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

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Abstract

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

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

JEL Classification: D04, L51, Q53, Q56

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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. The concern for environmental protection can be magnified when disadvantaged groups and/or minorities are disproportionately exposed to trash placement.

This paper studies the effects of environmental protection policies on the spatial and demographic distribution of waste disposal. I use a novel data set on solid waste flows by origin county and by destination facility in California to explore the effects of several "not-in-my-backyard" (NIMBY) policies, such as county bans on out-of-county imports and county taxes on imports. These NIMBY policies are of interest because a number of federal bills have been proposed to allow state and local governments to restrict interjurisdictional waste flows.[2] Additionally, I explore the effects of a fuel tax, an important environmental regulation that aims to reduce pollution and the possibility of global warming. Although a fuel tax is not directly targeted at the solid waste industry, it is advocated to compensate for the externality of transporting an environmental nuisance, such as trash, along its route.

To study the effects of these policies, I employ a structural econometric approach because I do not observe market outcomes where the trade barriers actually happened. The one intercounty waste restriction that occurred in California was during a period for which data are not available. In 1984 Solano county enacted Measure E that limited out-of-county imports, but it was prevented from enforcing the measure in 1992 due to a concern about violating the Commerce Clause. Several states and local governments have attempted to restrict waste imports from adjacent places since the late 1970s, but their enactments have been challenged by Supreme Court decisions. Legislative efforts to limit interstate waste flows have been introduced in several bills in Congress but none of these bills have passed.

To account for the fact that waste flows are the result of economic incentives in the industry, I study the haulers' decisions about where to deposit their collected waste by modeling their preferences for disposal prices, transport distance, and facility quality (captured by facility fixed effects). Modeling the choice of haulers is also important because it explains why there are waste flows from one trash generation county to multiple destination facilities.[3] The hauler may exploit the variation

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

[2] In 2017 Congress proposed the Trash Act to allow state and local governments to fee on out-of-state waste and to restrict out-of-state waste coming from states that have lower waste handling standards than the receiving state.

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

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

Given the estimated parameters underling the haulers' decisions, I quantify how haulers' decisions about where to deposit waste would change in several counterfactual scenarios, holding facilities' characteristics constant. I consider four counterfactual experiments. The first three policies are proposed NIMBY tools that allow states and local governments to restrict interjurisdictional waste flows. Specifically, the first is an import ban that outlaws waste flows across county border lines. The second is an import tax that taxes tipping fees of all waste that flows across county lines at a fixed rate. The third is a universal waste tax that taxes all waste at a fixed rate. This tax is motivated by the case in which everyone wants to protect themselves and justifies the tax as a means to compensate the communities that are affected by nearby trash sites. The final policy I consider is a fuel tax that taxes diesel fuel at a fixed rate.

The results show that these policies would reduce the quantity of waste that flows across county lines, as would the distance haulers transport waste from the population center of a county to a disposal facility. The import ban and fuel taxes would also reduce the tipping fees haulers pay for waste disposal. This finding shows that haulers cart waste to disposal facilities outside the waste-generating county for other benefits rather than tipping fees and distance. These might include high acceptance rates, flexible operation hours, capacity, loose regulation on nonlocal waste, etc. Forgoing these good quality facilities would result in a loss of economic surplus for haulers after the policies.

As mentioned above, I focus on not only the spatial distribution of waste flows but also how waste is distributed across facilities with different local demographics. Examining the demographic distribution of waste is important because the environmental justice literature has documented an uneven distribution of the location of environmental hazards among race groups.[4] In

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

addressing the question of environmental justice, I explore how many people live within three miles of a trash site as a share of the county population for each racial/ethnic group. I then examine the relationship between the demographic composition of the communities within three miles of a disposal facility and the waste flows that are sent to the facility. The results emerge three facts. First, there are fewer people of all racial groups near the facilities that receive the most waste. Second, waste is more likely to be hauled to facilities in high percent minority communities than white communities. The disparity is eliminated for Asian communities once I control for income, disposal fees, and distance, but even with these controls, the disparities remain for black communities and Hispanic communities, suggesting unobserved characteristics of facilities and neighborhoods matter in haulers' decisions. Third, among facilities outside of the waste-generating county, waste is more likely to be sent to facilities in black communities. This suggests that policies that reduce intercounty waste would have the potential to distribute waste more evenly across demographic groups. My structural model can help us understand whether these policies would direct more waste to facilities in minority communities within the waste-generating county.

I find that the policies that limit waste flows would generally not lead to a more equitable distribution of waste. Waste that is sent to facilities near black communities would remain fairly constant. Waste that is sent to facilities near white residents would be rerouted toward facilities near Hispanic residents, potentially exacerbating distributional concerns. One potential reason is that these facilities in Hispanic communities may have low tipping fees and be closer to the population center of the waste-generating county while facilities near white residents tend to be predominantly in less populated areas.

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

The paper also complements studies that address interstate waste flow controls. In the hazardous waste market, Levinson (1999a,b) find that interstate waste taxes decrease shipments of waste to states enacting high taxes, and provided an estimate of the magnitude of tax elasticities. In the solid waste market, Ley et al. (2000, 2002) find that limitations on the size of shipments can perversely increase interstate waste shipments since states export smaller volumes to more

Mohai and Saha (2007)

destinations. They use the aggregate data at the state level and consider state planners' problem assuming the demand for waste disposal services is linear and a competitive equilibrium. My model, however, considers the haulers' decisions about where to deposit waste from each county. This accounts for the fact that disposal landfills are differentiated in prices, distances, and quality, thereby explaining the impacts of environmental protection law that aims to influence prices, transport costs, and the number of disposal options.

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

The rest of the paper is structured as follows. Section 2 provides legislative background of interjurisdiction waste restrictions. Section 3 shows general picture of waste disposals in California. Section 3.3 frames the environmental justice concerns in the paper. I emphasize that the inequitable distribution of waste flows by race and ethnicity is not fully explained by economic factors, namely, income, disposal prices, and transport distance to a facility. Hence, when modeling the waste flows to study distribution impacts by race, it is important to include facility fixed effects. Section 4 presents the structural model of haulers' decisions about where to deposit waste from each county, which is the demand for waste disposal. Section (5) reports results of counterfactual policy experiments. Section (6) concludes.

2 Background: NIMBY Legislation in Solid Waste Industry

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

Several states became overwhelmed by the increasing waste imports from others and attempted to limit these flows by taxing out-of-state waste or even banning waste imports.[5] However, these attempts were overturned by the Supreme Court's decisions on the basis that they interfered with interstate commerce.[6] These cases, for example, include a New Jersey statute that prohibited out-of-state waste imports in *Philadelphia v. New Jersey (1978)*, an Alabama statute that imposed a special fee on out-of-state hazardous waste in *Chemical Waste Management Inc., v. Guy Hunt, Governor of Alabama (1992)*, an Oregon statute that imposed surcharge on out-of-state solid waste in *Oregon Waste Systems Inc. v. Department of Environmental Quality of the State of Oregon (1994)*, and a Wisconsin statute that required out-of-state communities to adopt Wisconsin recycling standards if exporting to Wisconsin facilities in *National Solid Waste Management Association v. Meyer (1999)*.

The legislative efforts to limit interstate waste transport have been put to a number of crafted bills in Congresses. In every Congress since 1990, legislation aiming to authorize states to control interstate waste flows has been introduced but have not been successfully enacted. In 1994, both the House and Senate passed the "State and Local Government Interstate Waste Control Act" that prohibit a landfill or incinerator from receiving out-of-state solid waste unless it obtains authorization from the affected local government to receive such waste. However, the bill was not enacted due to lack of agreement on common language in enactment.[7] In the most recent Congress, 2017-2018, a bill was introduced to both the Senate and the House under the name Trash Act. This bill aims to allow state and local governments to restrict out-of-state waste coming from states that have lower waste handling standards than the receiving state and to fee on out-of-state waste. I study the effects of interstate waste controls on the short-run market outcomes and welfare when disposal facilities would not change their pricing strategies and capacity investments.

To study interstate waste transport restraints, I use California solid waste quantity data by county of origin and by disposal facility of destination to model the effects of restraints on intercounty waste transport. While 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, they are not in all other states. Furthermore, the proposed federal bills were about interstate waste transport, but the interstate waste restrictions could set a precedent for interjurisdictional waste transport within a state. In 1984 Solano county in California enacted Measure E that limited imported quantities. It was then prevented from enforcing the measure in 1992 due to a concern

[5] They reasoned their restriction on the grounds of preventing environmental harm and preserving their own natural resources that are dwindling landfill spaces.

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

[7] 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.

about violating the Commerce Clause. In 2009, opponents of the landfill expansion in Solano filed a lawsuit aiming to reinstate Measure E. However, California passed a bill in 2012 that prohibits local ordinances from restricting the importation of solid waste into a local privately-owned disposal facility based on place of origin. The state of South Carolina also prepared a similar Senate Bill 203 in 2013, but this currently resides in the Senate.

It is important to notice that interstate waste transport is a special case of a more general waste flow control. A general waste flow control is about whether state and local governments can designate where solid waste must be disposed. In *C&A Carbone Inc. v. Town of Clarkstown, New York (1994)*, the Supreme Court held that flow control also violates the "dormant" Commerce Clause. In a recent case, *United Haulers Association, Inc. v. Oneida-Herkimer Solid Waste Management Authority (2007)*, the Supreme Court revealed a more flexible view on waste flow control. The Supreme Court upheld county ordinances that directed all locally generated trash to local publicly owned processing facilities, citing that *Carbone* had presented a privately owned facility. I do not consider the counterfactual of waste flow control, but I emphasize the interstate waste transport issue in this paper, leaving general flow control for future study.

3 Data

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

3.1 Waste Disposal In California

Figure (1) shows an overview of waste disposal in California from January 1995 to December 2015. The number of facilities decreases monotonically from nearly 200 facilities in 1995 to about 150 nowadays, a decline that is especially dramatic right after the national enactment of the RCRA 1994. Average tipping fee (weighted by waste shipments) plummets in 1997, which may be explained by expansion and consolidations of several landfills after the RCRA in 1994. Then the fee remains stable around \$33.50/ton between 1997 and 2004 before escalating to \$42/ton from 2005. The price escalation may be resulted from the increase in market power after the plunge in the number of facilities.

Figure (1d) shows the trend in waste disposal by a county on average, which exhibits clearly seasonal patterns of waste generation via quarterly fluctuations. Over years, waste disposal has increased but this expanding trend stopped after 2005. The fall in waste disposal after 2005 may be attributed by several reasons. First, it may follow the fall in consumption and production activities due to the 2008 recessions. Second, it may be resulted from an increase in recycling to respond to the fall in the number of disposal facilities, and the growing environmental regulations (and maybe the pressure from counties that host disposal sites in accepting waste imports).

Along with the drop in the number of disposal sites, the proportion of trash that is exported to other counties rather than being disposed within the generating county is climbing from 15% to nearly 40% over this period, see figure (1e). Closures of nearby disposal facilities also result in an increase in shipping distance. Figure (1c) shows trash is traveling farther and farther to reach a disposal site, from 24 miles in 1995 to 31 miles in 2015. Although waste is traveling farther to disposal facilities, the shipping distance is in a reasonable economic range. Conversations with waste collection companies as well as to a representative in National Waste & Recycling Association, a trade association for private sector haulers, recyclers, composters, and disposal companies, reveal that trucks generally cart waste to a disposal facility that is less than about 30–45 miles from the place of collection.

Figure (1f) confirms that waste amounts decrease in transport distance. It plots the percentage of waste in California in 2010 that is transported farther than a certain driving distance. The carted waste plummets quickly from 30 to 60 miles, following by a flat tail (until 700.17 miles in the California waste flow data). Consequently, when I move to my analysis of waste flows, I limit the analysis to waste flows within 60 miles between the population weighted centroid of the trash-generating county and the destination facility. I assume each county is an independent market in which households generate municipal solid waste that must be disposed of. Haulers in the market collect the waste and choose amongst all disposal facilities within 60 miles of the population-weighted centroid of the county to dispose of waste. Using the 60-mile market boundary, this paper aims to explain economic incentives underlying these disposal choices, which makes up more than 90% of the waste generated in California. In the next section, I test the assumption of 60-mile market boundary. Specifically, I examine how trash flows respond to disposal price (tipping fees) and driving distance by distance from origin county to destination facility.

3.2 Market Boundary of Waste Flows

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

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

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

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

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

Table (2) shows summary statistics of the main sample that is used for my analysis, which includes all combination of flows within 60 miles. Panel A shows the characteristics of the waste flows, and contrasts the main sample with the raw data of positive flows. The unit of observation is the quarter $\times$ origin county $\times$ destination facility. Contrasting waste shipments, distance, tipping fee, total trash generated in a county, and out-of-county exports, we can see that 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 37 miles and the average price is \$36/ton. Panel B shows the characteristics of the choice set. The unit of observation is the quarter $\times$ origin county. The panel shows the average size of a market (average trash amount a county generates) is about 175 thousand tons. A county on average exports 22% of their trash to other counties. On average, haulers in a market have 8 options to transport their collected waste to.

3.3 The Relationship between Race and Waste Flows

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

3.3.1 Who Lives Near Trash

How near is near? The choice of spatial unit to represent the hosting communities has been subject of considerable debate in the environmental justice literature. Previous studies have shown that the correlation between environmental hazards and demographics can be quite sensitive to community definitions; see Anderton et al. (1994); Sheppard et al. (1999); Mennis (2002). Data aggregated at higher levels such as a county have been documented to be less reliable as indicators of disproportionate burdens than data aggregated to smaller units such as census block groups. But the choice of whether to use blocks, block groups, or census tracts as community definition may be problematic either. They vary greatly in geographic size. For example, blocks in California range from $1/1,000,000$ of a square mile (1 square meter) to more than a thousand square miles (3 billion square meters). Hence, I 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 and counts by race at blocks are aggregated for counts in the community. Information that is not available at block level such as households, is first assigned to block by population shares from block-group values before being used to assign to community values. So, median household income at a block is the income at a block group that contains the block.

Panel A in table (3) shows the percentage of population who live within a buffer (3 miles, 7 miles, or 15 miles) of a trash site, relative to the population of the county that hosts the site, by race and ethnicity. On average, only three percent of the population in a county lives within three miles of a waste disposal facility. However, it appears that minorities are more likely to live near a trash site than white people. This patterns also persist in larger buffers, 7 miles and 15 miles.

To examine how the share of the county population that have a waste site in their 3-mile backyards for each racial/ethnic group relates to the waste amount the site, I estimate the following regression

$$\text{Affected Level}_j = \beta_0 + \beta_1 Waste_j + \beta_2 Income_j + \epsilon_j \tag{2}$$

where j indicates a facility. The dependent variable is the percentage of people of the race group of concern in the county hosting a disposal facility that live within 3 miles of the site, i.e. $\text{Affected Level}_j = \frac{\text{\#people of the race in a facility's 3-mile buffer}_j}{\text{\#people of the race in a facility's county}_j} \times 100$. Two key control variables are $Waste_j$, the total waste amount disposed at facility j in 2010, and $Income_j$, the median household income of people in the 3-mile community. Using 2010 decennial census data, the regression is estimated separately for each of four race groups of concern, white, black, Asian, and Hispanic to explore the differences among race groups in exposure to the waste amount of a nearby disposal facility.

The coefficients of primary interest are β_1. β_1 measures the change in percentage of people of the race group of concern that live in 3-mile affected communities when there is an increase in the waste amount in their backyards.

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

Overall, we see that there is not many people living near trash, comparing to the county population, and that there are less people living near a waste disposal site that receives more trash. However, in term of environmental injustice, let us consider the distribution of waste flows by race and ethnicity in the affected communities.

3.3.2 The Distribution of Waste Flows By Race in Affected Communities

Table (4) reports descriptive statistics of population in affected communities defind by different radii, 3 miles, 7 miles, 15 miles, and the destination county. The table also contrast the numbers to the California state level. At 3-mile buffers, the average population is 26,000 persons of which 49.4% are white, 2.7% are black, 8.1% are Asian, and 35.3% are Hispanic. When weighted by trash amount at a facility, percentages of whites, blacks, Asians, and Hispanics are 44.1%, 3.7%, 13.0%, and 35.7%, respectively. The differences between unweighted and weighted percentages by race imply that waste is disposed of more in minority communities and less in white communities. This pattern also persists for larger areas of affected communities. Waste seems to be disposed more in affected communities with higher percentages of minorities.

Since waste flows are a result of market activities, I now examine the distribution of waste flows after controlling for economic incentives of haulers such as price and distance. From now, I also define the affected communities as the area within 3 miles of a waste disposal facility. As mentioned above, using too large entities may dilute the impact of a waste site, since exposures to waste odor and landfill outreach may be at the most local neighborhoods. For caution, affected communities are defined as blocks being within 3 miles of a facility. I use 2010 decennial census data and waste flows in 2010 for the analysis because this is the most recent demographic data available at block levels. The regression equation is:

$$q_{cj} = \beta_0 + \beta_1 \% Race_j + \beta_2 Income_j + \beta_3 Price_j + \beta_4 Distance_{cj} + \beta_5 Nonlocal_{cj} + \delta_c + \epsilon_{cj} \tag{3}$$

where c indicates the county origin of waste flow, and j denotes the facility destination of the flow. The dependent variable, q_{cjt}, is the waste amount generated by county c to be disposed at facility j in year 2010. $\%Race_j = \frac{\text{\#people of the race in facility j's community}}{\text{\#people in facility j's community}} \times 100$. $Income_j$ is median household income at community around facility j. $Price_j$ is average tipping fee of facility j in year 2010. $Distance_{cj}$ is the distance between population centroid of county c to location of facility j. $Nonlocal_{cj}$ is the dummy variable that equals 1 if facility j is not located in county c. This dummy captures the sociopolitical control of waste flows because waste management is a decentralized subject at local level. The county that hosts a disposal facility manages permit registration, capacity expansion approval, and directly enact environmental ordinances on the facility. I also consider a specification that includes market fixed effects δ_c. This fixed effect separates the effects in urban areas versus rural areas. Specifically, some facilities receive a huge amount of waste because they are within 60 miles of a big county that generates a lot of waste.

Table (5) reports results. Column (1) shows that waste is disproportionately sent to minority community and white community in which waste is sent most to black communities, Hispanics, and Asians, respectively. One percentage point increase in the percentage of black in affected areas (on a mean of 3.34%) is associated with an increase in waste amount shipped from each county by 1,403 tons or 1.66% of the average shipment size in year 2010.

After controlling for household income, the coefficients of black percentage and Hispanic percentage becomes bigger and significant while the coefficient of Asian percentage becomes negative and insignificant; see column (2). This change implies that income is negatively correlated with percent black and Hispanic and positively correlated with percent Asian and total trash amount. The positive coefficient of income implies that high income areas are clustered in urban region in which more trash is generated and dumped within the region. Although trash is carted from a county to another county, it does not travel unusually far to reach a rural area.

Columns (3) and (4) report the trash amount by race after controlling for disposal price and distance from population center of the origin county to a destination facility. The results show that the positive signs and significance of black percentage and Hispanic percentage coefficients persist even when controlling for disposal price and distance. This implies that factors uniquely correlated with race are associated with the waste coming to the facility. These factors could include housing discrimination, heterogeneous environmental regulations, or differences in political power across communities. These factors create benefits for facilities located in black and Hispanic communities, which have opposite impacts on haulers' preferences to the impacts of price and distance. In other words, the negative effects of price and distance on waste amount may be offset by the positive effects of these factors, depending on which effects are dominant.

Regarding the change in coefficient magnitudes between column (2) and column (3), because we see a negative bias in black percentage coefficient when omitting price, we can infer that price is positively correlated with percentage of blacks, holding all the others constant. For Hispanics, the positive correlation is much smaller. For Asians, the correlation is negative.

The change in demographic coefficients between columns (3) and (4) reveals the sign of bias when omitting distance. Given the % black coefficient in column (4) is more positive than in (3), we can infer that distance is positively correlated with % black, holding all the others constant. On the other hand, the decreases in coefficients of % Hispanic and % Asian reveal a negative correlation between distance and % Hispanic, and % Asian.

Adding the dummy variable $Nonlocal$ in column (5) increases the coefficient of percent minority, especially the percent black. Since the dummy is negatively correlated with waste amount, the negative bias in percent black coefficient when omitting the dummy reveals that percent black is positively correlated with the dummy. In other words, more trash is disposed of near black communities because of intercounty trash. One reason is the low political influence of black communities on waste controls, which becomes evident when the flow is not originated from local.

Column (6) shows the disparity in waste flows between minority groups and the white group disappears after controlling market fixed effects. This implies that the disparity is an urban-rural story. Minority tends to live in urban areas surrounding big cities and counties that generate a large amount of waste and send waste to sites within 60 miles.

Table (6) report results using intercounty and local observations separately. As seen from column (1) in table (5), waste is sent more to minority communities. However, there is substantial heterogeneity in intercounty flows and local flows. Columns (1) and (4) in table (6) show that the disparity in waste disposal between Hispanic, Asian and white happens only in local flows. This confirms that waste coming more to facilities in Asian communities than in white areas is because Asians generate a large amount of waste and most waste is dumped locally. On the other hand, the black percentage coefficient is positive in both samples of intercounty flows and local flows, though it is significant in only intercounty flow sample, implying facilities in black communities receive more waste than white areas even when they are not located in the counties that generate the most waste. Other columns report the distribution after controlling for income, tipping fees, and transport distance. We can see that the disparity patterns persist after adding these controls. Facilities in Asian areas receive more waste than the ones in white communities because they are near to places of generation. Facilities in black and Hispanic communities have benefits that offset negative effects of high prices and far distances on receiving waste.

In summary, all three minority groups tend to receive a disproportionate amount of waste. For Asians, this effect is eliminated when we control for economic factors such as price and transport distance. For blacks and Hispanics, the effect is even stronger after controlling for economic factors, which suggests that either discrimination or unobserved differences matter. Hence, it is important to include facility fixed effects when modeling the economic incentives underlying the choice of disposal facilities.

Another important result is that much of the reason why more trash ends up near black communities is due to intercounty trash. The uneven distribution of waste flows seems to happen because they tend to live in extended regions surrounding big counties, 60 miles within the county's population centroid, that more likely generate a large amount of trash. However, after controlling for market fixed effects, waste is more likely to be sent to facilities in high percentage of black residents, among nonlocal options. Hence, policies that reduce intercounty trash at least have the potential to distribute waste more evenly across demographic groups. A structural model is useful to understand whether these policies would just lead to more waste going to facilities in black communities within the county.

The structural model is also necessary because I do not observe the data had these policies, especially NIMBY enactments, happened. Using a revealed preference approach, multinomial logit discrete choice model, I uncover parameters underlying the economic choices of where to dump, identifying the demand parameters of haulers for disposal facilities. I then use estimated demand parameters to quantify the change in waste flows and distribution of waste flows under several counterfactual policy experiments that intervene choice sets, disposal prices, and transport costs. I currently consider only the demand side, assuming 100% of policy burden on haulers for transparency in impact mechanisms via prices and choice sets. Understanding how the supply of waste disposal sites will respond to these counterfactual policies is left for future work.

4 A Model of Waste Flows

4.1 Demand for Disposal Facilities

Every hauler i picks up a waste amount q_{ict} in county c in quarter t. The hauler chooses a facility j to dump the waste amount to minimize its operation costs. Equivalently, the hauler maximizes profits conditional on a quantity of waste shipped and a payment from the county to collect waste. Let the utility of disposing of waste at facility j be $U_{ijct}(X_{ijct}, \epsilon_{ijct})$, where X_{ijct} are observables such as tipping fees and transport costs (measured by the interaction between distances and fuel prices), and ϵ_{ijct} is the unobservable match quality between hauler i hauling from county c and facility j in quarter t. The utility of choosing a disposal facility does not depend on waste amount q_{ict} for either of two reasons. First, picked up waste amount is exogenous to haulers. The optimal route of collecting and carting waste to a landfill may be predetermined before picking up the waste. Second, haulers often use the same size of trucks to travel to all destinations. Given the observed price and distance, I specify the utility specifically as

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

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

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

This model share similarities with multinomial logit discrete choice models (see McFadden (1974); Berry (1994); Berry et al. (1995)) but has three distinct features. First, there is no outside option. A hauler must choose a facility to dump all of their trash. The hauler does not keep trash themselves.

Second, I observe market level data. Although the model describes individual hauler behaviors, data at individual haulers are not available. Such situation has been estimated using the method in Berry (1994); Berry et al. (1995). The contraction mapping result in Berry (1994); Berry et al. (1995) show that there exists a unique mean utility vector to match the model implied choice probability to observed market shares. However, this result only applies to the case of positive market shares. In my model, zero market share can happen because a feasible facility that is within 60 miles of the population centroid of trash-generating county may be never chosen by any haulers in the county in a quarter. Estimation that ignores these zero shares would have bias selection. To deal with this situation, I propose the following maximum likelihood estimation. This approach assumes no heterogeneity in the choice probability of hauler/trip i, and in the waste amount of a trip, within a market.

4.2 Model Likelihood

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

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

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

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

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

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

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

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

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

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

The first estimator assumes that the number of haulers across different markets is the same. This implies that market sizes differ because the picked-up waste amounts vary across markets. The log likelihood function is

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

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

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

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

4.3 Identification

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

However, the difficulty in estimating price coefficient consistently is to overcome bias due to measurement error. This is because I observe listed prices instead of contracted prices. Hence, to overcome both endogeneity and measurement error, I use sum of total waste in the other markets that include the facility in their choice sets (excluding the instrumented market). This is different from the literature where exogenous cost shifters, BLP instruments, Hausman instruments, Nevo instruments are used; see Berry et al. (1995); Hausman (1996); Nevo (2001).

On the one hand, the market-size instrument is correlated with price because the facility is setting one common listed price for all markets.[8] On the other hand, this instrument is exogenous with the demand in the instrumented market because it excludes demand factors of the instrumented market. Even though market sizes of the other markets may be correlated with the waste amount in the instrumented market via common geographical shocks such as growth of state economy, they do not affect the individual hauler's choices in the instrumented market.

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

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

4.4 Model Results

Table (7) reports results of the model. Column (1), (2), and (3) show the estimates of facility fixed effect, linear control function, and quadratic control function specifications, respectively. As expected, the facility fixed effects specification does not resolve all bias in price coefficient estimate. Although its estimate of price coefficient has the correct sign, it is extremely small and statistically insignificant, and the resulted price elasticity is -0.03. Using market sizes of the other relevant markets to instrument price, the upward bias is mitigated. The magnitude of price coefficient becomes two order of magnitude bigger; price elasticity is -4.20. The positive sign of the first coefficient of control function confirms the upward bias is corrected.

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

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

[8]Due to Commerce Clause, facilities are not allowed to discriminate waste based on waste origin.

portation in American (2007) reports that revenues per ton mile for Class I general freight common carriers (basic truck transport) ranged from roughly \$0.29–\$0.35 over 1983–2003. Third, previous studies in waste transportation in 1990 and 1992 report transport costs from \$0.16 to \$0.36 per ton mile; see Fischer et al. (1993).

4.5 Model Fit

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

4.6 Sensitivity Checks

In this section, I discuss the robustness of the baseline results to different estimators of the model. Instead of using the market-weighted estimator that maximizes objective function (12), we can use the unweighted estimator (11). This estimator aims to maximize goodness of fit in all markets equally, instead of emphasizing the fit in the big markets as does the estimator in (12).

Table (8) reports results. When weighting all markets equally, price coefficients becomes bigger while transport cost coefficient is similar to the case of market-weighted estimates. This reveals that big markets are less responsive to price.

5 Counterfactual Policies

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

I consider four counterfactual policies: import bans that outlaw intercounty waste flows, import taxes that tax waste flows that cross county lines, fuel taxes that tax diesel prices at a percent rate, and universal trash taxes that tax all trash disposal at an equal rate. These are environmental protection policies that aim to reduce intercounty waste flows but they intervene economics choices of haulers by affecting haulers' choice sets, tipping fees, and transport cost. It is, hence, important to use a structural model that accounts for hauler's choice sets, tipping fees, transport costs, and facility quality to explore the effectiveness of these policies. Furthermore, as shown in section (3.3), waste that is sent to nonlocal facilities is likely to end up near black communities. Policies that aim to restrict intercounty trash would have the potential to distribute waste more evenly across demographic groups, but the structural model is useful to understand whether these policies would just lead to more waste going to facilities in black communities within the waste generation county.

In this section, I begin with the analysis on the change in intercounty waste flows and the economic impacts of the counterfactual policies. I then consider the implications of policies on demographic distribution of waste disposal.

5.1 Intercounty Waste Transport and Economic Impacts

Panel A in table (9) shows the effects of the four policies on intercounty waste transport (exports) and the economic impacts on hauler surplus of an average county market, compared to the baseline level (prediction in the absence of policies). There are two baseline levels, one is used to quantify the effects of import bans, and the other one is used for the comparison with import taxes, fuel taxes, and waste taxes. The reason why there are two baseline levels is that a few counties do not have any disposal facilities within their border lines, namely, Alpine, Amador, Del Norte, Nevada, San Francisco, and Tuolumne. I exclude those counties in calculating the change in economic factors and demographic distribution of waste flows for the import ban scenario (columns (1) and (2)).

Because an import ban that interdicts intercounty waste transport would restrict the choice set of a hauler in a waste generating county to only facilities within the county border line (local options), the policy would reduce exports by 100%. Specifically, the amount is about 570,000 tons in an average market (trash generating county) for year 2010 (row 1 in column 2). The distance to transport trash would also decrease unless most of trash is generated near the county border line rather than the county center. This is demonstrated by a reduction by 10,300 kiloton-mile in trash mileage, or equivalently around 3 miles in transporting trash from population center of generating county to a disposal facility.

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

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

The third policy I consider is a fuel tax that taxes diesel prices at a percent rate and hence, makes the trash transport more expensive. As a result, waste would be carted to nearer facilities, resulting in a reduction in trash travel mileage. Column (7) shows that a fuel tax at 15% would reduce nearly 5,000 kiloton-miles in trash mileage, or equivalently 1.35 miles in a journey from population center of generating county to a disposal facility. Because out-of-county facilities are generally farther from where waste is generated than local alternatives, the fuel tax would also reduce exports. At the tax of 15%, exports would fall by 116,000 tons, which is 20% of the baseline level.

The change in total tipping fees in the case of fuel tax is theoretically ambiguous because of two opposite directions. First, switching to a nearer facility is costly because the nearer facility is expensive, which is the reason the hauler did not opt for. Second, switching to a nearer facility would save the hauler on paying tipping fees because the nearer facility is cheap. The reason why the hauler did not opt for this cheap nearer facility is that it did not offer other benefits rather than tipping fees and transport costs, such as high acceptance rates, operation hours, capacity, etc., which are captured by facility fixed effects in my model. Row 2 in columns (6) and (7) reveals that the second effect is dominant. Overall haulers in a market would save 1.5 million dollars (a reduction by 1.11%) in paying tipping fees, or 21 cents per ton, after a fuel tax of 15%. However, forgoing good quality facilities would cost haulers 8 million dollars, or equivalently $2.11 per ton.

The final policy of interest is a universal waste tax that taxes all trash disposal at an equal rate. This tax is motivated by the scenario where everyone wants to protect themselves and justifies the tax as a mean to compensate for communities nearby trash sites. At an equal percent rate, the waste tax would penalize expensive facilities more than less expensive facilities. The policy impact on interstate trash transport is theoretically ambiguous because of two opposite directions. First, if haulers cart trash to out-of-county options because of cheap tipping fees, the waste tax would exacerbate intercounty trash flows. Second, if out-of-county facilities are expensive but haulers opt for them for reasons other than prices and distances, the waste tax would mitigate intercounty trash transport. Columns (8) and (9) show that the second effect is dominant: Exports fall by 20,000 tons (3.45%) at the waste tax of 15%. Total tipping fees haulers in a market have to pay disposal facilities increase 14 million dollars (10.21%), or \$4.45 per ton because of the tax. Trash mileage decreases slightly by 2.78%, or 0.29 miles for a trip, revealing that switching to less expensive facilities do not necessarily mean higher cost of transportation. Hauler surplus falls by 20.9 million dollars, or \$5.94 per ton due to the waste tax of 15%. Overall, the result of the waste tax effects is also consistent with the results of the other three policies in which they imply haulers generally benefit greatly from factors that are uniquely associated with the facility besides disposal prices and transport distance.

5.2 Demographic Distribution of Waste Flows

Panel B in table (9) shows the effects of the four policies on the demographic distribution of waste disposal. Specifically, the panel computes the percent trash in a market that ends up at disposal facilities by race and ethnicity of affected communities for the baseline estimates (before counterfactuals) and the percentage point change after polices. For example, assuming that trash from a generating market c that is sent to disposal facility j affects all people living three miles of the facility location equally, the percent trash of the market c exposes on white community is

$$\%\text{ trash to white} = \frac{\sum_{j\in J_c} q_{cj} \times \text{Number of whites in j's 3-mile buffer}_j}{\text{Total population in j's 3-mile buffer}_j} \cdot \frac{1}{\sum_{j\in J_c} q_{cj}} \times 100 \quad (13)$$

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

As seen in section (3.3), among facilities that are out of generating-county borders, trash is more likely to end up at facilities near black communities. Policies that reduce intercounty waste flows would have the potential to reduce waste that is sent to black communities. However, that would not happen if trash is redirected to local facilities near black communities. In fact, section (3.3) shows that among local options (facilities within trash-generating county borders), trash is also more likely to end up at the ones near black communities. Therefore, it is important to explore which effect is dominant. Is a reduction in intercounty trash exported to facilities near black communities bigger than the increase in trash that would be redirected to local facilities near black communities? Another concern is that whether a reduction in trash that is sent to black communities happens at the expense of an increase in trash that is sent to other minority groups.

Column (2) shows that after the ban on intercounty waste transport, the percent waste that is sent to Blacks and Asians would fall because of dominant falls in exports to Blacks and Asians. However, the percent waste that is sent to Hispanics would enlarge because the increase in trash that is sent to local facilities near Hispanic communities offsets the fall in exports to nonlocal facilities near Hispanic areas.

In contrast to the import ban, an import tax would result in an increase in percent waste, see columns (4) and (5). A reason is that an import tax tries to reduce intercounty waste flows by intervening the disposal price rather than restricting the choice set of haulers to only local facilities. Under the import tax, a hauler may switch from nonlocal black facilities (facilities that are in high percent black communities) to either other nonlocal black facilities that are relatively cheaper or local black facilities. The fact that percent exports to black facilities decrease while total percent trash to black facilities increase implies that switching to local black facilities happens more strongly than switching to nonlocal black facilities.

Columns (6) and (7) show that fuel taxes at 5% and 15% would nearly not change the percent trash that is sent to black communities although they would reduce the exports to black communities. This implies that a hauler would highly likely switch to local black facilities after giving up on nonlocal black facilities that would become costly in transportation after the fuel tax. In fact, the percent trash that is sent to all minority groups increases while the percent trash that is sent to white communities decreases after the fuel tax. This reveals that overall facilities in minority communities are nearer to population weighted centroid of trash generating county than the facilities in white communities.

Column (8) and (9) show that the waste tax would overall decrease the percent trash that is sent to all race groups except Hispanics. This reveals that facilities in Hispanic communities may have cheap tipping fees, since the tax would make expensive facilities much more expensive than less expensive facilities. Another noticeable point is that exports do not fall uniformly in all race groups. Exports to black and exports to Hispanics in fact increase. Although the increase in exports to Hispanic communities can be explained by that facilities in Hispanic communities are less expensive, the increase in exports to black communities may not generally be accounted by disposal price factor. The reason is that if facilities in black communities are generally cheap, they would receive more trash after the tax overall, which contradicts with the finding in columns (8) and (9). Hence, the negative sign in change in percent trash to Blacks and the positive sign in change in percent exports to Blacks imply that facilities in black communities may have additional benefits rather than disposal price and that are associated with nonlocal flows. For example, black communities may have low political influence at county level to resist intercounty trash flows.

6 Conclusion

This paper documents the disproportionate distribution of waste disposal by race and ethnicity. Although there are not many people who live near (three miles) a trash site, there is a strong disparity between the amount of trash that is sent to facilities in highly present minority groups and that is sent to facilities in predominantly white communities. Furthermore, intercounty trash is highly likely to end up at facilities in black communities, suggesting NIMBY policies may induce a more equitable distribution of waste. However, since waste flows are the result of several economic factors such as tipping fees, transport costs, and facility quality, a structural model is useful to assess the effects of these policies.

Using a structural model to estimate the demand for waste disposal, I find that policies that limit interjurisdictional waste flows would not generally lead to a more equitable distribution of trash. Making intercounty waste transport costlier by taxing gasoline prices, taxing out-of-county waste, or even banning interjurisdictional flows would generally not reduce waste that is sent to facilities near black residents. The reason is that haulers may switch from out-of-county facilities to other out-of-county facilities or within-waste-generating-county facilities near black communities. Additionally, the policies tend to substitute waste away from facilities near white residents toward facilities near Hispanic residents because the facilities in Hispanic communities are cheap and close to the population center of the waste-generating county.

This paper is the first study that explores the demographic distribution of solid waste flows and how environmental protection policies affect the waste flows, taking into account of market factors of hauling decisions. However, several extensions are useful. First, I have not examined deeply the reasons underlying the inequitable distribution of waste flows. Do minority communities generate fewer but receive more waste than white communities? What else in addition to tipping fees and transport distance that could explain the waste flows that go to minority communities? Is it because the minorities have lower political capability? Is it because the minorities come to nuisance for low housing costs and high-income opportunity in waste disposal industry? Is it because the minorities seek to live in urban areas that generate a massive amount of trash and dump trash within these extended urban areas (i.e. waste cannot be hauled too far due to expensive transport costs)?

A second extension is to consider the equilibrium effects. Adding the supply side to the structural model is useful to account for the fact that disposal facilities may change their prices upon a counterfactual policy. This relaxes the current assumption that haulers bear the full costs of policies. Additionally, it is also useful to distinguish the competition behaviors between private facilities and public facilities to consider the effects of another class of waste flow controls.

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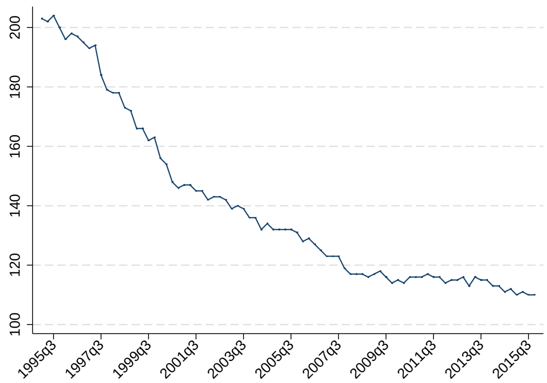
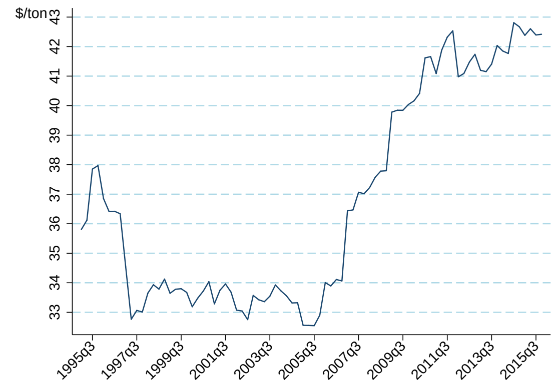
Figures

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

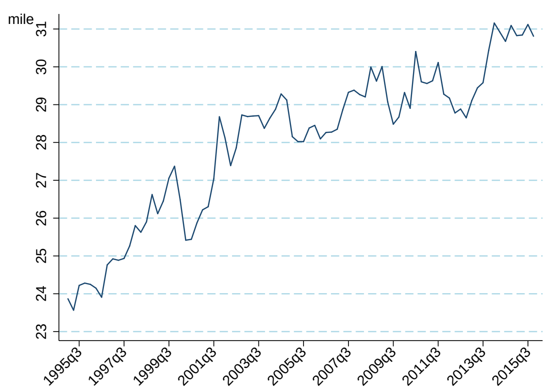
(A) Number of disposal facilities



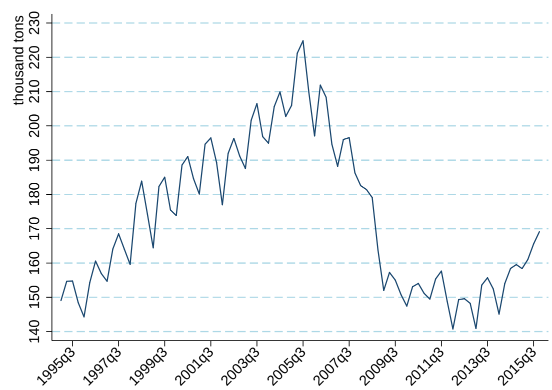
(B) (Waste weighted) average disposal price (in 2000 dollars) haulers in a county pay



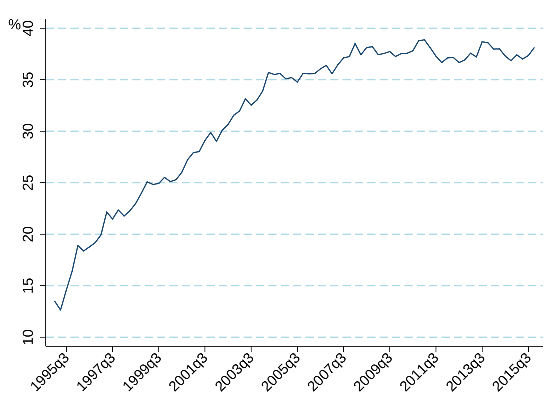
(C) (Waste weighted) average distance haulers in a county travel



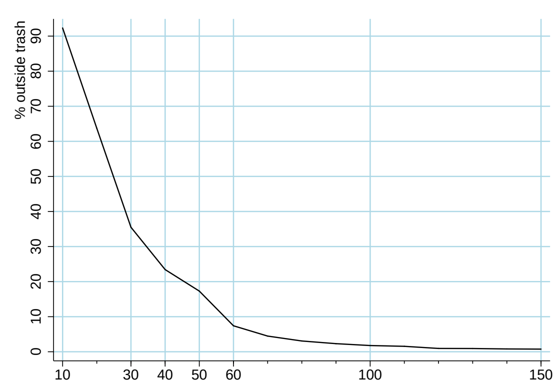
(D) Total waste amount generated by the average county



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

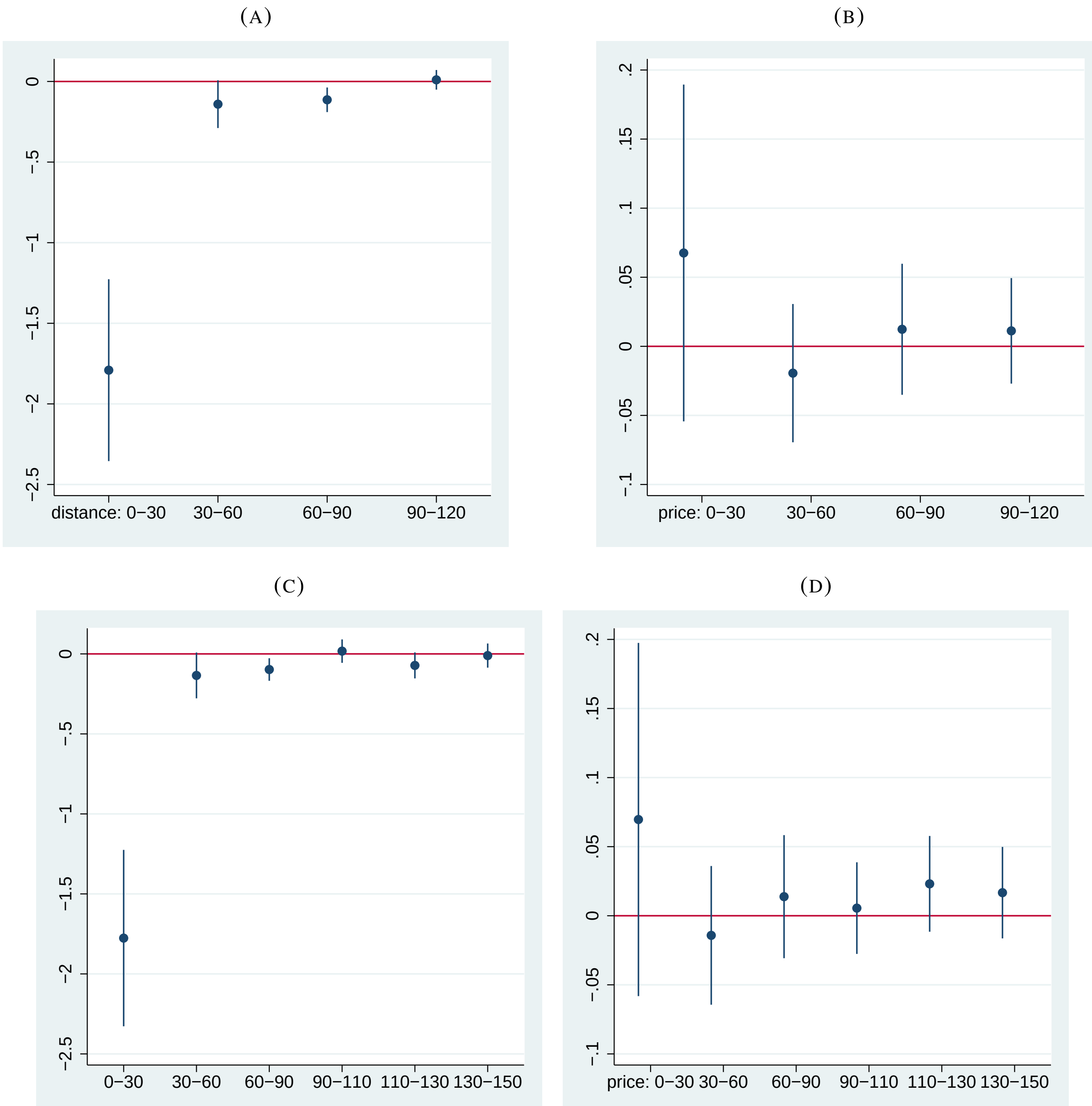


(F) Percentage of waste that travels beyond a given distance



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

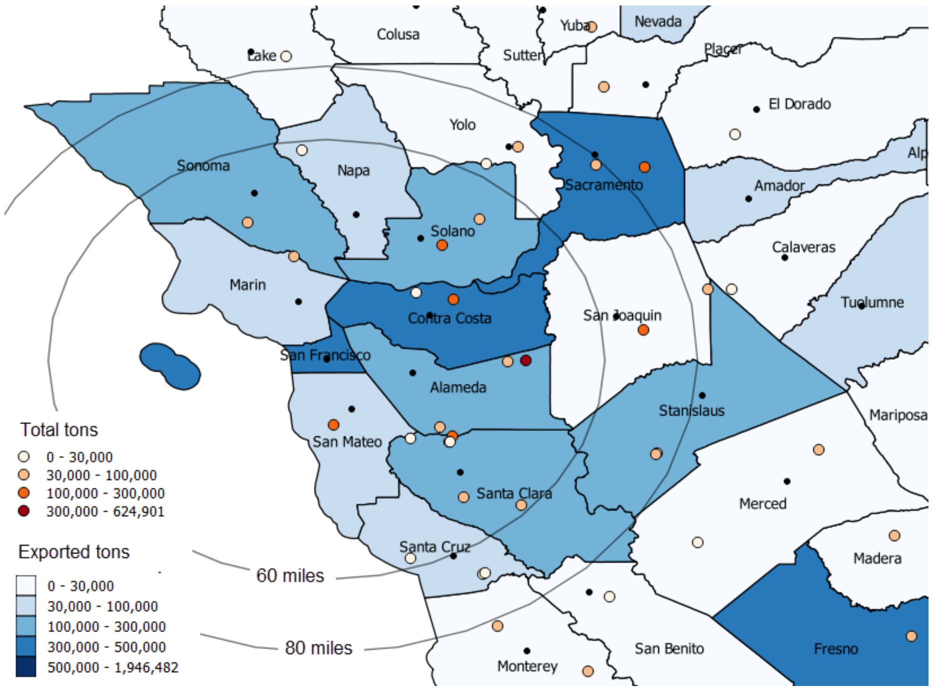
FIGURE 2: Price response and distance response by distance



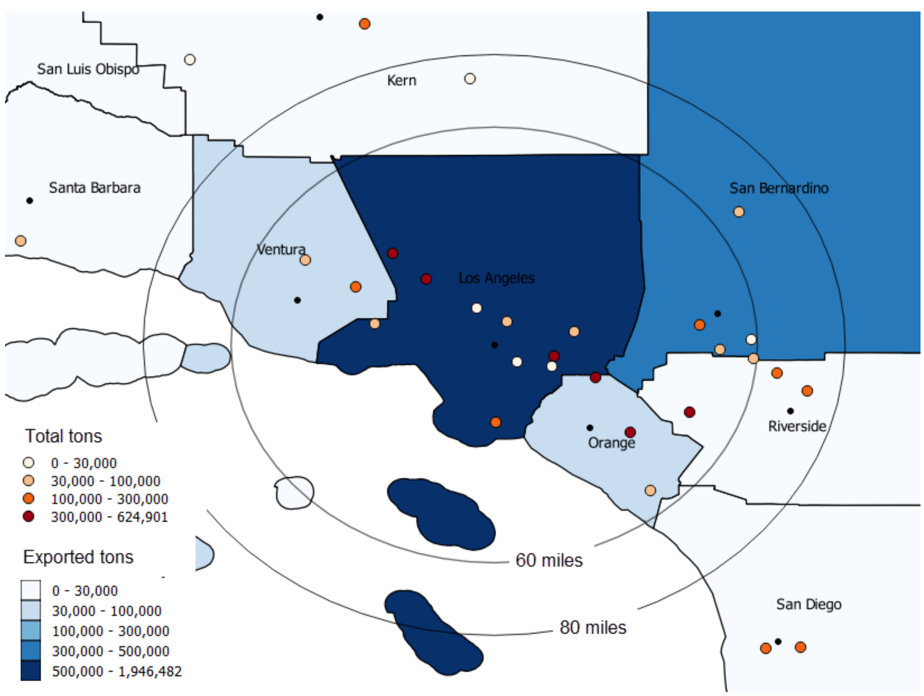
Note: Figure shows the coefficients on distance and price at different knots of distance(linear splines) from the quarter by origin county fixed effect regression, where dependent variable is trash amount from a county to a facility. Figures (2a) and (2b) use the sample of all combinations of flows by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

FIGURE 3: Sizes of Choice Sets

(A) Choice Set of San Francisco Market



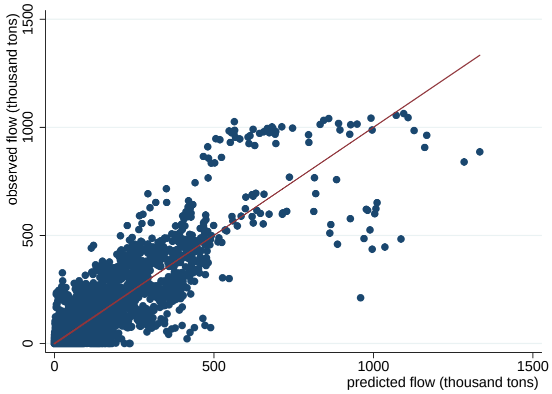
(B) Choice Set of Los Angeles Market



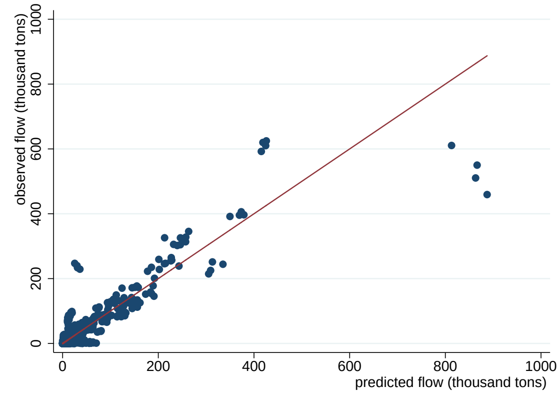
Note: The graph shows how wide 60-mile and 80-mile markets are from the population center of San Francisco and Los Angeles. Black dots represent population center coordinates of counties. Counties are blue colorized by out-of-county exports of waste. Facilities are red colorized by total waste amount.

FIGURE 4: Model fit

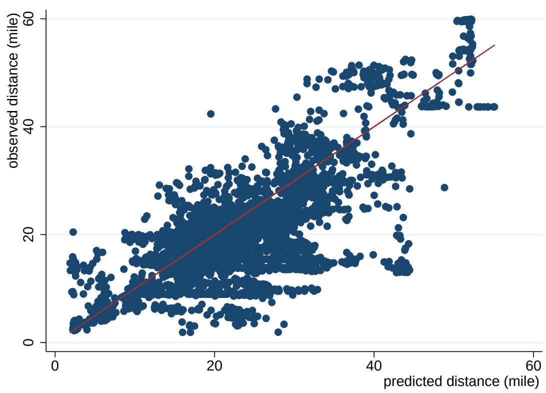
(A) Correlation = 0.8965



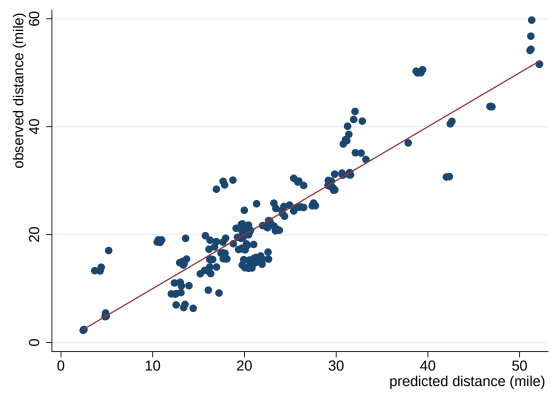
(B) Correlation = 0.9128



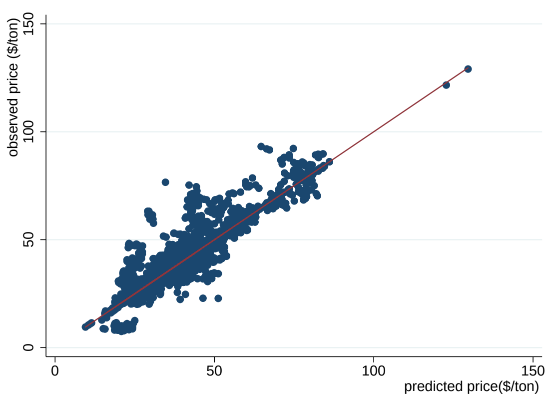
(C) Correlation = 0.8175



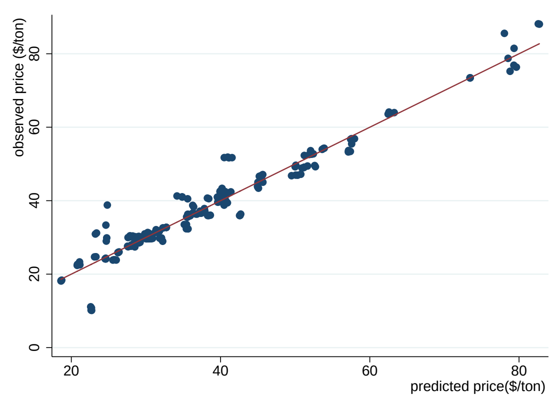
(D) Correlation = 0.9205



(E) Correlation = 0.9268



(F) Correlation = 0.9712



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

Tables

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

Dependent var.			Trash amount from an origin county to a facility in a quarter					
	(1)	(2)		(3)	(4)		(5)	(6)
price: 0–40	-0.06364	-0.03198	price: 0-30	0.06965	-0.02376	price: 0-30	0.07001	-0.02376
	(0.04634)	(0.02037)		(0.06521)	(0.03562)		(0.06532)	(0.03562)
price: 40–70	0.05275**	-0.00814	price: 30-60	-0.01419	-0.01343	price: 30-60	-0.01254	-0.01344
	(0.02515)	(0.01160)		(0.02561)	(0.01083)		(0.02548)	(0.01084)
price: 70–100	0.01563	-0.00515+	price: 60-90	0.01381	-0.01180**	price: 60-80	0.02314	-0.01302
	(0.02059)	(0.00309)		(0.02272)	(0.00569)		(0.02648)	(0.00924)
price: 100–130	0.02122	-0.00335	price: 90-110	0.00553	-0.00381	price: 80-100	0.01674	-0.00662**
	(0.01515)	(0.00862)		(0.01691)	(0.00283)		(0.02625)	(0.00260)
price: 130+	0.01071	-0.00264	price: 110-130	0.02309	-0.00245	price: 100-125	0.02024	-0.00259
	(0.01567)	(0.00250)		(0.01768)	(0.01259)		(0.01590)	(0.01038)
price			price: 130-150	0.01671	-0.00267	price: 125+	0.00576	-0.00349
				(0.01689)	(0.00249)		(0.01482)	(0.00218)
distance: 0–40	-1.47229***		dist: 0-30	-1.77620***		dist:0-30	-1.77634***	
	(0.17090)			(0.28125)			(0.28109)	
distance: 40–70	0.00055		dist: 30-60	-0.13456+		dist: 30-60	-0.13769+	
	(0.05521)			(0.07302)			(0.07451)	
distance: 70–100	-0.04842		dist: 60-90	-0.09757***		dist: 60-80	-0.12132	
	(0.03408)			(0.03597)			(0.07673)	
distance: 100–130	-0.01693		dist: 90-110	0.01740		dist: 80-100	-0.02853	
	(0.02176)			(0.03732)			(0.05008)	
distance: 130+	-0.02160		dist: 110-130	-0.07194+		dist: 100-125	-0.00182	
	(0.03922)			(0.04144)			(0.02939)	
distance			dist: 130+	-0.01043		dist: 125+	-0.03487	
				(0.03848)			(0.02765)	
quarter × origin cnty FE	Y			Y			Y	
origin × des cnty FE		Y			Y			Y
Observations	151969	151969		151969	151969		151969	151969
Adjusted R^2	0.444	0.879		0.446	0.879		0.446	0.879

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

TABLE 2: Summary statistics of panels of waste flows

	count	mean	sd	min	max
Panel A: Flows characteristics (unit: quarter $\times$ origin county $\times$ destination facility)					
A1: Flows within 60 miles of the population-weighted centroid of a county					
quantity (ton)	36,186	21,453.27	70,161.38	0	1,063,515
distance (mile)	36,186	37.12	14.91	1.737	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 $\times$ origin county)					
B1: Within 60 miles					
market size (ton)	4,431	175,199.3	416,191	1.6	3,573,185
out-of-county exports (%)	4,431	21.68	33.34	0	100
number of options	4,431	8.17	5.24	1	30
B2: All choices in California					
market size (ton)	4,788	173,560.3	426,099.1	.37	3,881,458
out-of-county exports (%)	4,788	31.62	38.05	0	100

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

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

Panel A: Descriptive statistics of the affected communities by distance

	3-mile buffer		7-mile buffer		15-mile buffer	
	mean	sd	mean	sd	mean	sd
% affected white	3.26	6.36	16.41	15.69	57.47	44.35
% affected black	3.69	8.33	17.47	18.42	79.10	54.58
% affected Asian	3.50	6.40	18.11	19.42	61.94	56.28
% affected Hispanic	3.95	8.62	18.19	19.05	61.99	51.33

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

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

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

TABLE 4: Summary statistics of the distribution of trash flows by demographics in affected communities

	3-mile buffer		7-mile buffer		15-mile buffer		hosting county		California
	unweighted	weighted	unweighted	weighted	unweighted	weighted	unweighted	weighted	level
population	25,938	36,085	181,131	313,222	772,612	1,457,449	1,689,346	3,550,303	37,253,956
	(43,949)	(40,852)	(267,271)	(281,444)	(1,168,876)	(1,297,803)	(2,808,017)	(3,539,681)	
white	8,359	11,339	60,765	102,470	257,626	478,201	569,291	1,181,551	14,956,253
	(12,600)	(11,466)	(76,086)	(77,921)	(302,711)	(310,067)	(794,328)	(946,047)	
black	1,027	1,416	7,947	11,632	44,212	68,700	116,516	248,290	2,163,804
	(2,256)	(2,515)	(14,734)	(13,452)	(87,852)	(73,952)	(236,562)	(313,591)	
asian	3,632	5,650	29,616	55,648	123,824	220,327	227,325	481,614	4,775,070
	(7,425)	(7,269)	(56,045)	(65,241)	(225,390)	(247,583)	(397,684)	(490,828)	
hispanic	12,095	16,596	76,938	134,077	321,655	646,768	723,394	1,530,798	14,013,719
	(31,336)	(28,459)	(163,264)	(177,073)	(603,372)	(744,433)	(1,343,598)	(1,753,682)	
% white	49.36	44.09	47.57	41.53	45.86	39.61	45.79	39.74	40.15
	(24.71)	(20.85)	(22.56)	(18.24)	(20.79)	(14.45)	(17.73)	(10.82)	
% black	2.73	3.73	3.62	4.20	4.10	4.87	4.26	5.80	5.81
	(3.62)	(3.92)	(3.78)	(3.47)	(3.60)	(2.95)	(3.52)	(3.42)	
% asian	8.11	13.01	8.45	13.75	8.27	12.17	8.74	12.67	12.82
	(11.98)	(12.02)	(10.52)	(9.73)	(8.81)	(6.96)	(8.31)	(6.90)	
% hispanic	35.33	35.72	36.31	36.94	37.92	39.88	37.29	38.21	37.62
	(25.53)	(22.32)	(21.99)	(18.56)	(20.40)	(15.19)	(17.03)	(11.19)	
median hh	66,071	82,062	62,737	74,913	60,895	69,984	45,670	49,402	48,072
income	(25,672)	(23,769)	(21,504)	(19,492)	(19,185)	(16,870)	(10,216)	(8,622)	

Note: This table shows summary statistics of population in a community nearby a disposal site. A nearby community is defined by a fixed 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 total waste amount of the facility (using 2010 waste levels).

TABLE 5: Current distribution of trash amount in 3-miles buffers of facilities

	Mean	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	84,670	trash amount					
% black	3.34	1402.55	2786.28	2970.09	3656.90	5449.69**	-304.40
		(2813.79)	(2585.56)	(2532.57)	(2592.00)	(2516.99)	(2703.09)
% Hispanic	31.19	938.00*	1655.71**	1658.58**	1491.80**	1530.31**	-664.06
		(537.69)	(688.77)	(698.18)	(657.44)	(627.68)	(899.49)
% Asian	11.90	813.77	-484.77	-580.37	-621.28	66.95	291.81
		(1423.25)	(946.81)	(906.37)	(884.99)	(894.26)	(795.92)
Income ($1000s)	58		2431.24**	2754.58**	2894.23***	3388.77***	
			(947.02)	(1037.10)	(793.65)	(785.58)	
price	40			-695.14	-624.28	-467.85	767.64
				(590.44)	(597.05)	(549.72)	(622.14)
distance	37.46				-13429.67***	2032.35	-9858.36**
					(3673.98)	(5193.87)	(3960.69)
distance^2					122.56**	-13.66	80.89
					(47.02)	(61.89)	(50.23)
nonlocal						-289332.09***	
						(62571.33)	
Origin county FE							Yes
N		374	374	374	374	374	374
adj. R^2		0.000	0.022	0.021	0.116	0.222	0.272

Note: This table shows the descriptive regression of the demographic distribution of waste flows. Dependent variable is waste flow between an origin county and destination facility in the county's choice set. $\%Race_j$ and $Income_j$ (median household income) are characteristics of community within 3 miles of facility j. Variables are valued at 2010 level. Separate regressions for intercounty flows and local flows are reported in table (6) below. Standard errors are clustered by destination county. Significant level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE 6: Current distribution of trash amount in 3-miles buffers of facilities

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable	trash amount							
% black	2784.67**	3158.62**	3158.16***	2726.16**	3290.20	7249.75	8652.08	1371.83
	(1169.66)	(1196.26)	(1153.32)	(1290.95)	(8200.04)	(6733.23)	(6527.18)	(16019.96)
% Hispanic	-55.15	129.21	164.44	-155.46	1961.94	3911.98**	3864.77**	3900.19
	(148.84)	(141.89)	(162.64)	(326.45)	(1347.19)	(1752.04)	(1669.79)	(3104.09)
% Asian	-232.89	-493.18*	-565.25*	-664.82	9791.87	3021.92	3729.59	13036.64*
	(236.13)	(276.54)	(315.82)	(442.83)	(7515.70)	(5617.49)	(6085.63)	(7310.12)
Income ($1000s)		568.25	819.60	573.37		8779.82***	8863.31***	10104.08*
		(347.39)	(508.23)	(360.45)		(2053.77)	(1754.81)	(5277.10)
price			-313.26	-318.76			-128.24	7556.67
			(278.08)	(290.18)			(1837.88)	(6660.30)
distance			-7635.41	-7376.11*			8991.65	15435.74
			(4772.16)	(4229.79)			(9407.97)	(23005.03)
distance^2			95.26	86.93			-102.34	-213.40
			(62.00)	(53.81)			(151.64)	(423.23)
observations	intercounty	intercounty	intercounty	intercounty	local	local	local	local
Origin county FE				Yes				Yes
N	273	273	273	273	101	101	101	101
adj. R^2	0.007	0.016	0.026	0.215	0.052	0.163	0.148	0.122

Note: This table report the demographic distribution of waste flows for two different samples, intercounty flows and local flows. Dependent variable is waste flow between an origin county and destination facility in the county's choice set. $\%Race_j$ and $Income_j$ (median household income) are characteristics of community within 3 miles of facility j. Variables are valued at 2010 level. Stacked regression using all observations is reported in the previous table (5). Standard errors are clustered by destination county. Significant level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE 7: Results from logit demand, baseline model, using market-size-weighted estimator

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

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

TABLE 8: Results from logit demand using market-equally-weighted estimator

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

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

TABLE 9: Change relative to baseline levels after counterfactual policies

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

Note: Metrics are calculated for every county market and then averaged over markets using market sizes (total trash generated) as weights to get the above reported average. All measures use 2010 levels. Hauler surplus is implied from logit model, $\frac{1}{-\beta_{price}} \log\left(\sum_j^{J_m} \exp(\beta X_{jct})\right) + C$, where C is an unknown constant that represents the fact that the absolute level of utility cannot be measured; so, there is no reference for percent change in hauler surplus. The measure "% trash to white" is the percent share of market trash that is sent to white, i.e. $= \frac{\sum_{j\in J_c} q_{cj} \times \#\text{ whites in j's buffer}_j / \text{total population in j's buffer}_j}{\sum_{j\in J_c} q_{cj}} \times 100$. The measure "% export to white" is the percent portion of exports that is sent to white to total trash generated in the origin county market, i.e.$= \frac{\sum_{j\in J_c} \mathbf{1}(\text{j is not located in c}) \cdot q_{cj} \times \#\text{ whites in j's buffer}_j / \text{total population in j's buffer}_j}{\sum_{j\in J_c} q_{cj}} \times 100$. In the case of import bans, five counties, Alpine, Amador, Del Norte, Nevada, San Francisco, and Tuolumne do not have any local facilities. Hence, I drop those counties in calculating the above averages. These account for 1.91% of waste in California in 2010.

APPENDIX

A Data Handling and Format

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

For out-of-state exports in California solid waste, I observe the export amount, but I do not observe the place of destination.[9] 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.

B Test of Market Boundaries Using 2SLS Models

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

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

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

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