# When Not-in-My-Backyard Does Not Mean Protection: NIMBY and Environmental Justice*

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**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:** solid waste, intercounty trash flows, NIMBY, distributional effects, environmental justice

**JEL Classification:** D04, L51, Q53, Q56

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# 1 Introduction

Every year the United States generates more than two hundred million tons of solid waste.[1] Where to dispose of this trash is a long-running question because of the externalities associated with the transport and disposal of solid waste. To avoid becoming a repository for waste from adjacent places, several state and local governments have attempted to restrict waste imports since the late 1970s. In the 115th Congress (2018–2018), 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 efficiency costs of NIMBY policies in terms of haulers' costs and the implications of NIMBY regulations on environmental justice.

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

I, hence, 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 fit the features of the solid waste industry correctly, the model differs from the conventional model in two respects. First, the model does not have an outside option because picked-up trash must be disposed of at some disposal facility. Second, the estimation includes observations of zero waste quantity to avoid selection bias from restricting observations to those with positive quantities. Estimated transportation cost is $\$0.43$ per ton-mile given diesel prices at the 2000 level ($\$1.672$/gal). This estimate agrees with the estimates from several publications, such as $\$0.46$ per ton mile for shipping cement in Miller and Osborne (2014), \$0.29–\$0.35 per ton mile over 1983–2003 for basic truck transport in Transportation in American (2007) (cited in Miller and Osborne, 2014),

[1] Short tons are referred unless specified. The U.S. Environmental Protection Agency (2017) reports there are 268 million tons of solid waste generated in 2017.

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

and \$0.16–\$0.36 per ton mile for shipping waste in 1990 and 1992 in Fischer et al. (1993).

Given the estimated parameters underlying the haulers' decisions, I quantify how haulers' decisions about where to deposit waste would change in several counterfactual scenarios, holding facilities' characteristics constant. Four counterfactual NIMBY policies are considered: transboundary waste prohibition, transboundary waste tax, trash tax (no matter what its origin), and fuel tax.[3] Results show NIMBY policies would reduce the waste amount that crosses county lines. However, import ban and fuel taxes would reduce the disposal fees haulers pay for waste disposal, implying that haulers carted waste to disposal facilities outside the waste-generating county for other benefits besides disposal fees. These benefits are associated with the facility features such as high capacity, flexible operation hours, high acceptance rates in terms of low hassle costs of intermediary diversion before disposal, etc. In all cases, NIMBY would impose economic costs on haulers, by rerouting disposal to expensive facilities or giving up other benefits at previous preferred facilities. For example, an intercounty waste transport ban in California would stop 17% of generated waste one county ships to other counties in 2010, but cost haulers in the shipment-origin county on average 4 million dollars.

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 enacting 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 perversely increase interstate waste shipments since states would export smaller volumes to more destinations. They use the aggregate data at state level and characterize the intertemporal allocation of waste disposal of the state planner, assuming the demand for waste disposal services is linear and a competitive equilibrium.[4] My model, however, considers the decision of haulers about choosing which disposal facilities 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 disposing waste is a differentiated service in prices and in distances from generating places to disposal facilities. This accountability helps evaluate and explain the impacts of NIMBY regulations in the way they interfere with the hauling decision to dispose collected trash.

This paper also contributes to the literature of environmental justice by being the first addressing the racial distribution of waste *flows* and the implications of NIMBY regulations on this distribution. Previous studies have examined the disproportionate exposure to undesirable matters by focusing on total concentration of hazard at a facility and comparing demographic composition between a nearby exposed neighborhood and extended areas that are far away; for example, Baden and Coursey (2002);

[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 temporal planning problem.

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 from the population center of the waste-generating county, does the demographic feature of the neighborhood surrounding the facility explain the choice for the facility?

The analysis of the status quo correlation between race and waste flows in California in 2010 shows waste is more likely sent to facilities in high percent minority communities than white communities. The disparities for black communities and Hispanic communities persist once I control for income, disposal fees, and distance. 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.

While it is beyond the scope of this paper to establish a causal effect or to show exactly the causes of environmental injustice, 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 toward 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 captivate haulers' preferences. Although the exact reasons are not examined, the results suggest policies that target disposal prices and transport costs would not affect significantly 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 focus on. 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 there are no nearby landfills or incinerators, he may unload the trash at a transfer station. The transfer station consolidates waste into a larger vehicle and transports the trash to a landfill or incinerator. The transfer station also often removes hazardous materials and divert waste for recycling or reuse prior to final disposal. Of the 268 million tons of MSW in 2017, 52 percent were landfilled, 35 percent were recycled, and 12 percent were 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 percent, from 10 million tons to 30 million tons (Repa, 2005).

Several states became overwhelmed by the huge 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, these attempts were overturned by the Supreme Court’s decisions on the basis that they discriminate 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 it clear that under the “dormant” Commerce Clause of the Constitution, states may not erect barriers to interstate commerce unless Congress explicitly

[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) comment that prior to the RCRA, most every town in the U.S. has 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 percent in 1984 to 36 percent in 1998.

allowed 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 have 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 fee on 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 (no matter where the waste is from) 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 that the control prevented them from accessing economic landfills. Ley et al. (2002) and Macauley (2009) comment that long-haul waste shipments became popular to exploit the wide differences among disposal fees that justified incurring transportation costs.[9] I, hence, focus on how NIMBY policies, by interfering disposal fees, fuel costs, or alternative options of facilities, affect the waste flows and the efficiency in terms of the costs of haulers.

A growing number of recent research has also explored the waste industry. Greenstone and Gallagher (2008), Gamper-Rabindran and Timmins (2011) study the effects of Superfund-sponsored cleanups of hazardous waste sites on housing values. Currie et al. (2011) find 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 merger between two disposal firms. Kawai (2011) explores the recycling stage and studies auction design when sellers have incentive to invest for quality improvement in municipal plastic recycling auctions in Japan. Salz (2017) focuses

[7]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 special fee on out-of-state hazardous waste in *Chemical Waste Management Inc., v. Guy Hunt, Governor of Alabama (1992)*, an Oregon statute that imposed surcharge on out-of-state solid waste in *Oregon Waste Systems Inc. v. Department of Environmental Quality of the State of Oregon (1994)*, and a Wisconsin statute that required out-of-state communities to adopt Wisconsin recycling standards if exporting to Wisconsin facilities in *National Solid Waste Management Association v. Meyer (1999)*, etc.

[8]In 1994, both the House and Senate passed the "State and Local Government Interstate Waste Control Act" that prohibit a landfill or incinerator from receiving out-of-state solid waste unless it obtains authorization from the affected local government to receive such waste. However, the bill was not enacted due to lack of agreement on common language in enactment. Another bill in later session (S. 534 in 1995) that authorizes states to prohibit out-of-state solid waste and to reinforce local waste flow control ever exercised before 1994 was passed in Senate but retained in the House.

[9]Of course, the long-haul shipments are also means to access the large-scale facility, 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 to differences in disposal fees. Ley et al. (2002) gave an example that the trend in interstate waste from Northeast to Midwest during early 1990s was because of the closing of many landfills in New York and New Jersey. This caused a sharp rise 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, it can remain cheaper for northeastern states to export waste to the Midwest.

on the collection stage and studies the role of intermediaries between commercial establishments and private waste haulers in New York trade waste collection market.

## 2.2 Environmental justice

In addition to the economic efficiency 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 1994 executive order and federal actions to address environmental justice in minority population and low-income population, 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 Warren County site, which was predominantly low income and black, was chosen. Followed protests 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.

Literature have been gathering evidences 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 of 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, etc. 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), and Depro et al. (2015) 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 that race and English speaking 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 total concentration of undesirable matters at a site. They compare neighborhood that is exposed to the matters 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 be 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 because not many states in the U.S. report waste flows. Whereas microdata about solid waste amount 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 percent during 1995–2015, which allows our 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 also interesting by itself. In 1984 Solano county in California enacted Measure E that limited imported quantities. The measure was then prevented from enforcing in 1992 due to the concern about violating the Commerce Clause. In 2009 opponents of the landfill expansion in Solano filed a lawsuit aiming to reinstate Measure E. In 2012, however, California passed a bill that prohibits local ordinances from restricting the importation of solid waste into a local privately-owned disposal facility based on place of origin.[10] The legislations 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 data set is then combined with the data on quarterly disposal price (tipping fees) from Waste Business Journal, an industry research and analysis company. In the waste industry, tipping fee is known as the fee charged per ton to unload solid waste at a landfill or transfer station. 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

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

to a facility location using HERE API.[11] For more details about the data and how it was formatted for the analysis, see appendix (A).

The data show that the trends in waste disposal in California mirror the national trends. Figure 1a shows total waste amount generated by a county increased steadily in 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 percent 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 1990s due to the enforcement of the RCRA, a large number of disposal facilities were closed. There were more than 200 facilities in California in 1995 but the number fell to 170 in 1998.

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

It is hence not surprising to see an increase in long-haul shipments of trash. 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.

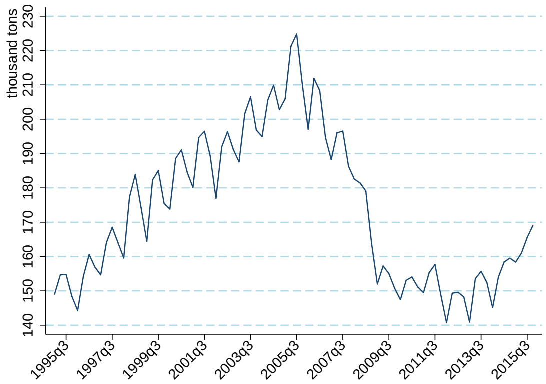
However, it is worth noticing that the shipping distance is still in a reasonable economic range. My conversations with waste collection companies as well as to a representative in National Waste & Recycling Association, a trade association for private waste management sector, reveal that trucks generally 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 amount of trash is shipped to a facility if the transport distance increases. The carted amount of trash plummets quickly for the distance ranging from 30 to 60 miles, following by a flat tail for distances beyond 60 miles (up until 700.17 miles according to the 1995–2015 data).

The reason for the focus on the reasonable economic range of shipping distance is to define the economic choice set of disposal facilities for a hauler that I will describe in detail in the next section. As of now, 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.

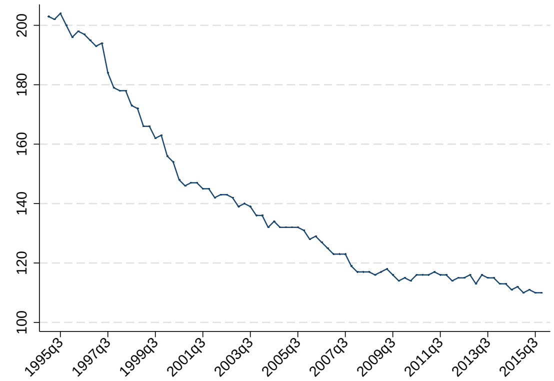
[11] HERE is a company working on digitizing mapping and in-car navigation systems, `https://www.here.com/company`.

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

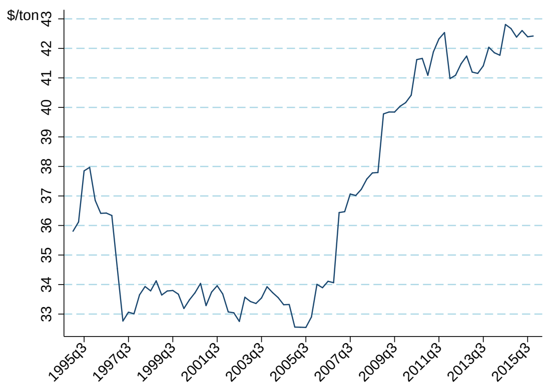
(A) Total waste amount generated by one county



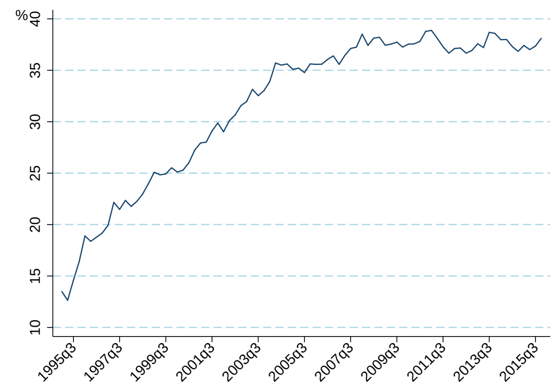

(B) Number of disposal facilities in California



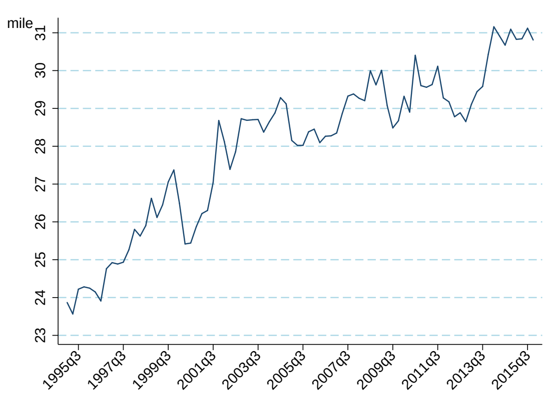

(C) (Waste weighted) average disposal price (in 2000 dollars) paid by haulers in one county



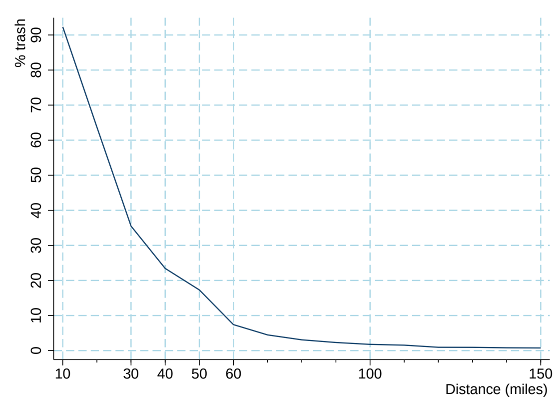

(D) Percentage of waste one county sends to other counties




(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 waste-generating county to a disposal facility. Panel 1f shows the percentage of waste that is transported beyond a given distance in 2015.

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 economic incentives underlying the 60-mile waste flows, which makes up above 90 percent of the waste generated in California.

# 4 Modelling waste flows

In the MSW industry, activities in the collection stage are resulted 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 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, it is more difficult for a municipality to control waste flows. The disposal market has both public landfills owned by municipality and private facilities. Trash collected by haulers is disposed 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 where 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 remains 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 a means to consolidate economy of scale and ensure that large volumes of waste could be collected to supply large-scale facilities. As McCarthy (2004) notices, consolidated firms often ship waste to their own disposal facility across a border, rather than an in-state facility owned by a rival. However, Kamita (2001) suggests the disposal market remains rooms for competition. In fact, many merger and acquisitions cases have been challenged by the U.S. Department of Justice.[13]

In this paper, I consider the final places of waste disposal with 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

[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. in 1988, U.S., New York Pennsylvania and Florida v. Waste Management, Inc., et al. in 1998, U.S. v. Allied Waste Industries, Inc. and Republic Services, Inc. in 2000, U.S. v. Waste Industries USA, Inc. in 2005, U.S. v. Waste Management, Inc. and Deffenbaugh Disposal, Inc. in 2015, etc.

long-haul shipments with the opportunity to arbitrage differences in disposal fees.

## 4.1 The model

Assuming a hauler $i$ picks up a waste amount $q_{ict}$ in county $c$ in quarter $t$, he chooses a facility $j$ to dump the trash to maximize his utility $U_{ijct}(X_{ijct}, \epsilon_{ijct})$, which is a function of $X_{ijct}$ and $\epsilon_{ijct}$. $X_{ijct}$ are observables that include tipping fees and transport costs. Transportation costs are measured by the interaction between driving distances from population weighted centroid of waste-generating county to landing facility location and fuel prices.[14] $\epsilon_{ijct}$ 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 hauler level. I instead observe the data at 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 costs of disposal in terms of the surplus of waste collectors. The observed waste flows, without policy intervention, reflects 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 picked up waste amount 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 aspect, $i$ is considered as an 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 economy of scale.

Fourth, I control for facility fixed effects $\gamma_j$. As described, vertical integration and public vs. 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 of the variation in which consolidated firms are big firms with high capacity landfills.

Assuming $\epsilon_{ijct}$ follows type I extreme value distribution, the probability that the facility $j$, of

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

available options in the choice set $C_{ct}$, is chosen in the 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 that there is no outside option. A hauler must choose a facility to dump all of their trash. The hauler does not keep trash himself. This also means there is no illegal dumping.

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. This means 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 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 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 from the population weighted centroid of a county that generates trash. This means the choice set for a hauler in county $c$ in quarter $t$ is the set of facilities within driving distance of 60 miles. As a further examination of economic incentives underlying these trash flows, I estimate the following regression:

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

The dependent variable $q_{cjt}$ is the waste amount generated in county $c$ to be disposed 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 ($\gamma_{ct}$) and facility fixed effects ($\eta_j$). The second specification includes quarter fixed effects and origin county by facility fixed effects to further test for price response, because price is endogenous due to omitted variables. Of course the price endogeneity problem cannot be solved completely, but we will deal with it in the 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 do not respond to price and distance any more. This confirms our assumption that there is a certain limit of distance under which trash flows economically respond to price and distance. If waste is transported farther than that limit, it must haven been a reporting error or a designation beyond the economic reasons.

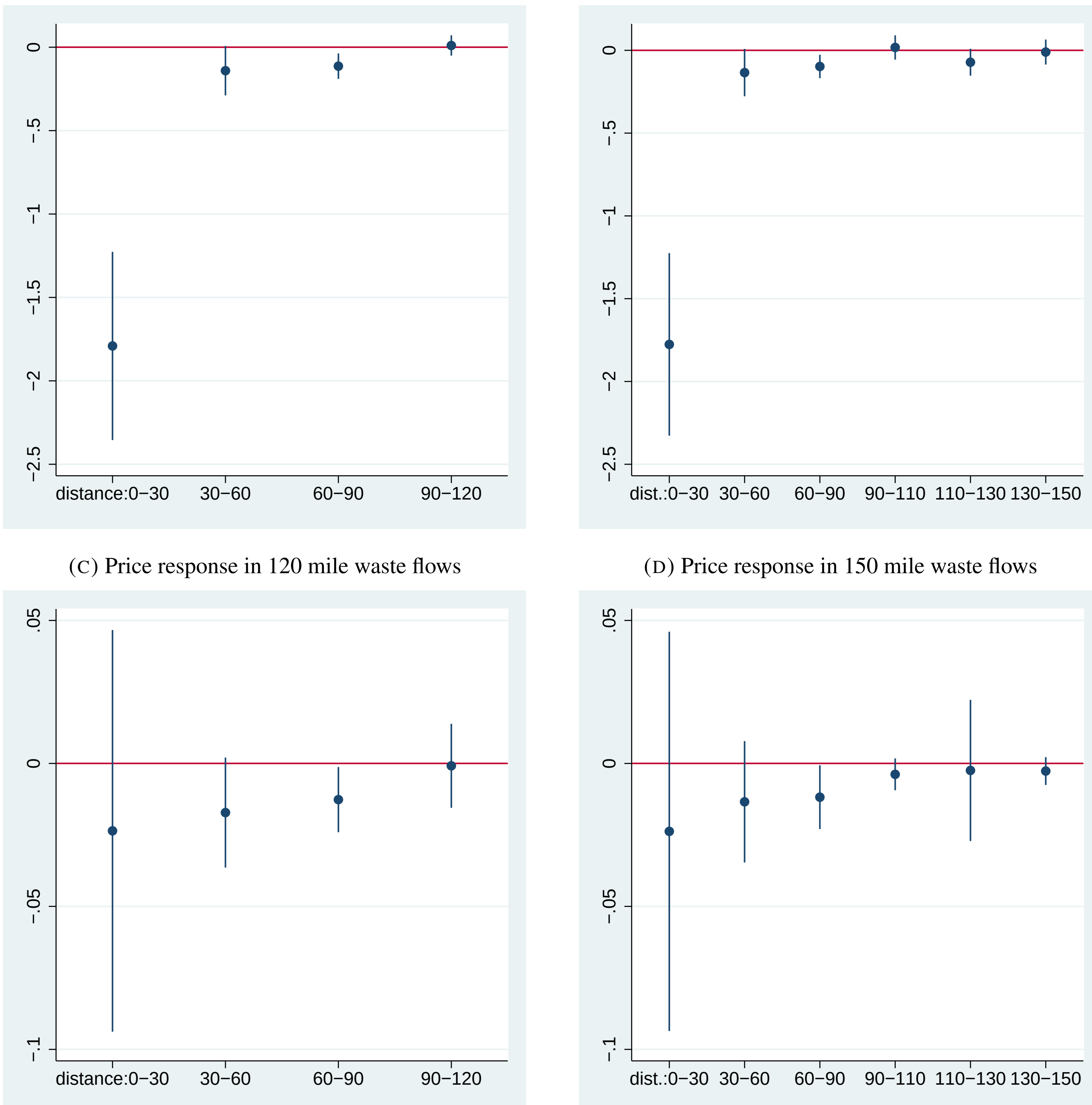
As said, I use 60 miles to define the market radius, which aims to explain at least 93 percent of waste disposal in California. A market is a county that generates trash. Decision makers are haulers (either private or public) in the county, and face a choice set of alternative options that consists of all disposal facilities within 60 miles in driving distance from the population weighted centroid of the county. Figure 1b 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 though).

Table 1 shows summary statistics of this sample, i.e. all combination 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 thousand tons of waste to a facility. The average distance is 24 miles and the average price is $36/ton. Panel B shows the characteristics of the choice set 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. Average size of a market (average trash amount a county generates) is about 175 thousand tons. A county exports about 22% of their trash to other counties in the main sample. Haulers in a market have averagely 8 options to dispose their collected waste.

## 4.3 Estimation

Estimating multinomial logit discrete choice models with data at market level has been well documented in Berry (1994); Berry et al. (1995). The contraction mapping result in Berry (1994) shows there exists a unique mean utility vector to match the model implied choice probability to observed

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 $q_{cjt} = \beta_d f_d(\text{distance}_{cj}) + \beta_p f_p(\text{price}_{jt}) + \gamma_{ct} + \eta_j + \epsilon_{cjt}$. Figures 2a and 2b shows 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 shows 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 × origin county × destination facility)* | | | | | |
| *A1: Flows within 60 miles of the population-weighted centroid of a county* | | | | | |
| quantity (ton) | 36,186 | 21,453.27 | 70,161.38 | 0 | 1,063,515 |
| distance (mile) | 36,186 | 37.12 | 14.91 | 1.737 | 59.93 |
| waste-weighted distance (mile) | 36,186 | 23.52 | 12.90 | 1.73 | 59.93 |
| waste-weighted price ($/ton) | 36,186 | 36.40 | 12.10 | 1.50 | 181.00 |
| *A2: All positive flows in California, including shipments beyond 60 miles* | | | | | |
| quantity (ton) | 53,957 | 15,401.27 | 58,388.94 | .01 | 1,063,515 |
| waste-weighted distance (mile) | 53,957 | 28.00 | 23.23 | 1.73 | 700.17 |
| waste-weighted price ($/ton) | 53,957 | 36.49 | 12.18 | 1.50 | 181.00 |
| *Panel B: Choice set characteristics (unit: quarter × origin county)* | | | | | |
| *B1: Within 60 miles* | | | | | |
| market size (ton) | 4,431 | 175,199.3 | 416,191 | 1.6 | 3,573,185 |
| out-of-county exports (%) | 4,431 | 21.68 | 33.34 | 0 | 100 |
| number of options | 4,431 | 8.17 | 5.24 | 1 | 30 |
| *B2: All choices in California* | | | | | |
| market size (ton) | 4,788 | 173,560.3 | 426,099.1 | .37 | 3,881,458 |
| out-of-county exports (%) | 4,788 | 31.62 | 38.05 | 0 | 100 |

*Note:* Panel A shows summary statistics of the sample of trash flows; the unit of observation is quarter × origin county × destination facility. Panel A1 includes all waste flow pairs between an origin county and a destination facility in a quarter (36,186 observations) within 60 miles, of which there are 24,473 observations of positive waste flows. Panel A2 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 from population centroid of the county (number of options). Panel B2 is similar to panel B1, but covering all choices in California (including choices resulted from the waste flows beyond 60 miles).

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. This is similar to the work by Martin (2008) (cited in chapter 13 in Train, 2009).[15] The limitation is that it

[15] Martin (2008) studies consumers' choice between incandescent and compact fluorescent light bulbs, where advertising and promotions occurred weekly and varied over stores, but it was common for a store not to sell any fluorescent light bulbs in a given week.

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 to choose

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

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

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

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

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

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

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

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

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

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

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

The second estimator assumes that the picked-up waste amounts across different markets have the same size, i.e. $q_{ct} = q\ \forall c,t$. This means that the trash collection trucks have the same size in the whole California. The log likelihood function becomes

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

The second estimator implies that market sizes differ across markets because the number of collection trips and the number of haulers vary across markets. Given this situation is more plausible, the second estimator will be used for the main results. Appendix C shows 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 both identify the price preference and control other factors that explain the choice of a facility. Without facility fixed effects, estimate for the price parameter is 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 are added up to high disposal fees.

In addition to reducing upward bias in estimating price parameter, facility fixed effects explains variation in trash shares beyond the explanation from transport costs and disposal fees. For example, vertical 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 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 will see that the fixed effects also capture the factors, other than transport costs and disposal price, that are correlated with the demographics of a community living nearby a facility.

When having 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 cost shifters, BLP instruments, Hausman instruments, Nevo instruments; see Berry et al. (1995); Hausman (1996); Nevo (2001).

The first feature of this market-size instrument is that it is correlated with price even though there may be deviations between observed listed prices and actual contracted prices. The reason is that disposal facility has strictly nonlinear costs with economy of scale or diseconomy of scale on certain ranges of received trash amount. For example, suppose the landfill is having economy of scale. Its incurring 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 while not cutting the markup. Such landfill has been receiving a lot of waste from its surrounding markets (to reach the 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 from the landfill location. $s_c(p_c)$ is the 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, i.e. total waste generated by county $c$. Hence, $s_c(p_c)Q_c$ is the waste amount the landfill receives from county $c$. Given the nonlinear cost $C(\cdot)$ depends on 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 highly likely exogenous with 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 concern 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 economy. In that case, however, it should be noticed 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 instrument in a nonlinear model, I apply control function approach. Following the literature, control function is estimated using polynomial of residuals obtained from the first stage in which price is regressed on exogenous variables and instruments. In the main model, the polynomial terms enter as extra explanatory variables, see Petrin and Train (2010). I estimate models with linear polynomial and quadratic polynomial of control terms.

## 4.5 Estimation results

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

TABLE 2: Results from multinomial logit discrete choice model

| Model | (1) Facility fixed effects | (2) IV linear control function | (3) IV quadratic control function |
|---|---|---|---|
| price | $-0.0011$ | $-0.1592$*** | $-0.1593$*** |
| | (0.0016) | (0.0238) | (0.0238) |
| distance∗fuel | $-0.0442$*** | $-0.0412$*** | $-0.0411$*** |
| | (0.0010) | (0.0011) | (0.0011) |
| control term | | 15.9038e$-$2*** | 15.9199e$-$2*** |
| | | (0.0240) | (0.0241) |
| control term$^2$ | | | $-0.2507$e$-4$ |
| | | | (0.4580e$-4$) |
| facility FE | Y | Y | Y |
| First stage results | | price | |
| total market sizes (hundred thousand tons) | | $-0.2205$*** | |
| | | (0.0108) | |
| **1**(serve at least 2 markets) | | $-2.9998$*** | |
| | | (0.9919) | |
| distance∗fuel | | 0.0200*** | |
| | | (0.0013) | |
| 1st stage $R^2$ | | 0.6685 | |
| F test | | 212.62 | |
| price elasticity | $-0.0277$ | $-4.1983$ | $-4.2007$ |
| transport elasticity | $-1.7138$ | $-1.5945$ | $-1.5943$ |

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

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

The ratio between transport cost coefficient and price coefficient captures hauler's willingness to pay for proximity to the disposal facility. This is the cost of transportation. The estimates imply that transportation costs $\$0.43$ per ton-mile given diesel prices at the 2000 level ($\$1.672$/gal). This agrees with the estimates from several publications. First, Miller and Osborne (2014) report the transportation costs $\$0.46$ per ton mile for shipping cement. Second, the 20th edition of Transportation in American (2007) (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

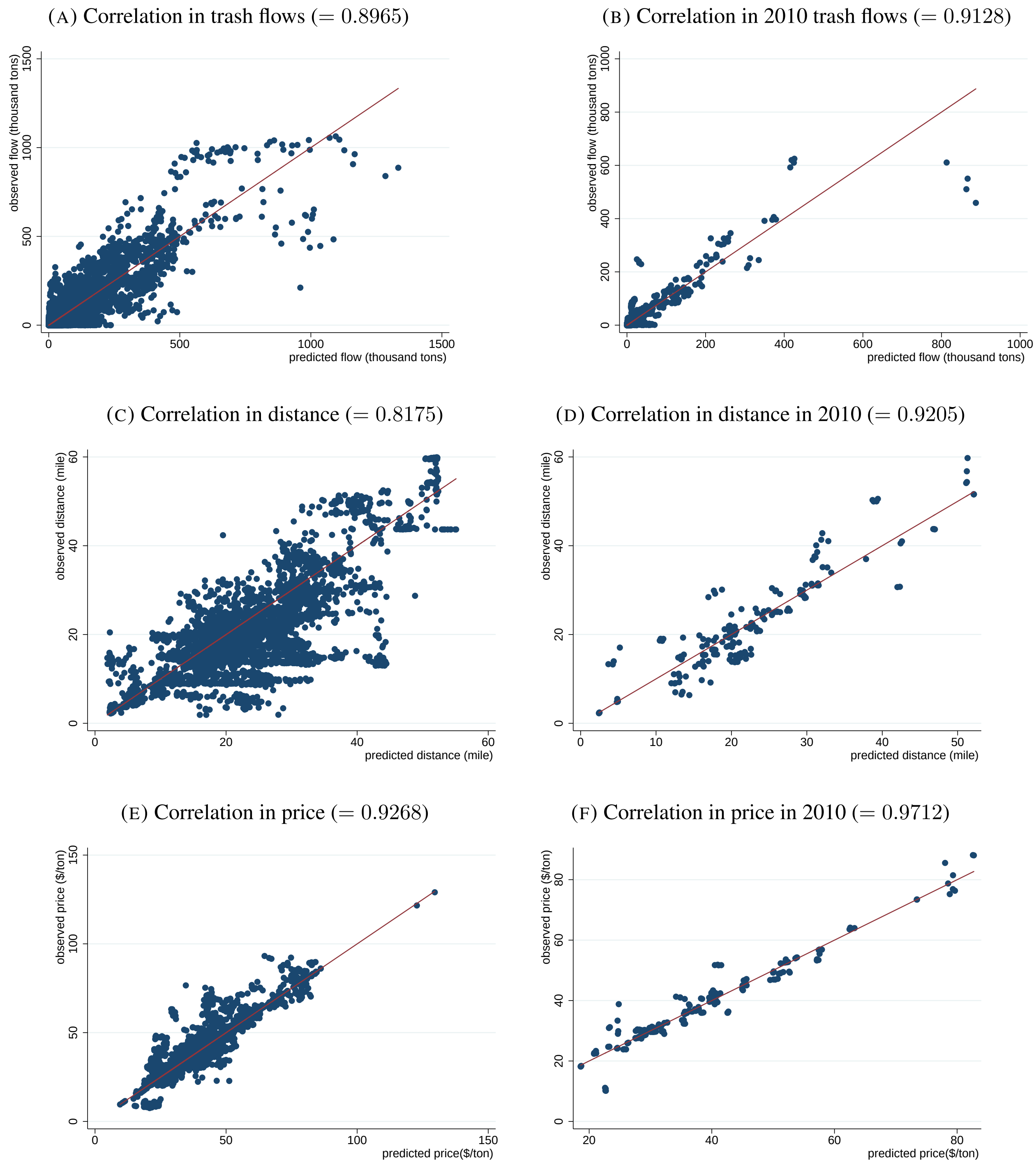
Figure 3 shows the scatter plots and correlation coefficients between observed values and fitted values of key variables. The key variables I consider are waste flows, waste-weighted average distance, and waste-weighted average price because it is important to match waste movements well to study the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

## 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

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

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 (= 0.9205)

(E) Correlation in price (= 0.9268)

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

*Note:* The graph shows the correlation coefficient between observed values and fitted values 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.

formula:

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

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) exports (tons) | (2) tipping fees (thousand \$) | (3) trash mileage (kiloton-mile) | (4) hauler cost (thousand \$) | (5) tipping fees (\$/ton) | (6) trash mileage (mile) | (7) hauler cost (\$/ton) |
|---|---|---|---|---|---|---|---|---|
| (1) | baseline 1 | 573,678 | 145,000 | 90,500 | | 39.96 | 22.22 | |
| (2) | import ban | −573,678 | −748 | −10,300 | 3,964 | −0.12 | −3.08 | 1.25 |
| | | (−100%) | (−0.52%) | (−11.38%) | | (−0.29%) | (−13.88%) | |
| (3) | baseline 2 | 568,381 | 142,000 | 88,700 | | 40.32 | 22.58 | |
| (4) | import tax 5% | −130,419 | 582 | −2,307 | 993 | 0.19 | −0.68 | 0.36 |
| | | (−22.95%) | (0.41%) | (−2.60%) | | (0.46%) | (−2.99%) | |
| (5) | import tax 15% | −313,451 | 876 | −5,579 | 2,323 | 0.34 | −1.64 | 0.87 |
| | | (−55.15%) | (0.62%) | (−6.29%) | | (0.83%) | (−7.26%) | |
| (6) | fuel tax 5% | −41,264 | −527 | −1,739 | 2,826 | −0.07 | −0.48 | 0.72 |
| | | (−7.26%) | (−0.37%) | (−1.96%) | | (−0.18%) | (−2.12%) | |
| (7) | fuel tax 15% | −115,927 | −1,579 | −4,976 | 8,316 | −0.21 | −1.35 | 2.11 |
| | | (−20.40%) | (−1.11%) | (−5.61%) | | (−0.53%) | (−5.98%) | |
| (8) | trash tax 5% | −5,497 | 4,971 | −822 | 7,059 | 1.52 | −0.11 | 2.0 |
| | | (−0.97%) | (3.50%) | (−0.93%) | | (3.78%) | (−0.47%) | |
| (9) | trash tax 15% | −19,585 | 14,500 | −2,469 | 20,900 | 4.45 | −0.29 | 5.94 |
| | | (−3.45%) | (10.21%) | (−2.78%) | | (11.03%) | (−1.28%) | |

*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. There are two status quo baselines. Baseline 1 is a benchmark for import ban policy. Baseline 2 is a benchmark for import tax, fuel tax, and trash tax. The reason is that five counties, Alpine, Amador, Del Norte, Nevada, San Francisco, and Tuolumne do not have any local facilities. Hence, these counties are dropped when calculating the baseline 1. These counties account for 1.91% of 60-mile waste (or 1.89% of total waste) in California in 2010.

Table 3 presents the results. There are two baseline levels. One is used to evaluate the effects of import bans. The other one is used for the comparison with import taxes, fuel taxes, and trash taxes. The reason for two baseline levels is that six out of fourty six counties in California, namely, Alpine, Amador, Del Norte, Nevada, San Francisco, and Tuolumne, do not have disposal facilities within their border lines in 2010.[17] These counties account for 1.91% of 60-mile waste (or 1.89% of total waste) in California in 2010. I exclude those counties when contrasting with the import ban scenario.

Because an import ban that interdicts intercounty waste transport would restrict the choice set of a

[17] California has 58 counties in total. Six out of fifty eight counties have waste transported all beyond 60 miles, and are excluded from the main sample of analysis. These counties, Humboldt, Mendocino, Modoc, Plumas, Siskiyou, and Trinity, generate 0.58% of total waste in California in 2010.

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 570,000 tons, as a 17 percent of its generated trash amount, in 2010. 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 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 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. Column 2 reveals the overall effect of import bans on tipping fees is dominated by the second mechanism. Particularly, haulers in one county would pay $750,000, or 12 cents per ton less if being forced to dump at local places. However, haulers' costs in one county would increase by 4 million dollars, or $1.25 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) become more expensive relative to local alternatives. As a result, the tax would reduce intercounty waste flows. Consider a tax of 15%, or $5.46/ton on average, which is 20% higher than the current fees imposed in Alameda (one of the top three waste-importing counties in California).[18] Column 1 shows that the 15% tax would reduce about 300,000 tons of one-county exports, which is 55% of the current exports. Total tipping fees would increase by nearly $900,000, or 34 cents per ton because both options of switching to local facilities and staying at nonlocal facilities would become more expensive than previous. Trash mileage would fall by 5.5 million ton-miles, or 1.6 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 rise by 2 million dollars, or 87 cents per ton.

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 7 shows a fuel tax at 15%, which is on average $30.6 cents per gallon or 65% of the 2019 fuel tax level, would reduce nearly 5 million ton-miles in trash mileage, or equivalently 1.35 miles in a journey from population center of generating county to a disposal facility. Because out-of-county facilities are generally farther from waste-generating origin than local alternatives, the fuel tax would also reduce exports. At the tax of 15%, exports would fall by 116,000 tons, or 20%.

The change in total tipping fees in the case of fuel tax is theoretically ambiguous because of two opposite directions. First, switching to a nearer facility is costly because the nearer facility is

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

expensive, which was the reason the hauler did not opt for. Second, switching to a nearer facility would save the hauler on paying tipping fees, but it did not offer other benefits beyond tipping fees and transport costs, such as high acceptance rates, operation hours, capacity, etc., which are captured by facility fixed effects in my model. Column 2 and row 7 reveal the second effect is dominant: Haulers in one county would overall save 1.5 million dollars (a reduction by 1.11%), or 21 cents per ton, in tipping fees. However, forgoing "good" facilities would cost the haulers 8 million dollars, or $2.11 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 mean to compensate for affected communities nearby 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 directions. 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 (3.45%) at the waste tax of 15%.[19] Total tipping fees haulers in a county would have to pay the disposal facilities would increase 14 million dollars (10.21%), or $4.45 per ton. Trash mileage would decrease slightly by 2.78%, or 0.29 miles for a trip, revealing again that switching to less expensive facilities do not necessarily mean higher cost of transportation. Overall, costs would jump by 20.9 million dollars, or $5.94 per ton.

# 6 NIMBY and the distribution of waste disposal by race

As mentioned, this paper also focuses on environmental justice perspective of NIMBY policies by considering the distribution of waste flows by race. To begin with, let us explore the current distribution of 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 census block level, and household income at block group level.[20]

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

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

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

groups or blocks. However, the choice of whether to use blocks, block groups, or census tracts as communities may be also problematic, because these units vary greatly in geographic size. For example, blocks in California range from 1/1,000,000 of a square mile to more than a thousand square miles. Hence, I use aggregate demographic data at available smallest census units, blocks, to construct demographic data for fixed circle communities centering disposal sites. A block is considered to be in the affected community if its centroid location is in the fixed circle centering the facility. Population count at blocks are aggregated for counts in the community.[21]

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

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

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

For the main analysis, I use 3-mile buffer zones to refer to affected communities nearby disposal facilities. Appendix D shows the results for 1-mile buffers and 2-mile buffers. Table 4 reports mean demographic composition in 3-mile affected communities. The table also contrasts the demographic composition at county level in term of receiving trash with generating trash. In 3-mile affected communities, the average population is 26,000, of which 49.4% are white, 2.7% are black, 8.1% are Asian, and 35.3% are Hispanic. When weighted by trash amount at a facility, percentages of white, black, Asian, and Hispanic residents are 44.1%, 3.7%, 13.0%, and 35.7%, respectively. The differences between unweighted and trash weighted percentages by race imply that more waste is disposed in minority communities than in white communities. The disparity becomes more apparent when

[21] 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).

comparing waste-weighted demographics in receiving community with generating county. While the percentage of white is higher in generating county than receiving community, the percentages of black, Asian, and Hispanic residents are lower.

Since waste flows are results of market activities, I now examine the correlation between waste shipments and race after controlling for 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 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 zero 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 race of interest as a percentage of the population in the affected community. Control variable income$_j$ is the median household income at community surrounding facility $j$. I also include quarter fixed effects $\gamma_t$ and market fixed effects $\delta_c$. The regression is weighted by market size (total trash generated in a county), and uses observations in year 2010.

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

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dependent var. | | market share ($\times 100$) | | |
| % black | 0.015 | 0.303 | 0.289 | 0.948*** |
| | (0.255) | (0.299) | (0.294) | (0.264) |
| % Hispanic | −0.026 | 0.162** | 0.154** | 0.122 |
| | (0.057) | (0.068) | (0.071) | (0.084) |
| % Asian | 0.049 | 0.026 | 0.035 | −0.084 |
| | (0.095) | (0.079) | (0.078) | (0.083) |
| income ($1000s) | | 0.345*** | 0.325*** | 0.417*** |
| | | (0.077) | (0.083) | (0.097) |
| price | | | 0.059 | 0.078 |
| | | | (0.078) | (0.087) |
| distance*fuel | | | | −0.214*** |
| | | | | (0.038) |
| quarter FE | Y | Y | Y | Y |
| ori cnty FE | Y | Y | Y | Y |
| 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). Dependent variable is market shares, i.e. share of a generating county's waste to a facility. Demographic characteristics of facilities are characteristics of community within 3 miles of a facility. The sample only includes observations in 2010. The Tobit regression includes quarter fixed effects and waste-origin county fixed effects. Significant level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5 reports results. Column 1 shows that no significant differences are found in the receiving waste amount between minority communities and white community. However, controlling for income, waste is sent more to black and Hispanic communities (column 2). We see that the coefficients of black percentage and Hispanic percentage become bigger and statistically significant, implying that facilities in black and Hispanic communities receive more trash for other reasons that are not related to income.

It may be surprising that the coefficient of income is positive. However, it is noticed 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 from the variation in income *among* affected communities nearby 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 as income happens to correlate 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 income than the neighborhoods of other facilities may be less attractive (to haulers) because these higher income communities have higher resistance to coming waste shipments, either because of higher willingness to move out or higher political resistance. On the other hand, facilities in communities with higher income than communities surrounding other facilities may be large scale and high capacity facilities. We have seen that it is not efficient to carry waste for a very long journey. The large scale facilities, hence, are likely located still reasonably near counties that generate a lot of trash, where median income is also potentially higher than remote areas. Since haulers prefer large scale facilities, they may happen to ship more trash to facilities in areas with higher income than facilities in areas with lower income. (Still, income in these areas may be lower than income in the place that generates the trash.) The empirical result of positive sign in this paper implies the second story. However, one should notice 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 the relation between waste shipments and race.

Columns 3 and 4 show that disparities in receiving trash quantity between black, Hispanic communities and white community persist after controlling for prices and transport costs of disposing trash. The coefficient of 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 to populated center of waste-generating counties.

Surprisingly, the coefficient of black percentage becomes statistically and economically significant after controlling prices and transport costs. One percentage point increase in the percentage of black population living nearby a trash site (on a mean of 3.34%) is associated with an one percentage point increase in the market share. This 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 to the 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 at landfills, etc.

In summary, my evidence of disproportionate distribution of waste flow remains persistent after controlling for waste shipment distances and disposal fees. This, given the controls of distance, disposal fees, income, may be not enough to establish an 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 effects 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 there is something unobservable about waste facilities in black areas that 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 cost preferences of haulers, could have environmental justice implications, especially when the regulations aim to provide collected taxes for affected communities.

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 | % export to white | % export to black | % export to asian | % export to hispanic |
|---|---|---|---|---|---|---|---|---|
| baseline 1 | 42.27% | 3.40% | 13.52% | 37.46% | 8.19% | .60% | 2.70% | 4.93% |
| import ban | −1.08 | −.02 | −.54 | 1.71 | −8.19 | −.60 | −2.70 | −4.93 |
| | (−2.55%) | (−.58%) | (−4.01%) | (4.57%) | (−100.0%) | (−100.0%) | (−100.0%) | (−100.0%) |
| baseline 2 | 42.56% | 3.39% | 13.44% | 37.19% | 9.13% | .65% | 2.83% | 5.28% |
| import tax 5% | −.26 | .01 | −.16 | .43 | −1.77 | −.12 | −.65 | −.98 |
| | (−.62%) | (.35%) | (−1.21%) | (1.15%) | (−19.42%) | (−17.91%) | (−23.07%) | (−18.49%) |
| import tax 15% | −.65 | .02 | −.36 | 1.02 | −4.27 | −.29 | −1.53 | −2.39 |
| | (−1.54%) | (.62%) | (−2.65%) | (2.75%) | (−46.74%) | (−44.49%) | (−54.19%) | (−45.28%) |
| fuel tax 5% | −.24 | −1.19e−3 | .05 | .20 | −.57 | −.04 | −.14 | −.35 |
| | (−.57%) | (−.04%) | (.40%) | (.53%) | (−6.22%) | (−6.61%) | (−5.06%) | (−6.69%) |
| fuel tax 15% | −.70 | −.87e−3 | .15 | .58 | −1.58 | −.12 | −.41 | −.98 |
| | (−1.64%) | (−.03%) | (1.13%) | (1.55%) | (−17.35%) | (−18.29%) | (−14.35%) | (−18.56%) |
| waste tax 5% | −.28 | −.01 | −.06 | .37 | −.07 | .01 | −.05 | .05 |
| | (−.66%) | (−.44%) | (−.45%) | (1.0%) | (−.75%) | (1.28%) | (−1.69%) | (1.03%) |
| waste tax 15% | −.85 | −.05 | −.18 | 1.12 | −.16 | .03 | −.13 | .21 |
| | (−1.99%) | (−1.34%) | (−1.35%) | (3.01%) | (−1.71%) | (4.40%) | (−4.58%) | (4.02%) |

*Note:* The table presents changes in percentage point of percentage of trash sent to a specific demographic group. Number in brackets shows 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. There are two status quo baselines. Baseline 1 is a benchmark for import ban policy. Baseline 2 is a benchmark for import tax, fuel tax, and trash tax. The reason is that five counties, Alpine, Amador, Del Norte, Nevada, San Francisco, and Tuolumne do not have any local facilities. Hence, these counties are dropped when calculating the baseline 1. These counties account for 1.91% of 60-mile waste (or 1.89% of total waste) in California in 2010.

Table 6 shows the impacts of the four counterfactual policies on the demographic distribution of waste disposal. The table computes the percent 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 that trash from a generating county $c$ that is sent to disposal facility $j$ affects all people living three miles of the facility location equally, the percent trash of the market $c$ exposes on white community is

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

This percentage is calculated for every waste-generating county and then weighted by market size (total trash generated in a county). There are 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 percent waste that crosses county borders to export to Hispanic residents would fall. However, the total percent waste that is sent to Hispanic communities would increase, while the waste sent to white communities would decrease. This implies that 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 to 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 nearer facilities would increase shipments to facilities in Hispanic areas.

Note that 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 the trash tax, with an equal percent rate on all trash, will penalize expensive facilities more than less expensive facilities. This result also agrees with the analysis of the status quo that shows the coefficient of Hispanic percentage becomes smaller after controlling for price, though still significant.

While NIMBY policies would increase waste to Hispanic communities, the policies would nearly not produce any changes on waste sent to black areas. Waste that is sent to black residents would generally remain the same or fall by a modest amount less than the reduction in white communities (under the trash tax). The reason is 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, etc. Although explaining exactly what are the 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 maintain a right 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 efficiency costs of NIMBY regulations in terms of the costs of haulers in a short run, when disposal fees and capacity are not adjusted by disposal facilities in response to the regulations. The paper also considers the environmental justice perspective of NIMBY. I find that NIMBY would reduce intercounty waste flows but with significant costs and 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 to waste-generating places.

The paper has several limitations that suggest future research themselves. First, considering how disposal facilities set disposal fees and/or set capacity adjustment is helpful to explore the passthrough of policies on the landfill side. Second, identifying what underlies the attractiveness of facilities in black communities will help spotting a more appropriate "protection" policies. For example, several states that advocate NIMBY argue on the ground of protection of public health and safety. However, if disposal facilities in some areas are preferred because they do not keep the right environmental standards on purpose, enforcing those standards will be more effective than NIMBY taxes and import bans. Third, when the data are available, it is useful to explore the relation between waste flows and the relative income at waste destination to income level at waste origin. Exploiting variation in income at both waste destination and waste origin levels may help answer the question whether the high income areas send trash to the low income areas. Fourth, 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? Is it possible that minorities move in these areas for these opportunities and better off than previously?

Despite limitations, the finding in this paper suggests 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 on NIMBY is understandable because NIMBY was not emerged to mean to address environmental justice at the beginning.

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# APPENDIX

## A Data Handling and Format

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

For out-of-state exports in California solid waste, I observe the export amount, but I do not observe the place of destination.[22] I construct an out-of-state disposal option for haulers in California by assuming a hauler would export to a nearest out-of-state facility, if export is considered.

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

[22] Since 2006, the state of destination has been observed but the out-of-state facility of destination 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

| | : Trash amount 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 | 0.0528** | −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 | −0.0034 | 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) | | | (0.2813) | | | (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) | | | (0.0277) | |
| 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 150 miles to price and distance by different knots of driving distance. The formal regression is $q_{cjt} = \beta_d f_d(\text{distance}_{cj}) + \beta_p f_p(\text{price}_{jt}) + \gamma_{ct} + \eta_j + \epsilon_{cjt}$. Standard errors are clustered by origin county.

# C Another demand estimator using equally-market-size-weighted estimator

As mentioned above, there is an alternative estimator if the model assumes a fixed number of haulers across different markets. Intuitively, the alternative estimator aims to maximize the goodness of fit in all markets equally, instead of emphasizing the fitness in the big markets as does the estimator of the main results. Results in table C2 show that when weighting all markets equally, price coefficients becomes bigger while transport cost coefficient is similar to the case of market-weighted estimates. These higher price elasticities when using the market-equally-weighted estimator reveals that big markets are less responsive to price.

TABLE C2: Results from logit demand using market-equally-weighted estimator

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

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

# 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 and 2-mile buffers from disposal facilities. When considering these narrow neighborhoods, there are a few affected communities where nobody lives. Tables D3 and D4 show NIMBY policies would reroute waste away from facilities in white communities toward facilities in Hispanic areas but with modest effects. Tables D5 and D6 report results for 2-mile affected communities, which also show a substitution pattern of waste from facilities in white areas toward facilities in Hispanic areas if NIMBY policies took effect. Overall, there are very few people live very near to the disposal facilities (within 1 mile). Yet, at bigger neighborhoods, facilities in predominantly black and Hispanic neighborhoods tend to receive more waste than other facilities.

TABLE D3: Current distribution of county waste share in 1-mile-buffer neighborhoods of facilities

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dependent | | market share | | |
| No population | −0.499 | 2.943 | 1.393 | −0.004 |
| | (7.767) | (8.622) | (8.411) | (8.686) |
| % black | −0.035 | −0.002 | 0.030 | 0.223 |
| | (0.136) | (0.149) | (0.157) | (0.201) |
| % Hispanic | −0.021 | −0.004 | −0.010 | −0.042 |
| | (0.046) | (0.047) | (0.047) | (0.059) |
| % Asian | 0.047 | 0.037 | 0.040 | −0.007 |
| | (0.066) | (0.066) | (0.062) | (0.073) |
| income ($1000s) | | 0.055 | 0.030 | 0.023 |
| | | (0.060) | (0.057) | (0.071) |
| price | | | 0.142* | 0.208** |
| | | | (0.083) | (0.105) |
| distance*fuel | | | | −0.182*** |
| | | | | (0.043) |
| 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. Dependent variable is trash shares, i.e. 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 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 1-mile-buffer affected communities after NIMBY policies

| | % trash to white | % trash to black | % trash to Asian | % trash to Hispanic | % export to white | % export to black | % export to Asian | % export to Hispanic | % trash to no population |
|---|---|---|---|---|---|---|---|---|---|
| base line 1 | 42.73% | 2.37% | 15.75% | 33.19% | 8.07% | .37% | 3.21% | 4.27% | 2.30 |
| import ban | −.49 | .10 | −.75 | 1.24 | −8.07 | −.37 | −3.21 | −4.27 | −.01 |
| | (−1.16%) | (4.31%) | (−4.77%) | (3.73%) | (−100.0%) | (−100.0%) | (−100.0%) | (−100.0%) | (−.29%) |
| baseline 2 | 42.99% | 2.36% | 15.65% | 33.02% | 9.0% | .40% | 3.36% | 4.65% | 2.28 |
| import tax 5% | −.12 | .02 | −.22 | .32 | −1.72 | −.08 | −.79 | −.86 | .01 |
| | (−.28%) | (.88%) | (−1.40%) | (.98%) | (−19.12%) | (−19.74%) | (−23.38%) | (−18.59%) | (.53%) |
| import tax 15% | −.31 | .051 | −.49 | .76 | −4.14 | −.19 | −1.84 | −2.11 | .02 |
| | (−.71%) | (2.15%) | (−3.11%) | (2.31%) | (−46.03%) | (−48.34%) | (−54.89%) | (−45.44%) | (.96%) |
| fuel tax 5% | −.22 | .01 | .10 | .21 | −.59 | −.03 | −.16 | −.28 | −.09 |
| | (−.50%) | (.61%) | (.63%) | (.62%) | (−6.56%) | (−6.48%) | (−4.74%) | (−5.99%) | (−4.02%) |
| fuel tax 15% | −.63 | .04 | .28 | .59 | −1.65 | −.07 | −.46 | −.77 | −.26 |
| | (−1.46%) | (1.81%) | (1.78%) | (1.80%) | (−18.28%) | (−17.62%) | (−13.55%) | (−16.63%) | (−11.47%) |
| waste tax 5% | −.19 | −.02 | −.06 | .32 | −.04 | .0 | −.03 | .02 | −.03 |
| | (−.45%) | (−.99%) | (−.40%) | (.97%) | (−.45%) | (−.64%) | (−.82%) | (.41%) | (−1.35%) |
| waste tax 15% | −.60 | −.06 | −.20 | .98 | −.08 | .0 | −.08 | .11 | −.10 |
| | (−1.38%) | (−2.57%) | (−1.26%) | (2.96%) | (−.84%) | (−.39%) | (−2.28%) | (2.46%) | (−4.28%) |

*Note:* The table presents changes in percentage point of percentage of trash sent to a specific demographic group in 1-mile neighborhoods surrounding disposal facilities. Number in brackets shows 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. There are two status quo baselines. Baseline 1 is a benchmark for import ban policy, which excludes five counties, Alpine, Amador, Del Norte, Nevada, San Francisco, and Tuolumne, that do not have any local facilities. These counties account for 1.91% of waste in California in 2010. Baseline 2 is a benchmark for import tax, fuel tax, and trash tax.

TABLE D5: Current distribution of county waste share in 2-mile-buffer neighborhoods of facilities

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dependent | | market share | | |
| No population | 0.637 | 17.591 | 15.357 | 16.316 |
| | (9.383) | (11.669) | (11.807) | (11.618) |
| % black | 0.065 | 0.133 | 0.128 | 0.699*** |
| | (0.225) | (0.235) | (0.236) | (0.205) |
| % Hispanic | −0.003 | 0.110* | 0.098 | 0.032 |
| | (0.053) | (0.064) | (0.067) | (0.081) |
| % Asian | 0.090 | 0.087 | 0.088 | −0.035 |
| | (0.091) | (0.089) | (0.086) | (0.112) |
| income ($1000s) | | 0.236*** | 0.209** | 0.228** |
| | | (0.085) | (0.089) | (0.104) |
| price | | | 0.077 | 0.126 |
| | | | (0.076) | (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. Dependent variable is market shares (share of a generating county's waste to a facility). The regression 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 D6: Change in percentages of waste going to 2-mile-buffer affected communities after NIMBY policies

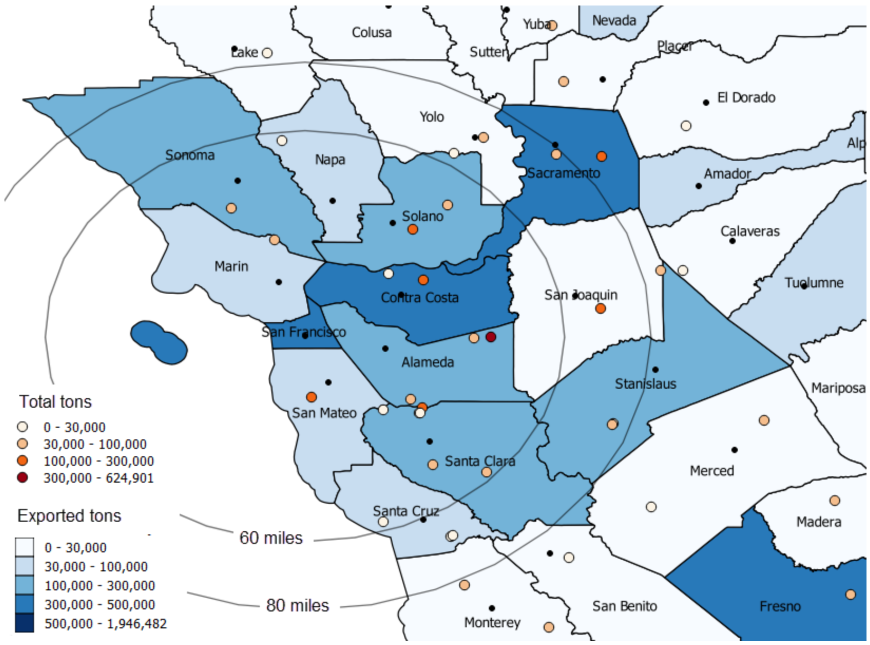
| | % trash to white | % trash to black | % trash to Asian | % trash to Hispanic | % export to white | % export to black | % export to Asian | % export to Hispanic | % trash to no population |
|---|---|---|---|---|---|---|---|---|---|
| base line 1 | 42.03% | 3.28% | 13.56% | 36.41% | 7.80% | .66% | 2.76% | 4.97% | 1.32 |
| import ban | −.80 | −.11 | −.63 | 1.58 | −7.80 | −.66 | −2.76 | −4.97 | .03 |
| | (−1.90%) | (−3.46%) | (−4.63%) | (4.33%) | (−100.0%) | (−100.0%) | (−100.0%) | (−100.0%) | (2.31%) |
| baseline 2 | 42.24% | 3.27% | 13.48% | 36.27% | 8.66% | .70% | 2.89% | 5.42% | 1.30 |
| import tax 5% | −.18 | −.01 | −.19 | .38 | −1.67 | −.13 | −.67 | −1.01 | .01 |
| | (−.43%) | (−.32%) | (−1.41%) | (1.06%) | (−19.31%) | (−18.61%) | (−23.35%) | (−18.6%) | (.69%) |
| import tax 15% | −.46 | −.04 | −.42 | .92 | −4.03 | −.32 | −1.58 | −2.46 | .02 |
| | (−1.10%) | (−1.08%) | (−3.10%) | (2.55%) | (−46.47%) | (−46.37%) | (−54.74%) | (−45.41%) | (1.65%) |
| fuel tax 5% | −.14 | −2.12e−3 | .06 | .17 | −.54 | −.05 | −.15 | −.34 | −.1 |
| | (−.32%) | (−.06%) | (.45%) | (.48%) | (−6.23%) | (−6.89%) | (−5.06%) | (−6.30%) | (−7.68%) |
| fuel tax 15% | −.40 | −2.48e−3 | .17 | .50 | −1.51 | −.13 | −.42 | −.95 | −.28 |
| | (−.95%) | (−.08%) | (1.29%) | (1.38%) | (−17.45%) | (−18.76%) | (−14.38%) | (−17.49%) | (−21.63%) |
| waste tax 5% | −.21 | −.03 | −.1 | .39 | −.03 | .01 | −.05 | .03 | −.04 |
| | (−.49%) | (−1.04%) | (−.71%) | (1.06%) | (−.38%) | (1.11%) | (−1.67%) | (.54%) | (−2.87%) |
| waste tax 15% | −.61 | −.10 | −.29 | 1.15 | −.05 | .03 | −.14 | .14 | −1.11 |
| | (−1.45%) | (−2.95%) | (−2.15%) | (3.17%) | (−.63%) | (4.25%) | (−4.73%) | (2.65%) | (−8.75%) |

*Note:* The table presents changes in percentage point of percentage of trash sent to a specific demographic group in 2-mile neighborhoods surrounding disposal facilities. Number in brackets shows 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. There are two status quo baselines. Baseline 1 is a benchmark for import ban policy, which excludes five counties, Alpine, Amador, Del Norte, Nevada, San Francisco, and Tuolumne, that do not have any local facilities. These counties account for 1.91% of waste in California in 2010. Baseline 2 is a benchmark for import tax, fuel tax, and trash tax.

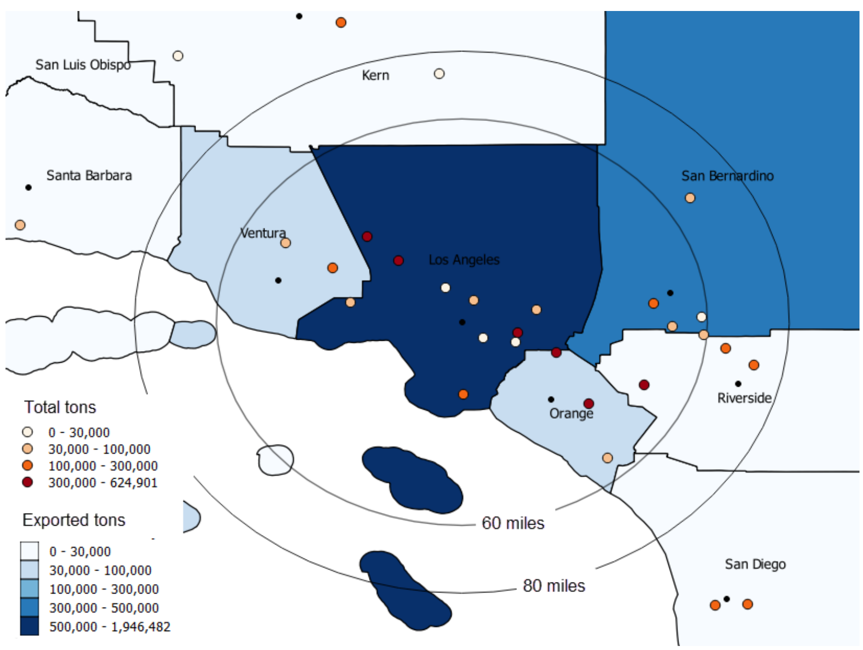
# E Additional descriptive data

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

(A) Choice set for haulers in San Francisco county




(B) Choice set for haulers in Los Angeles county




*Note:* The graph illustrates the set of available disposal options within 60 miles and 80 miles for haulers in the counties San Francisco and Los Angeles. This illustration uses air distance instead of driving distance that 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.