-80	−0.1213	
	(0.0389)			(0.0341)			(0.0360)			(0.0767)	
distance: 90–120	0.0103		dist.: 100–130	−0.0169		dist: 90-110	0.0174		dist: 80-100	−0.0285	
	(0.0311)			(0.0218)			(0.0373)			(0.0501)	
			dist.: 130–150	−0.0216		dist: 110-130	−0.0719*		dist: 100-125	−0.0018	
				(0.0392)			(0.0414)			(0.0294)	
						dist: 130+	−0.0104		dist.: 125–150	−0.0349	
							(0.0385)			(0.0276)	
facility FE	Y	Y		Y	Y		Y	Y		Y	Y
quarter FE	Y	Y		Y	Y		Y	Y		Y	Y
quarter × origin cnty FE	Y			Y			Y			Y	
origin × des cnty FE		Y			Y			Y			Y
Observations	109,596	109,596		151,969	151,969		151,969	151,969		151,969	151,969
Adjusted R^2	0.4661	0.8814		0.4442	0.8786		0.4465	0.8786		0.4463	0.8786

Note: This table shows the responses of all trash flows within 120 and within 150 miles to the price and distance by different knots of driving distance. The formal regression is $s_{cjt} = \beta_d f_d(\text{distance}_{cj}) + \beta_p f_p(\text{price}_{jt}) + \text{fixed effects} + \epsilon_{cjt}$. Standard errors are clustered by waste-origin county.

C Another demand estimator using unweighted estimator

As mentioned above, an alternative estimator exists 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 estimator of the main results. Results in Table C1 show that when weighting all markets equally, price coefficients becomes bigger, whereas the transport-cost coefficient is similar to the case of market-size-weighted estimates. The higher price elasticities when using the unweighted estimator reveals big markets are less responsive to price.

TABLE C1: Results from logit demand using unweighted estimator

Model	(1) Facility fixed effects	(2) IV linear control function	(3) IV quadratic control function
price	-0.0014	-0.2487***	-0.2576***
	(0.0014)	(0.0369)	(0.0376)
distance$*$fuel	-0.0539	-0.0490***	-0.0488***
	(0.0007)	(0.0011)	(0.0011)
control term		0.2477***	-0.2568***
		(0.0370)	(0.0378)
control term^2			$-12.584\text{e}{-6}$
			$(0.3207\text{e}{-4})$
facility FE	Y	Y	Y
price elasticity	-0.0371	-6.4242	-6.6541
transport elasticity	-2.0693	-1.8805	-1.8737

Note: Specification (1) is facility-fixed-effects model. Specifications (2) and (3) use sum of other relevant market sizes as an instrument and the 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. Significance level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

D Demographic distribution of waste by different ranges of neighborhood

This section provides the environmental justice perspective of NIMBY policies when affected communities are defined as blocks with their centroids within 1-mile, 2-mile, 4-mile, and 5-mile buffers of disposal facilities. When considering the narrow neighborhoods (1-mile and 2-mile buffers), I found a few affected communities where nobody lives. Yet, in bigger neighborhoods (4-mile and 5-mile buffers), facilities in predominantly black and Hispanic neighborhoods tend to receive more waste than other facilities, a similar results to the case of 3-mile buffers.

TABLE D1: Current distribution of county waste share in 1-mile-buffer neighborhoods of facilities

	(1)	(2)	(3)	(4)
Dependent		market share		
No population	5.463*	3.934	1.758	−1.121
	(3.121)	(4.792)	(4.920)	(7.039)
% black	−0.276	−0.285	−0.402*	−0.034
	(0.228)	(0.226)	(0.232)	(0.362)
% Hispanic	0.029	0.021	0.019	−0.026
	(0.048)	(0.051)	(0.051)	(0.072)
% Asian	0.202***	0.214***	0.214***	0.169**
	(0.075)	(0.069)	(0.068)	(0.083)
income ($1000s)		−0.022	−0.034	−0.072
		(0.058)	(0.057)	(0.076)
price			0.153*	0.182*
			(0.087)	(0.105)
distance*fuel				−0.176***
				(0.045)
quarter FE	Y	Y	Y	Y
origin cnty FE	Y	Y	Y	Y
observations	1478	1478	1478	1478
non-zero observations	1114	1114	1114	1114

Note: This table reports coefficients of a Tobit model. The dependent variable is trash shares, that is, the share of a generating county's waste to a facility. Dependent variable is weighted by market size (total waste generated by a county). Demographic characteristics of facilities are characteristics of community within 1 mile of a facility. The sample only includes observations in 2010. Significant level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE D2: Change in percentages of waste going to 1-mile-buffer affected communities after NIMBY policies

	% trash to				% of county trash that is exported to				% trash to
	white	black	Asian	Hispanic	white	black	Asian	Hispanic	no population
baseline	30.75	1.57	9.98	27.98	5.19	0.17	1.82	3.68	27.15
import ban	0.61	0.18	−0.26	0.94	−5.18	−0.17	−1.81	−3.68	−1.7
	(1.98%)	(11.46%)	(−2.61%)	(3.36%)	(−99.81%)	(−100%)	(−99.45%)	(−100%)	(−6.26%)
import tax 5%	0.12	0.04	−0.03	0.19	−1.05	−0.04	−0.4	−0.83	−0.39
	(0.39%)	(2.55%)	(−0.3%)	(0.68%)	(−20.23%)	(−23.53%)	(−21.98%)	(−22.55%)	(−1.44%)
import tax 15%	0.27	0.09	−0.1	0.49	−2.56	−0.09	−0.97	−2	−0.92
	(0.88%)	(5.73%)	(−1%)	(1.75%)	(−49.33%)	(−52.94%)	(−53.3%)	(−54.35%)	(−3.39%)
fuel tax 5%	−0.21	0.01	−0.02	0.18	−0.36	−0.01	−0.1	−0.24	0.03
	(−0.68%)	(0.64%)	(−0.2%)	(0.64%)	(−6.94%)	(−5.88%)	(−5.49%)	(−6.52%)	(0.11%)
fuel tax 15%	−0.64	0.04	−0.06	0.54	−1.01	−0.03	−0.29	−0.66	0.12
	(−2.08%)	(2.55%)	(−0.6%)	(1.93%)	(−19.46%)	(−17.65%)	(−15.93%)	(−17.93%)	(0.44%)
trash tax 5%	−0.17	−0.03	−0.05	0.26	0.09	0	0	−0.02	−0.03
	(−0.55%)	(−1.91%)	(−0.5%)	(0.93%)	(1.73%)	(0%)	(0%)	(−0.54%)	(−0.11%)
trash tax 15%	−0.47	−0.09	−0.17	0.8	0.32	0	−0.01	−0.01	−0.12
	(−1.53%)	(−5.73%)	(−1.7%)	(2.86%)	(6.17%)	(0%)	(−0.55%)	(−0.27%)	(−0.44%)

Note: The table presents percentage-point changes in the amount of trash sent to a specific demographic group in 1-mile neighborhoods surrounding disposal facilities. Numbers in brackets show the percentage-point change in percentage. 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.

TABLE D3: Current distribution of county waste share in 2-mile-buffer neighborhoods of facilities

	(1)	(2)	(3)	(4)
Dependent		market share		
No population	0.517	17.874	15.773	16.620
	(9.379)	(11.654)	(11.796)	(11.617)
% black	0.040	0.113	0.111	0.687***
	(0.221)	(0.232)	(0.234)	(0.204)
% Hispanic	−0.004	0.113*	0.101	0.034
	(0.053)	(0.063)	(0.067)	(0.081)
% Asian	0.090	0.088	0.089	−0.034
	(0.091)	(0.089)	(0.086)	(0.111)
income ($1000s)		0.240***	0.215**	0.232**
		(0.085)	(0.089)	(0.104)
price			0.071	0.124
			(0.074)	(0.092)
distance*fuel				−0.207***
				(0.037)
quarter FE	Y	Y	Y	Y
ori cnty FE	Y	Y	Y	Y
observations	1478	1478	1478	1478
non-zero observations	1114	1114	1114	1114

Note: This table reports coefficients of a Tobit model. The dependent variable is trash shares, that is, the share of a generating county's waste to a facility. Dependent variable is weighted by market size (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. Significant level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE D4: Change in percentages of waste going to 2-mile-buffer affected communities after NIMBY policies

	% trash to				% of county trash that is exported to				% trash to
	white	black	Asian	Hispanic	white	black	Asian	Hispanic	no population
baseline	42.22	3.22	13.59	36.27	7.8	0.66	2.76	4.96	1.32
import ban	−0.77	−0.12	−0.62	1.55	−7.79	−0.66	−2.76	−4.96	0.03
	(−1.82%)	(−3.73%)	(−4.56%)	(4.27%)	(−99.87%)	(−100%)	(−100%)	(−100%)	(2.27%)
import tax 5%	−0.18	−0.01	−0.19	0.39	−1.72	−0.13	−0.69	−1.03	0.01
	(−0.43%)	(−0.31%)	(−1.4%)	(1.08%)	(−22.05%)	(−19.7%)	(−25%)	(−20.77%)	(0.76%)
import tax 15%	−0.46	−0.05	−0.42	0.93	−4.12	−0.33	−1.62	−2.52	0.02
	(−1.09%)	(−1.55%)	(−3.09%)	(2.56%)	(−52.82%)	(−50%)	(−58.7%)	(−50.81%)	(1.52%)
fuel tax 5%	−0.14	0	0.07	0.17	−0.55	−0.05	−0.15	−0.36	−0.1
	(−0.33%)	(0%)	(0.52%)	(0.47%)	(−7.05%)	(−7.58%)	(−5.43%)	(−7.26%)	(−7.58%)
fuel tax 15%	−0.4	0	0.19	0.49	−1.53	−0.13	−0.41	−0.99	−0.29
	(−0.95%)	(0%)	(1.4%)	(1.35%)	(−19.62%)	(−19.7%)	(−14.86%)	(−19.96%)	(−21.97%)
trash tax 5%	−0.23	−0.03	−0.1	0.41	−0.03	0.01	−0.05	0.03	−0.04
	(−0.54%)	(−0.93%)	(−0.74%)	(1.13%)	(−0.38%)	(1.52%)	(−1.81%)	(0.6%)	(−3.03%)
trash tax 15%	−0.68	−0.08	−0.3	1.22	−0.06	0.03	−0.14	0.15	−0.12
	(−1.61%)	(−2.48%)	(−2.21%)	(3.36%)	(−0.77%)	(4.55%)	(−5.07%)	(3.02%)	(−9.09%)

Note: The table presents percentage-point changes in the amount of trash sent to a specific demographic group in 2-mile neighborhoods surrounding disposal facilities. Numbers in brackets show the percentage-point change in percentage. 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.

TABLE D5: Current distribution of county waste share in 4-mile-buffer neighborhoods of facilities

	(1)	(2)	(3)	(4)
Dependent		market share		
% black	−0.005	0.316	0.286	0.862***
	(0.221)	(0.243)	(0.241)	(0.226)
% Hispanic	−0.030	0.155**	0.146*	0.148
	(0.058)	(0.076)	(0.078)	(0.092)
% Asian	0.077	0.065	0.080	−0.047
	(0.090)	(0.082)	(0.079)	(0.086)
income ($1000s)		0.316***	0.290***	0.416***
		(0.081)	(0.087)	(0.112)
price			0.103	0.118
			(0.080)	(0.095)
distance*fuel				−0.211***
				(0.038)
quarter FE	Y	Y	Y	Y
ori cnty FE	Y	Y	Y	Y
observations	1478	1478	1478	1478
non−zero observations	1114	1114	1114	1114

Note: This table reports coefficients of a Tobit model. The dependent variable is trash shares, that is, the share of a generating county's waste to a facility. Dependent variable is weighted by market size (total waste generated by a county). Demographic characteristics of facilities are characteristics of community within 4 miles of a facility. The sample only includes observations in 2010. Significant level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE D6: Change in percentages of waste going to 4-mile-buffer affected communities after NIMBY policies

	% trash to white	% trash to black	% trash to Asian	% trash to Hispanic	% exported to white	% exported to black	% exported to Asian	% exported to Hispanic
baseline	40.92	3.71	14.26	37.79	7.83	0.69	2.78	5.1
import ban	−0.94	−0.04	−0.52	1.58	−7.82	−0.69	−2.78	−5.09
	(−2.3%)	(−1.08%)	(−3.65%)	(4.18%)	(−99.87%)	(−100%)	(−100%)	(−99.8%)
import tax 5%	−0.23	0	−0.15	0.39	−1.74	−0.14	−0.68	−1.05
	(−0.56%)	(0%)	(−1.05%)	(1.03%)	(−22.22%)	(−20.29%)	(−24.46%)	(−20.59%)
import tax 15%	−0.56	0	−0.33	0.93	−4.17	−0.35	−1.6	−2.57
	(−1.37%)	(0%)	(−2.31%)	(2.46%)	(−53.26%)	(−50.72%)	(−57.55%)	(−50.39%)
fuel tax 5%	−0.22	0	0.06	0.17	−0.55	−0.05	−0.15	−0.38
	(−0.54%)	(0%)	(0.42%)	(0.45%)	(−7.02%)	(−7.25%)	(−5.4%)	(−7.45%)
fuel tax 15%	−0.65	0	0.17	0.5	−1.54	−0.13	−0.43	−1.05
	(−1.59%)	(0%)	(1.19%)	(1.32%)	(−19.67%)	(−18.84%)	(−15.47%)	(−20.59%)
trash tax 5%	−0.26	−0.02	−0.02	0.32	−0.05	0	−0.04	0.04
	(−0.64%)	(−0.54%)	(−0.14%)	(0.85%)	(−0.64%)	(0%)	(−1.44%)	(0.78%)
trash tax 15%	−0.8	−0.07	−0.07	0.98	−0.12	0.01	−0.09	0.16
	(−1.96%)	(−1.89%)	(−0.49%)	(2.59%)	(−1.53%)	(1.45%)	(−3.24%)	(3.14%)

Note: The table presents percentage-point changes in the amount of trash sent to a specific demographic group in 4-mile neighborhoods surrounding disposal facilities. Numbers in brackets show the percentage-point change in percentage. 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.

TABLE D7: Current distribution of county waste share in 5-mile-buffer neighborhoods of facilities

	(1)	(2)	(3)	(4)
Dependent		market share		
% black	0.027	0.378	0.345	0.934***
	(0.235)	(0.258)	(0.255)	(0.252)
% Hispanic	−0.027	0.161**	0.151*	0.168*
	(0.059)	(0.080)	(0.081)	(0.099)
% Asian	0.091	0.086	0.105	−0.036
	(0.087)	(0.086)	(0.082)	(0.094)
income ($1000s)		0.314***	0.285***	0.421***
		(0.083)	(0.086)	(0.119)
price			0.115	0.132
			(0.078)	(0.095)
distance*fuel				−0.208***
				(0.036)
quarter FE	Y	Y	Y	Y
ori cnty FE	Y	Y	Y	Y
observations	1478	1478	1478	1478
non-zero observations	1114	1114	1114	1114

Note: This table reports coefficients of a Tobit model. The dependent variable is trash shares, that is, the share of a generating county's waste to a facility. Dependent variable is weighted by market size (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. Significant level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE D8: Change in percentages of waste going to 5-mile-buffer affected communities after NIMBY policies

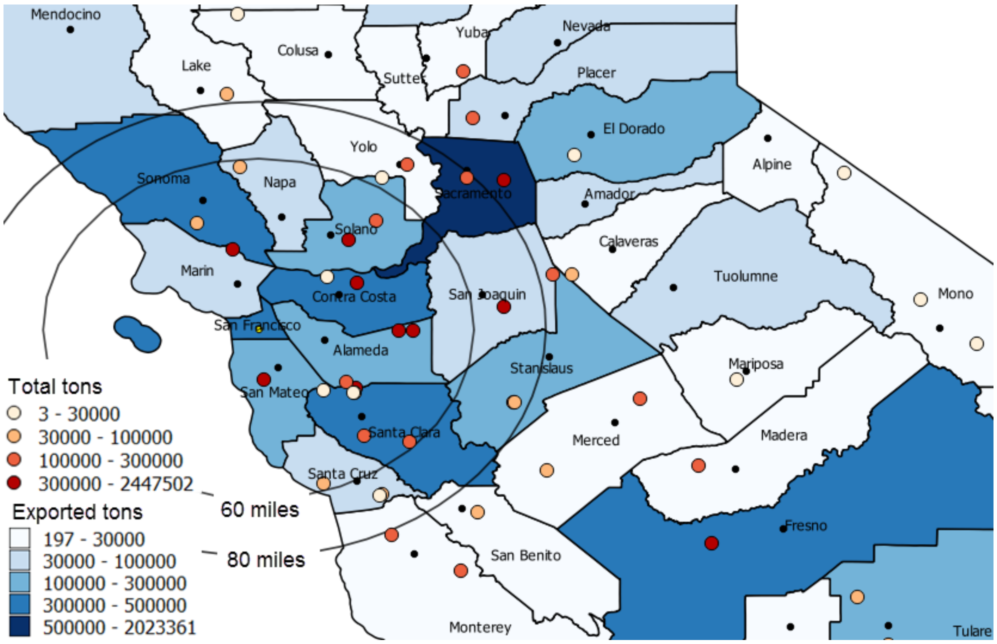
	% trash to white	% trash to black	% trash to Asian	% trash to Hispanic	% exported to white	% exported to black	% exported to Asian	% exported to Hispanic
baseline	40.25	3.76	14.62	37.89	7.67	0.66	2.87	5.18
import ban	−0.83	−0.01	−0.49	1.4	−7.66	−0.66	−2.87	−5.18
	(−2.06%)	(−0.27%)	(−3.35%)	(3.69%)	(−99.87%)	(−100%)	(−100%)	(−100%)
import tax 5%	−0.21	0.01	−0.14	0.35	−1.69	−0.14	−0.7	−1.07
	(−0.52%)	(0.27%)	(−0.96%)	(0.92%)	(−22.03%)	(−21.21%)	(−24.39%)	(−20.66%)
import tax 15%	−0.51	0.01	−0.31	0.84	−4.05	−0.33	−1.65	−2.63
	(−1.27%)	(0.27%)	(−2.12%)	(2.22%)	(−52.8%)	(−50%)	(−57.49%)	(−50.77%)
fuel tax 5%	−0.2	0	0.07	0.14	−0.53	−0.04	−0.16	−0.39
	(−0.5%)	(0%)	(0.48%)	(0.37%)	(−6.91%)	(−6.06%)	(−5.57%)	(−7.53%)
fuel tax 15%	−0.58	−0.01	0.19	0.41	−1.49	−0.12	−0.45	−1.08
	(−1.44%)	(−0.27%)	(1.3%)	(1.08%)	(−19.43%)	(−18.18%)	(−15.68%)	(−20.85%)
trash tax 5%	−0.25	−0.03	0.01	0.28	−0.05	0	−0.03	0.03
	(−0.62%)	(−0.8%)	(0.07%)	(0.74%)	(−0.65%)	(0%)	(−1.05%)	(0.58%)
trash tax 15%	−0.75	−0.08	0.02	0.84	−0.11	0.01	−0.07	0.13
	(−1.86%)	(−2.13%)	(0.14%)	(2.22%)	(−1.43%)	(1.52%)	(−2.44%)	(2.51%)

Note: The table presents percentage-point changes in the amount of trash sent to a specific demographic group in 5-mile neighborhoods surrounding disposal facilities. Numbers in brackets show the percentage-point change in percentage. 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.

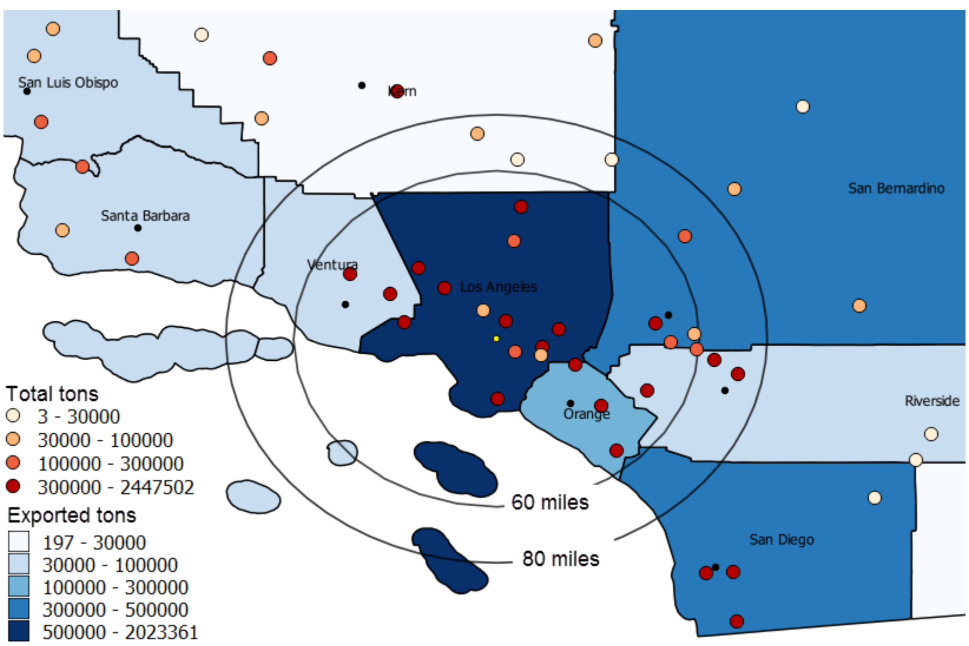
E Additional descriptive data

FIGURE E1: Illustration of choice sets in San Francisco and Los Angeles

(A) Choice set for haulers in San Francisco county in 2010



(B) Choice set for haulers in Los Angeles county in 2010



Note: The graph illustrates the set of available disposal options within 60 miles and 80 miles for haulers in the counties of San Francisco and Los Angeles. This illustration uses air distance instead of driving distance, which is used in the analysis. 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 receiving waste amount.