ESSAYS ON INDUSTRIAL ORGANIZATION AND ENVIRONMENTAL ECONOMICS

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Abstract

This dissertation consists of three essays on industrial organization and environmental economics. The first essay models the efficient pricing structure when consumers respond to average price rather than marginal price. Regulators have been using increasing block tariffs to regulate important markets such as water and electricity, although such tariffs are not shown to be efficient in the standard literature of industrial organization. In light of recent evidence regarding how consumers respond to complex price schedules, this essay re-examines the regulated non-linear pricing. Results show that increasing per-unit prices (hence increasing block tariffs) may be optimal when consumers respond to changes in average price rather than marginal price. This suggests the equity-efficiency trade-off associated with increasing block tariffs may be less severe than previously believed.

The second and the third chapters study the garbage industry. In the United States, waste has been transported across county lines and state borders. Several states and counties have attempted to legalize transboundary 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, the second essay 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.

In the third chapter, I look at the residential mobility hypothesis to explain the uneven distribution of waste by demographics. Forming sound environmental justice policy involves understanding whether the correlation between race and environmental bads results from the disproportionate siting of locally unwanted land uses or nuisance-driven residential mobility. This essay presents evidence of residential sorting using a difference-in-difference strategy. Specifically, I compare changes in population after an opening (and closing) of a trash site between blocks within one mile to faraway blocks. Results show a 11 percent decrease in white population and a 44 percent increase in Hispanic population in a block after a trash site opened within one mile. Closing the site does not change white population immediately while inducing a 11 percent fall in Hispanic population, relative to the operating period.

Chapter 1

Nonlinear Pricing, Biased Consumers, and Regulatory Policy

Price schedules with increasing block tariffs have been used by policy makers to regulate important markets such as water and electricity. Regulators sometimes argue that increasing block tariffs promote equity, resource conservation, and revenue stability. However, such tariffs are usually not argued to promote efficiency. This paper re-examines regulated non-linear pricing in light of recent evidence regarding how consumers respond to complex price schedules. Ito (2013) shows that, when confronted with complex price schedules, electricity customers respond to changes in average price (AP) rather than to changes in marginal price (MP). This paper characterizes the optimal regulated non-linear pricing when consumers respond to changes in average price. Optimal pricing under AP response behavior is shown to be independent of the consumer type distribution. A key result is that, fixing consumer preferences and the type distribution, increasing per-unit prices may be optimal when consumers respond to AP, while decreasing per-unit prices are optimal when consumers respond to MP. These results suggest that the equity-efficiency trade-off associated with increasing block tariffs may be less severe than previously believed.

1.1 Introduction

Nonlinear price schedules are observed for many goods and services. Firms offer quantity discounts on auto rentals, hotel room stays, and a wide variety of consumer goods. Cell phone service providers have complex nonlinear prices based on menus of three-part tariffs. Seminal papers by Mirrlees (1971), Spence (1977), Mussa and Rosen (1978), and Maskin and Riley (1984) show how firms with market power may use nonlinear pricing to engage in second-degree price discrimination and extract profits in excess of what could be achieved via uniform pricing. Profit-maximizing nonlinear price schedules exhibit decreasing marginal prices (i.e. quantity discounts) for a wide variety of environments, with the highest consumer type paying a marginal price equal to the firm's marginal cost.

Regulated firms also employ nonlinear pricing. For example, many regulated public utilities charge increasing block tariffs, in which consumers are charged higher marginal prices for higher consumed quantities. From an economic efficiency standpoint, increasing marginal price (IMP) schedule for a regulated firm is a puzzle. Suppose that the firm operates with economies of scale and the regulator wishes to set prices so as to maximize welfare subject to a break-even constraint for the firm. Then second-best optimal prices require distortions away from marginal cost, but these distortions will typically involve smaller mark-ups of marginal price over marginal cost for higher quantities; that is, decreasing marginal prices (which also follows the results in the context of non-regulated nonlinear pricing by Mirrlees (1971) and Maskin and Riley (1984)). The IMPs, represented by increasing block tariffs, however, are charged by many regulated public utilities since they are often argued to promote distributional goals.[1] For example, when energy costs increase significantly in the 1970s and 1980s, many electric utilities raised marginal rates on high-consumption service tiers, while keeping marginal rates low on lower tiers to protect lower income consumers. This, hence, points to the presence of an equity-efficiency trade-off for regulators, whereby distributional goals for pricing are achieved only by sacrificing efficiency. Borenstein (2012) provides evidence regarding the efficiency cost of increasing block tariffs used by California electric utilities though he analyzes the distortion away from setting an alternative flat rate schedule.

In this paper, we offer a different perspective on the equity-efficiency trade-off for price regulation. This perspective is based on recent empirical evidence on biased consumer responses to complex nonlinear price schedules. Ito (2014) uses customer billing data to examine how household electricity customers in California respond to changes in increasing block tariffs. He provides several types of empirical tests to show that consumers respond to changes in the average price of electricity, rather than to changes in marginal price. We formulate and analyze a nonlinear pricing model to show that biased consumer responses to price changes can have dramatic effects on second-best optimal prices. For reasonable configurations of consumer preferences and distributions of consumer types, the shape of the second-best optimal nonlinear price schedule may be *reversed* for average price response (APR) consumers compared to that for marginal price response (MPR) consumers. In particular, second-best prices for APR consumers may involve increasing marginal prices whereas second-best prices for MPR consumers involve decreasing marginal prices. This finding suggests that regulated increasing marginal prices may not imply an equity-efficiency trade-off, or that this trade-off may not be as significant as prior studies have suggested.

Our model is built on the standard literature of monopolist's nonlinear pricing in Mussa and Rosen (1978), Maskin and Riley (1984), and Stole (2007). We extend to also consider regulated nonlinear pricing in which the regulator designs the price that maximizes social welfare subject to a break-even constraint on the monopolist's profits. However, we depart from standard literature by assuming consumers respond to average price instead of marginal price. This price misperception is due to the misspecified beliefs of the nonlinear structures of prices, subsidies, and tax schedules.[2] Hence, consumers who face a possibly nonlinear pricing menu act as if they faced a linear price in which marginal rates were also average rates.

Assuming APR, we find that optimal price schedule does not depend on the consumer's type distribution. Moreover, given a fixed preference, the optimal price schedule may exhibit increasing marginal prices under APR whereas it is decreasing marginal prices under MPR. This implies that increasing marginal price

[1] See for example, Wichelns (2013), who also argues that increasing block tariffs promote energy conservation goals.

[2] see evidences on Liebman and Zeckhauser (2004), Liebman (1998), and Fujii and Hawley (1988) on tax rates; Ito (2013), Borenstein (2009) on electricity price; and Carter and Milon (2005), and Saez (2010) on water price.

schedules in the world of biased consumers with APR may achieve double goals of efficiency and equity.

We also examine the welfare and the welfare distribution by the type of consumers between pricing in the world of APR and pricing in the world of MPR. Compared to the society with optimally pricing in the world of MPR, the regulated pricing solution in the world of APR may lead to a society with a higher welfare owing to a higher consumer surplus. That is because pricing in the world of APR may result in a lower marginal price schedule than pricing in the world of MPR. There may be a situation in which the welfare between the two worlds is the same. However, in such situation, pricing in the world of APR leads to a more favored distribution in consumer surplus. Particularly, low type consumers (who consume a low amount of goods) obtain more benefits in the world of APR pricing than in the world of MPR in two aspects. First, low type consumers who could not afford the goods in the world of MPR pricing are able to consume a positive amount in the world of APR pricing. Second, for low type consumers who can consume the goods in both worlds, low type consumers in the world of APR obtain higher surplus than in the world of MPR pricing. This is, again, because of a lower marginal price schedule in the world of APR, which reduces the distortion when pricing away the marginal cost. The deadweight loss caused by pricing away the marginal cost is mitigated to transfer into the consumer surplus.

There is a longstanding interest in studying misbehavior of consumers. In markets with nonlinear price schedules such as public utility pricing and taxation, Saez (2010) and Borenstein (2009) show that rational consumers respond to expected marginal price due to the presence of uncertainty about consumption. Using a general perceived price form that allows all three possible perceptions (marginal price, expected marginal price, average price), Ito (2014) provides strong empirical evidence that consumers respond to average price. Esponda and Pouzo (2016) develop a theoretical framework to explain the misspecified behaviors as called Berk-Nash equilibrium. They explain APR as a self Berk-Nash equilibrium in which a consumer has a misspecified subjective belief of the unit costs, leading her to act as if she faced a linear price though she faces a possibly nonlinear price schedule. We formulate the optimal regulated pricing when such price misperception in consumers is taken into account.

A growing literature of behavioral economics in industrial organization also examines how firms react to and in some cases exploit biased or suboptimal responses of consumers to complex pricing. Those studies suggest consumers have non-standard preferences (eg. loss aversion, or present bias), are overconfident or fail to choose the best price due to suboptimal search, etc (readers can refer to a comprehensive survey by DellaVigna (2009)). For example, Heidhues and Kőszegi (2008) and Spiegler (2012) suggest that loss aversion may create kinks in demand curves, which can lead to price rigidities. Courty and Hao (2000); Eliaz and Spiegler (2008); Grubb (2009) study monopoly screening problem or price discrimination when consumers are overconfident. Grubb (2009), especially, analyzes nonlinear pricing by a monopoly cell phone service provider. Consumers in his model are uncertain of their desired consumption level when they select a pricing plan and in addition exhibit a biased underestimate of the variance of desired consumption. The monopolist exploits this bias by offering a three-part tariff similar to commonly observed cell phone plans; a fixed fee, a set quantity of service with zero marginal price, and a high marginal price for overages above the set quantity. We consider the monopoly pricing and regulated pricing when consumers misperceive nonlinear prices as linear prices and hence respond to average prices instead of marginal prices. Our model help explain the optimality of increasing marginal prices.

The shape of nonlinear price schedules is also especially important in taxation literature. The optimal shape of income tax rate has been well studied in Mirrlees (1971), Diamond (1998), and Dahan and Strawczynski (2000). Before the study by Diamond (1998), most analysis of optimal taxation supported decreasing marginal tax rates at high levels of income (see summary in Dahan and Strawczynski (2000)). Nevertheless, Diamond (1998) and the later comment by Dahan and Strawczynski (2000) demonstrated that the utility form and the worker skill distribution (equivalent to the consumer type distribution in product and service markets) account for the optimal tax rate shapes. The optimal tax rate, hence, may be increasing or U-shaped. We also consider the effect of utility form and type distribution on the shape of optimal marginal price but more importantly, the effect of APR rather than MPR. Liebman and Zeckhauser (2004) propose a "schmeduling" suboptimization in which consumers use average price as an approximation of marginal price due to the substantial cognitive cost of understanding complex pricing. Although Liebman and Zeckhauser (2004) model the scenario in which people respond to average tax rate, they do not study the impact on optimal tax shape. Furthermore, it is important to note that the nonlinear pricing model in labor economics, while similar to other product and service markets, exhibits significant differences in optimization constraints and in how uncertainty of the type of a consumer enters the preferences. Outside of labor economics (except Liebman and Zeckhauser (2004)), an exception that models the nonlinear pricing in APR is Sobel (1984). However, he only considers the conditions in which the monopolist optimal pricing schedule under APR has decreasing marginal prices. He does not fully contrast welfare between APR world and MPR world nor the distribution in welfare by the type of consumers.

The rest of the paper is organized as follows. Section 1.2 discusses the misperceived behaviors and the behavioral theory behind APR. Section 1.3 outlines the two pricing solutions—monopoly pricing and regulated firm pricing when consumers respond to marginal prices and when consumers respond to average prices. Section 1.4 presents the implications of APR pricing on the structure of the optimal price schedules. Section 1.5 shows the welfare implications. Section 6 concludes.

1.2 Modeling Average Price Response Behavior

In the monopoly pricing problem, the firm designs the price schedule (the pairs of price rate and consumption quantity) that maximizes expected profits given that consumers facing the price schedule will select the consumption to maximize individual utilities. That constraint is known as the incentive constraint where each type of consumers selects their own prescribed consumption and does not have incentive to buy the other consumptions (that are designed for other types).

In the world of MPR, a consumer of type θ selects a demand $q(\theta)$ in order to maximize their utility taking the entire total price schedule $P(q)$ as considered. Formally, it is written as

$$q(\theta) \text{ solves } \max \mathcal{U}(q, \theta, P(q)) \text{ for each } \theta \tag{1.1}$$

Under the conventional utility function $\mathcal{U}(q, \theta, P(q)) = U(q, \theta) - P(q)$, it is clear that the consumer of type θ compares the marginal utility to marginal price and opts to choose quantity $q(\theta)$ at which marginal utility equals marginal price, i.e $q(\theta)$ such that $U_q(q(\theta), \theta) = P_q(q(\theta))$ (subscripts denote derivatives).

In the world of APR, a consumer of type θ selects a demand $q(\theta)$ such that $U_q(q(\theta), \theta) = P(q(\theta))/q(\theta)$. That is because consumers misperceive the marginal price or the entire total price schedule because they have limited understanding of the price schedule or find the nonlinear price complicated to understand. We further elaborate the theory behind APR as follows.

Liebman and Zeckhauser (2004) identify conditions in three categories that can discourage people from perceiving the incentives at the margin. First, complexity, e.g. due to the nonlinear structure, makes it hard to determine marginal prices and costly to know where one is on the price schedule. Second, the connection between a consumer's choice and consumption is difficult to observe, especially in purchasing electricity and water. For example, how many kilowatts of electricity are used to cook a meal, and how much it costs to cook that meal is even more difficult to perceive. Third, nonstationary environment is not conducive for consumers to learning. Different seasons often lead consumers to stay at very different points on the price schedule (more heating is demanded in the winter). The pricing schedules are usually not displayed on the monthly bills and even the bills are presented in an incomprehensible measure such as kilowatts. The monthly payment also aggregates hundreds of disparate single activities (turning on the light, running the refrigerator, using the heater etc.) Therefore, Liebman and Zeckhauser propose that consumers perceive (or treat) the average price as the marginal price. This, which they call ironing, is because people smooth over the entire range of the schedule. "One decides whether to lower the heater by noting that \$300 per month represents an average price of 60 cents per therm, rather than 89 cents for the last (or next) therm of natural gas." (pg. 14).

In fact, Hortaçsu et al. (2015) imply a high possibility of APR instead of MPR behaviors. They document that the Public Utility Commission of Texas created a website that shows all available retail electricity provider options in order to inform consumers and provide transparency to the search process. That website, however, only displays average rates instead of marginal rates at different consumption plans. Such instruction may unintentionally lead consumers to focus on average prices rather than marginal prices.

Of course, people who are fiercely rational or who face very simple pricing schemes may know exactly their location on the price schedules and respond to marginal price. Some may use first-differencing to estimate marginal price or compare their own situation to that of a similar person to infer marginal price. Nevertheless, compared to marginal price, much less information is required to calculate average price (only the total payment and quantity are sufficient). Given the substantial cognitive cost of understanding complex pricing, consumers may respond to the average price of total payment as an approximation of their marginal price. This is empirically supported by Ito (2014). He shows that consumers do respond to price but they only perceive average price instead of marginal price because they are *inattentive* to the price schedule. In his model, he recovers the perceived price as $\tilde{p}(x) = \int p(x - \epsilon) w(\epsilon) d\epsilon$ where $p(x)$ is the marginal price of the price schedule, x is the consumption quantity, and $w(\epsilon)$ is uniformly distributed over $[0, x]$. In other words, consumers perceive the average price as the marginal prices weighted by uniformly distributed noise at smaller quantities. This is appropriate to the theory in Liebman and Zeckhauser (2004) proposing that consumers smooth over the entire range of the schedule and thus treat the average price as the marginal price.

All of the above papers, however, do not provide a formal theory to explain why consumers cannot learn about the marginal prices even if consumers may realize different average prices at different quantities. Sobel (1984) suggests a consumer who demands $q(\theta)$ thinks that she faces a linear price schedule with constant unit charge equal to $P(q(\theta))/q(\theta)$. In a formal model, it is written as:

$$q(\theta) \text{ solves } \max \mathcal{U}(q, \theta, P(q(\theta))/q(\theta)) \tag{1.2}$$

A reason for that, he explains, is that the consumer knows only the total amount she actually must pay for this purchase, not the entire price schedule. Sobel (1984) shows that consumers' behaviors adjust dynamically towards an APR convergence. The process suggests consumers respond to average prices because they know only the quantity and the total cost of their purchases. A consumer begins by making a purchase of q_0 and then learns about the value of $P(q_0)$. She makes the next demand under the assumption that the price is linear and the unit price is $P(q_0)/q_0$. In general, the consumer makes her nth purchase assuming the average price of the $(n-1)$th purchase is the constant unit cost. Sobel (1984) shows that this adjustment process converges to the problem (1.2). However, his theory of adjustment process is given under the conditions that lead to a decreasing marginal price schedule in the world of APR. The process cannot explain APR behavior in all types of price schedules.

A recent theory developed by Esponda and Pouzo (2016) can explain APR behaviors of consumers. They propose a concept of Berk-Nash equilibrium to model agents with misspecified environment. That is, instead of assuming people have a correctly specified view of their environment, each player is characterized by a subjective model which describes the set of feasible beliefs over payoff-relevant consequences as a function of actions. In a Berk-Nash equilibrium, each player follows a strategy that is optimal given her best fit belief. The notion of best fit belief is formalized in terms of minimizing the Kullback-Leibler divergence, which is endogenous and depends on the equilibrium strategy profile.

Applying their framework to the nonlinear pricing context, we see that the true environment is the set of all possible unit costs $\mathbb{Y} = \{y \in \mathbb{R} : y = p(q)/q, q \in \mathbb{R}\}$. The consumer incorrectly believes that she faces a (possibly random) linear price $y \in \mathbb{Y}$ that does not depend on her choice. Her misspecified subjective model is the set of all probability distributions over $\mathbb{Y}$. That is, $\Theta = \Delta(\mathbb{Y})$ where $\theta = (\theta_1, \ldots, \theta_k) \in \Theta$ and θ_j denotes the probability that the linear price is $P(q_j)/q_j$. The consumer's strategy is denoted by $\sigma = (\sigma_1, \ldots, \sigma_k) \in \Delta(\mathbb{Q})$, where σ_j is the probability that the consumer chooses quantity q_j. Esponda and Pouzo (2016) show that for a strategy σ, the weighted Kullback-Leibler divergence function is $K(\sigma, \theta) = \sum_{j=1}^{k} \sigma_j \ln \frac{1}{\theta_j}$ and the unique minimizer is $\theta(\sigma) = (\sigma_1, \ldots, \sigma_k)$. Given such best fit belief, the strategy σ also maximizes the consumer's surplus $\{U(q) - \left(\sum_{j=1}^{k}(P(q_j)/q_j)\sigma_j\right) q\}$. Thus, σ is a Berk-Nash equilibrium. A special case of σ that defines a pure strategy q_j and the belief of the linear price with unit cost $P(q_j)/q_j$ with probability of one is also a Berk-Nash equilibrium. This implies APR is a pure strategy Berk-Nash equilibrium.

Our model that characterizes nonlinear pricing in the world of APR fits with the APR behavior that is resulted from a pure strategy Berk-Nash equilibrium.

1.3 Defining Nonlinear Pricing Solutions

We consider the setting as in the standard model in Mirrlees (1971); Mussa and Rosen (1978) Maskin and Riley (1984); Wilson (1993). Given the total price schedule $P(q)$, a type-θ consumer whose preference is $U(q, \theta)$ has the surplus $U(q, \theta) - P(q)$ over the combination of quantity q and type θ; one-dimension type θ is distributed on $\Theta = [\theta_0, \theta_1]$ with density $f(\theta)$ and distribution $F(\theta)$. Assume that the outside option of not consuming is zero and firm faces a per-consumer cost $C(q)$ that is convex. Subscripts denote partial derivatives. Superscript m, a denotes the scenario where the consumer responds to marginal price and average price, respectively.

Assumption 1. Consumers' preferences satisfy:

1. $U_{qq} < 0$
2. $U_q > 0$
3. $U_\theta > 0$
4. $U_{q\theta} > 0$
5. $U_{q\theta} + qU_{qq\theta} > 0$
6. $2U_{qq} + qU_{qqq} < 0$

The first two assumptions ensure the positive marginal utility of consumption and the law of diminishing marginal utility. The third assumption aims to order the utility in the type of consumers. The fourth implies that the consumers with a higher type enjoy a higher marginal utility across every q (this is usually referred as the single-crossing condition). The last two assumptions guarantee monotonicity of consumption in consumer type under AP response price schedule.

It worths noticing that the consumer inverse demand in general is $U_q(q, \theta) = D_\theta(q) \equiv$ *Perceived Unit Price*. Under MP response, the consumer inverse demand is $U_q(q, \theta) = P_q(q) \equiv MP$. Under AP response, the consumer inverse demand is $U_q(q, \theta) = P(q)/q \equiv AP$.

We now define two pricing solutions, monopoly pricing and the regulated firm pricing (second-best pricing), for each case of price response behaviors.[3]

1.3.1 Monopoly Pricing Solution

Monopoly Pricing Under Marginal Price Response

As in the standard literature, the firm chooses the price schedule $P^m(q)$ to maximize expected profits subject to the incentive compatibility (IC) and individual rational (IR) constraints.

$$\max_{P^m(\cdot)} \int_{\theta_0}^{\theta_1} P^m(Q^m(\theta)) - C(Q^m(\theta))dF(\theta) \tag{1.3}$$

$$\text{subject to } \; Q^m(\theta) = argmax_{q \geq 0} U(q, \theta) - P^m(q) \; [IC] \tag{1.4}$$

$$U(Q^m(\theta)) - P^m(Q^m(\theta)) \geq 0 \; [IR] \tag{1.5}$$

[3]Later, we can see that the two pricing solutions share a similar form of mark-up ratio formula and even the first best pricing can be included in that formula.

The standard results in the literature are that the optimal consumption $Q^m = \max\{q^m(\theta), 0\}$ where $q^m(\theta)$ is nondecreasing and satisfies (see appendix A for more detailed results):

$$U_q - C_q = \frac{1-F}{f} \cdot U_{q\theta} \tag{1.6}$$

It should be noticed that the optimal price schedule $P^m(q)$ has the marginal price equal to marginal utility and hence, we can rewrite equation 1.6:

$$\frac{MP - MC}{MP} = \frac{U_q - C_q}{U_q} = \frac{1-F}{f} \cdot \frac{U_{q\theta}}{U_q} \tag{1.7}$$

To interpret this formula, fix a quantity q and consider the demand for the qth unit of consumption. This unit has the price p^m, which is the *marginal price* since consumers are responding to marginal price. In other words, we have the marginal price demand in this case. The proportion of consumers willing to buy this unit is

$$D(p^m) \equiv 1 - F(\theta^*(p^m)) \tag{1.8}$$

$$\Rightarrow \frac{dD(p^m)}{dp^m} = f(\theta^*(p^m))\frac{d\theta}{dp^m} \tag{1.9}$$

where $\theta^*(p^m)$ denotes the type of consumer who is indifferent between buying and not buying the qth unit at marginal price p^m:

$$U_q(q, \theta(p^m)) = p^m \tag{1.10}$$

$$\Rightarrow U_{q\theta} d\theta = dp^m \tag{1.11}$$

$$\Rightarrow \frac{d\theta}{dp^m} = \frac{1}{U_{q\theta}} \tag{1.12}$$

Therefore,

$$\frac{dD(p^m)}{dp^m} \cdot \frac{p^m}{D(p^m)} = \frac{f(\theta^*(p^m))}{1 - F(\theta^*(p^m))} \cdot \frac{p^m}{U_{q\theta}} \tag{1.13}$$

Note that $p^m = U_q$, hence

$$\frac{MP - MC}{MP} = \frac{U_q - C_q}{U_q} = \frac{1}{\frac{f}{1-F}} \cdot \frac{U_{q\theta}}{U_q} = \frac{1}{\epsilon} \tag{1.14}$$

This means that the monopolist's mark-up ratio depends on the marginal price elasticity of demand of the qth unit.

Monopoly Pricing Under Average Price Response

As mentioned in section 1.2, under the APR case, the constraint (1.4) is replaced by the ex post behavioral incentive constraint:

$$U_q = \frac{P^a}{q} \tag{1.15}$$

The monopoly pricing solution is to choose the price schedule $P^a(q)$ to maximize expected profits:

$$\max_{P^a(\cdot)} \int_{\theta_0}^{\theta_1} P^a(Q^a(\theta)) - C(Q^a(\theta))dF(\theta) \tag{1.16}$$

$$\text{subject to } \; Q^a(\theta) : U_q(Q^a(\theta)), \theta)) = \frac{P^a(Q(\theta))}{Q(\theta)} \tag{1.17}$$

$$U(q, \theta) - qU_q(q, \theta) \geq 0 \tag{1.18}$$

The profit maximization of the monopolist is transformed to

$$\max_{q} \int_{\theta_0}^{\theta_1} (qU_q(q, \theta) - C(q))dF(\theta) \tag{1.19}$$

$$\text{subject to } \quad U(q, \theta) - qU_q(q, \theta) \geq 0 \tag{1.20}$$

Since the constraint 1.20 is satisfied so long as the consumption is nonnegative, solving the problem requires maximizing the intergrand $qU_q(q, \theta) - C(q)$. This means that finding the monopolist's optimal AP response price schedule involves finding the most profitable uniform price for each θ-type consumer, and choosing the price schedule so that the average price for each type is equal to that corresponding most profitable uniform prices. The formal first order condition is at each θ:

$$U_q + qU_{qq} - C_q = 0 \tag{1.21}$$

$$U_q - C_q = -qU_{qq} \tag{1.22}$$

Apply the implicit function theorem to the above equation, we can see the change in optimal consumption in consumer type as follows:

$$\frac{dq}{d\theta} = -\frac{U_{q\theta} + qU_{qq\theta}}{2U_{qq} + qU_{qqq} - C_{qq}} \tag{1.23}$$

The assumptions (4) and (5) on the utility function and the weak convexity of the cost ensures the monotonicity and the uniqueness of the optimal consumption for each consumer type ($dq/d\theta > 0$). Since the monopolist shall designs the average price at the marginal utility of the optimal consumption, the price schedule is well defined in the sense that each consumer type facing such price schedule finds only one optimal consumption.

Lemma 1. *When the consumer responds to average price, the optimal consumption* $Q^a = \max\{q^a(\theta), 0\}$

where $q^a(\theta)$ satisfies:

$$U_q - C_q = -qU_{qq} \tag{1.24}$$

The optimal price schedule satisfies:

$$U_q = \frac{P^a}{q} \tag{1.25}$$

Equation 1.24 can be rewritten as:

$$\frac{U_q - C_q}{U_q} = \frac{-qU_{qq}}{U_q} \tag{1.26}$$

We now try to interpret the above mark up ratio by considering the *average price demand* in this case. Fix a type of consumer, the consumer of this type is different between buying and not buying the qth unit by comparing the marginal utility with the average price p^a of that unit:

$$U_q(q, \theta) = p^a \tag{1.27}$$

$$\Rightarrow U_{qq}dq = dp^a \tag{1.28}$$

$$\Rightarrow \frac{-qU_{qq}}{U_q} = -\frac{dp^a}{dq} \cdot \frac{q}{p^a} \equiv \frac{1}{\eta} \tag{1.29}$$

Therefore, we get

$$\frac{AP - MC}{AP} = \frac{U_q - C_q}{U_q} = \frac{-qU_{qq}}{U_q} = \frac{1}{\eta} \tag{1.30}$$

which means that the monopolist's mark-up price ratio depends on the *average* price elasticity of demand for each type of consumers since consumers respond to average price.

1.3.2 Regulated Firm Pricing (Second-best Pricing Solution)

Monopolist is often regulated by the price at which total welfare is maximized subject to the monopolist's profit at a fixed rate, often a break-even rate to just cover enough fixed costs F. This pricing method is also called Ramsey pricing which often refers to multiproduct contexts. We will consider the regulated monopoly pricing under MP response and under AP response. In fact, it later turns out that monopoly pricing and the regulated monopoly pricing, and even the first best solution, share a similar pricing form.

Regulated Firm Pricing Under Marginal Price Response

The regulator maximizes the social welfare subject to a constraint on the supplier's profit.

$$\max_{P^m(\cdot)} \int_{\theta_0}^{\theta_1} U(Q^m(\theta), \theta) - C(Q^m(\theta)) dF(\theta) \tag{1.31}$$

$$\text{subject to} \quad \int_{\theta_0}^{\theta_1} P^m(Q^m(\theta)) - C(Q^m(\theta)) dF(\theta) = FC \ \ \text{[Profit constraint]} \tag{1.32}$$

$$Q^m(\theta) = argmax_{q \geq 0} U(q, \theta) - P^m(q) \ \ \text{[IC constraint]} \tag{1.33}$$

$$U(Q^m(\theta)) - P^m(Q^m(\theta)) \geq 0 \ \ \text{[IR constraint]} \tag{1.34}$$

Solving this problem (see Appendix B for more detail) yields that the optimal consumption $q^m = \max\{Q^m(\theta), 0\}$ where $q^m(\theta)$ satisfies:

$$U_q - C_q = \left(\frac{\lambda^m}{1+\lambda^m}\right) \cdot \left(\frac{1-F}{f} \cdot U_{q\theta}\right) \tag{1.35}$$

where λ^m is the Lagrangian multiplier for the monopolist's profit constraint. The Lagrangian term λ^m, hence, has the interpretation that it is the marginal increase in welfare associated with a decrease in firm profit.

Notice this means

$$\frac{MP - MC}{MP} = \frac{\mathcal{R}^m}{\epsilon} \tag{1.36}$$

where $\mathcal{R}^m \equiv \frac{\lambda^m}{1+\lambda^m}$ is a constant number and $\mathcal{R}^m \in (0, 1)$ and ϵ is the marginal price elasticity of demand for qth unit across all types.

$$\epsilon = \frac{f}{1-F} \cdot \frac{U_q}{U_{q\theta}} \tag{1.37}$$

Regulated Firm Pricing Under Average Price Response

In contrast to the case where consumers respond to marginal price: $U_q = P^m_q$, the consumers here respond to average price (since they are not able to articulate the marginal price and use average as an estimate of marginal price to reason):

$$U_q = \frac{P^a}{q} \tag{1.38}$$

Therefore, the profit maximization of the monopolist is transfered to

$$\max_q \int_{\theta_0}^{\theta_1} (U(q,\theta) - C(q))dF(\theta) \tag{1.39}$$

$$\text{subject to} \quad \int_{\theta_0}^{\theta_1} (qU_q(q,\theta) - C(q))dF(\theta) = FC \tag{1.40}$$

$$U(q,\theta) - qU_q(q,\theta) \geq 0 \;\; \text{[IR constraint]} \tag{1.41}$$

Since the IR constraint is satisfied so long as the consumption is nonnegative, we have the following FOC (with the Lagrangian multiplier λ^a for the profit constraint):

$$U_q - C_q + \lambda^a(U_q + qU_{qq} - C_q) = 0 \tag{1.42}$$

$$U_q - C_q = \frac{\lambda^a}{1+\lambda^a} \cdot (-qU_{qq}) \tag{1.43}$$

Theorem 1 (Regulated firm pricing under AP response)**.** *When the consumer responds to average price and under regulated pricing scheme, the optimal consumption $q^a = \max\{Q^a(\theta), 0\}$ where $q = Q^a(\theta)$ satisfies:*

$$U_q - C_q = \frac{\lambda^a}{1+\lambda^a} \cdot (-qU_{qq}) \tag{1.44}$$

The optimal price schedule satisfies:

$$U_q = \frac{P^a}{q} \tag{1.45}$$

□

This implies

$$\frac{U_q - C_q}{U_q} = \frac{\lambda^a}{1+\lambda^a} \cdot \frac{-qU_{qq}}{U_q} \tag{1.46}$$

$$\Leftrightarrow \frac{AP - MC}{AP} = \frac{\mathcal{R}^a}{\eta} \tag{1.47}$$

where η is the average price elasticity of demand for qth unit for each of the types of consumers. Similar to the MP response scenario, $\mathcal{R}^a$ is a constant between 0 and 1.

The optimal mark-up price ratios imply that the monopoly pricing and the regulated firm pricing share a similar form.

$$\text{Under MP response} \qquad \text{Under AP response} \tag{1.48}$$

$$\frac{MP - MC}{MP} = \frac{\mathcal{R}^{(m)}}{\epsilon} \qquad \frac{AP - MC}{AP} = \frac{\mathcal{R}^{(a)}}{\eta} \tag{1.49}$$

It can be seen that the monopoly pricing, the first-best pricing, and the regulated monopoly pricing are encompassed by $\mathcal{R} = 1$, $\mathcal{R} = 0$, and $0 < \mathcal{R} < 1$, or by $\lambda \to \infty$, $\lambda = 0$, $0 < \lambda < \infty$, respectively[4]. In this paper, we call the constant $\mathcal{R}$ the policy number.

1.4 Pricing Structure Implications

In this section, we will consider the implications of the price response behaviors on the optimal price schedules. Recall that the two pricing solutions share the similar form (1.49), the proofs will use that general form although the intuition will be provided by working with the monopoly pricing for tractability.

Corollary. *When consumers respond to average price, the optimal pricing schedule does not depend on the consumer type distribution.*

Proof. Remind that the optimal pricing schedule under AP response satisfies the equations 1.15 and 1.24, which are independent of the type distribution. The intuition for this is that the monopolist can maximize total profits by maximizing profits point-wise across types. □

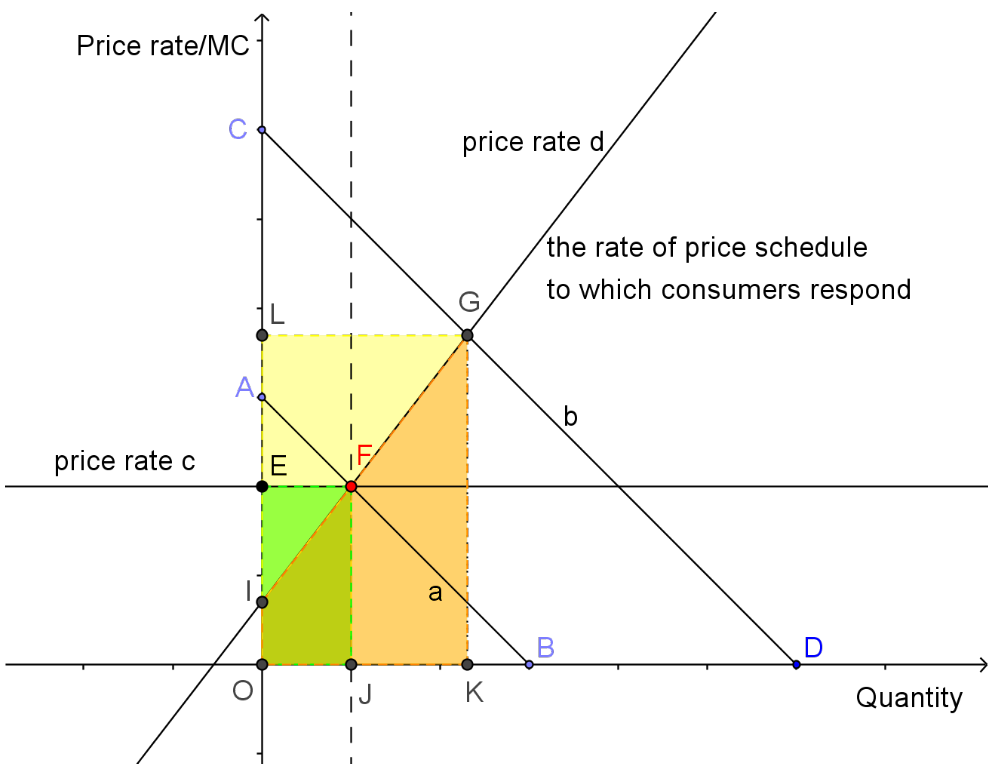


FIGURE 1.1: Monopolist's revenue under different response schemes.

Note: The horizontal axis is for quantity, the vertical axis is for the price rate to which consumers respond (either marginal rate or average rate, depending on how consumers respond to).

[4]Similar result for Ramsey pricing in the case that consumers respond to marginal price is obtained in Braeutigam (1989), section 7.3.

This appears to be surprising since the optimal mark-up pricing schedule under to-marginal-price response relies on the type distribution. However, figure 1.1 gives us the reason why. To simplify the argument, suppose the monopolist has zero cost and only needs to maximize the revenue. Consider any two types of consumers a, b, that have demand curves AB and CD, respectively. It should be also noticed that these are demand curve to which price the consumers respond. Hence, the intersection between the demand curves and the perceived price is the quantity that consumers purchase at a given price rate.

Consider the situation in which consumers respond to average price. If the monopolist designs the price rate d—average rate to which consumers respond, then the type a consumer responds at point F and type b responds at point G. The monopolist's total revenue consists the revenue $OEFJ$ collected in the type segment a and the revenue $OLGK$ collected in the segment b. We can see that the revenue in each segment does not depend on the price rate at other quantities except the quantity at which the consumers purchase. Particularly, the revenue $OLGK$ in type segment b is only determined by the specific design point G and not affected by other price rates designed at other quantities for other types.

On the contrary, if consumers respond to marginal price then the monopolist shall design the optimal marginal price scheme. If the marginal price rate is designed as the line d, the monopolist's revenue obtained from selling to consumer type a is $OIFJ$ and the revenue obtained in the type segment b is $OIGK$. We can see that the price design IG set on the first quantity unit to the final quantity unit (q^G) demanded by type b plays the role as a constraint on how much the monopolist can get from serving the segment b.

In summary, the pairs of price and quantity in the price schedule under AP response scheme are independent (disjoint relationship) thanks to two features. First, since consumers respond to average price, the monopolist can be rational by design the average price schedule. Second, the average price points are independent in the sense that the total revenue generated by any pair of price and quantity in the schedule does not depend on the other pairs.

The disjoint relationship among the monopolist's designed pairs of price and quantity when consumers respond to average price leads to an interesting result. As long as each consumer type demands different optimal quantities, the monopolist can just focus on maximizing each revenue obtained from selling to each type of consumers under AP response situation. Such action is in fact a point wise maximization in the sense that maximizing revenue obtained from selling to each type of consumers implies maximizing total revenue obtained from serving the whole market. As a result, the optimal price schedule does not depend on the distribution of consumer types[5].

Corollary (Quantity Discount)**.** *When consumers respond to marginal price, the optimal pricing schedule has decreasing marginal rate if the marginal price elasticity of demand across all types of consumers is increasing in consuming amount.*

Corollary (Quantity Premium)**.** *When consumers respond to average price, the optimal pricing schedule is increasing average rate if the average price elasticity of demand for each type of consumers is decreasing in consumption amount.*

[5] Meanwhile, under to-marginal-price response situation, the price for a qth unit will affect the monopolist's revenue from selling to all types that demand quantities at least q units. For that reason, under the MP response situation, the monopolist has to take into account the type distribution to quantify the weighted demand for the qth unit.

It should notice that increasing marginal rate implies the increasing average rate and vice versa.[6] Then the two results here appear to exclude each other but in fact they can hold together. In particular, there are situations in which the marginal price elasticity is increasing but the average price elasticity is decreasing.

If we have the utility form $U(q, \theta) = \theta V(q)$ then the condition in proposition is equivalent to that the hazard rate is increasing. This condition is well known in literature by Mussa and Rosen (1978) and Maskin and Riley (1984). Examples of increasing hazard rate include regular distributions such as uniform. Meanwhile, the decreasing hazard rate, for example, Pareto distribution would imply the decreasing marginal rate pricing schedule.

Corollary. *Assume the utility form $U(q, \theta) = \theta V(q)$. When the consumers respond to marginal price, the optimal pricing schedule is decreasing average rate if the hazard rate of the type distribution is increasing. Meanwhile, when the consumers respond to average price, the optimal pricing schedule is increasing average rate if the relative curvature $\frac{-qV''}{V'}$ is increasing.*

1.5 Welfare

1.5.1 The Distributional Effects in Consumer Welfare In the World of APR Price Schedule

Remark. In both the monopoly pricing solution and regulated firm pricing solution, APR may lead to a distributional effects in consumer welfare. Particularly, while both monopolist's profits and total consumer surplus are the same between MPR price schedule and APR price schedule, the distribution of consumer welfare by consumer types is contrast. Low type consumers may benefit in the world of APR price schedule while suffer in the wolrd of MPR price schedule.

To illustrate this result, we use an example with a quadratic utility function $U(q, \theta) = (1 + \theta)q - 1/2q^2$; $C(q) = cq$, and fixed cost F. Consumer type is uniformly distributed from 0 to 1, i.e. $\theta \sim Uniform[0, 1]$. Assume $1 \leq c \leq 2$.

Marginal Price Response, with Uniform Distributed Type

The cutoff type above which consumers can consume positive amounts of goods is:

$$\theta \geq \frac{c + \mathcal{R}^m - 1}{\mathcal{R}^m + 1} \tag{1.50}$$

Optimal consumption is

$$Q^{m,Uniform}(\theta) = \begin{cases} (\mathcal{R}^m + 1)\theta - \mathcal{R}^m + 1 - c, & \theta \geq \frac{c+\mathcal{R}^m-1}{\mathcal{R}^m+1} \\ 0, & \theta < \frac{c+\mathcal{R}^m-1}{\mathcal{R}^m+1} \end{cases} \tag{1.51}$$

[6] Suppose the price schedule P has the marginal price P_q and average price P/q. The rate change due to the change in q of the average price is $\frac{dP/q}{dq} = \frac{P_q \cdot q - P}{q^2}$. Consider the function $g(q) = qP_q - P$ that has $g_q = qP_{qq}$. Hence, decreasing marginal price means that $P_{qq} < 0$, which implies $g(q)$ is decreasing, i.e. $g(p) < g(0) = 0$. Hence, $P_q \cdot q - P < 0$. This means $\frac{dP/q}{dq} < 0$, i.e. decreasing average price.

The optimal pricing schedule satisfies

$$P_q^{m,Uniform} = \frac{c+2\mathcal{R}^m}{\mathcal{R}^m+1} - \frac{\mathcal{R}^m}{\mathcal{R}^m+1} \cdot q, \text{ for } \theta \geq \frac{c+\mathcal{R}^m-1}{\mathcal{R}^m+1} \tag{1.52}$$

Expected profits before the fixed cost:

$$\mathbf{E}\pi^{m,Uniform} = \frac{\mathcal{R}^m}{3(\mathcal{R}^m+1)^2}(2-c)^3 \tag{1.53}$$

Consumer surplus and expected consumer surplus:

$$CS^{m,Uniform} = \frac{((\mathcal{R}^m+1)\theta - c - \mathcal{R}^m + 1)^2}{2(\mathcal{R}^m+1)} \text{ for } \theta \geq \frac{c+\mathcal{R}^m-1}{\mathcal{R}^m+1} \tag{1.54}$$

$$\mathbf{E}[CS^m] = \frac{(2-c)^3}{6(\mathcal{R}^m+1)^2} \tag{1.55}$$

Average Price Response, with Uniform Distributed Type

The cutoff type above which consumers can consume positive amounts of goods is:

$$\theta \geq c-1 \tag{1.56}$$

This cutoff type is higher than the cutoff type under MP response case since $\frac{c+\mathcal{R}^m-1}{\mathcal{R}^m+1} \geq c-1 \; \forall \mathcal{R}^m \geq 0$.

The optimal consumption is

$$Q^{a,Uniform}(\theta) = \begin{cases} \frac{\theta+1-c}{\mathcal{R}^a+1}, & \theta \geq c-1 \\ 0, & \theta < c-1 \end{cases} \tag{1.57}$$

The optimal pricing schedule satisfies

$$AP^{a,Uniform} = \mathcal{R}^a q + c, \text{ for } \; \theta \geq c-1 \tag{1.58}$$

Expected profits before the fixed cost:

$$\mathbf{E}\pi^{a,Uniform} = \frac{\mathcal{R}^a}{3(\mathcal{R}^a+1)^2}(2-c)^3 \tag{1.59}$$

Consumer surplus and expected consumer surplus:

$$CS^a = \frac{(\theta-c+1)^2}{2(\mathcal{R}^a+1)^2} \text{ for } \theta \geq c-1 \tag{1.60}$$

$$\mathbf{E}[CS^a] = \frac{(2-c)^3}{6(\mathcal{R}^a+1)^2} \tag{1.61}$$

We see that in both the case of monopoly pricing ($\mathcal{R}^m = \mathcal{R}^a = 1$) and the case of regulated firm pricing, the expected before-the-fixed-cost profits remain unchanged:

$$\mathbf{E}\pi^{m,Uniform} = \mathbf{E}\pi^{a,Uniform} \tag{1.62}$$

The same as the expected consumer surplus, and hence social welfare (since $\mathcal{R}^m = \mathcal{R}^a$ due to the constant profit constraint in the regulated firm pricing and $\mathcal{R}^m = \mathcal{R}^a = 1$ in the monopoly pricing):

$$\mathbf{E}[CS^{a,Uniform}] = \mathbf{E}[CS^{m,Uniform}] \tag{1.63}$$

However, the price response behaviors lead to a surplus distribution that favors equity view. Notice the change in the difference in consumer surplus between APR and MPR as consumer type changes:

For those types who can buy the goods, i.e. $\theta \geq c/2$:

$$\begin{aligned} CS^{a,Uniform} - CS^{m,Uniform} = &-\frac{\mathcal{R}}{2(\mathcal{R}+1)^2}\big[(\mathcal{R}^2+3\mathcal{R}+3)\theta^2 - 2(\mathcal{R}^2+\mathcal{R}+\mathcal{R}c+2c-1)\theta \\ &+\mathcal{R}^2+2\mathcal{R}c+c^2-\mathcal{R}-1\big] \end{aligned} \tag{1.64}$$

While for those consumer types who are not able to buy the goods under MPR price schedule, i.e. for all $\theta \in [c-1; c/2)$: $CS^{a,Uniform} > 0 = CS^{m,Uniform}$

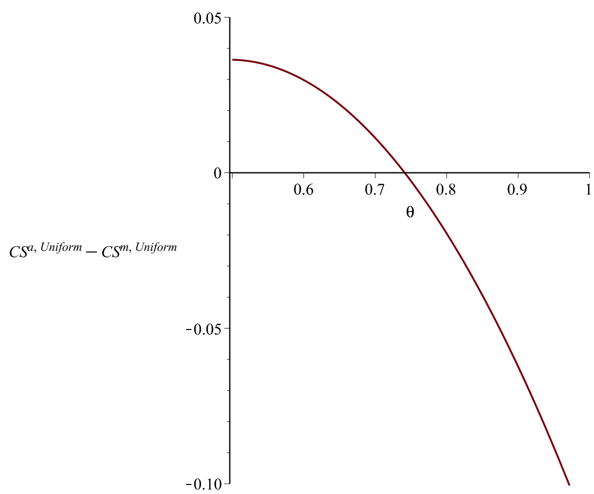


FIGURE 1.2: The difference in consumer surplus between the APR scheme and the MPR scheme in the case of uniform distribution.

Note: The horizontal axis is for the type θ, the vertical axis is for the difference in consumer surplus $CS^{m,Uniform} - CS^{a,Uniform}$. Parameter values are $c = 1, \mathcal{R} = 0.6$.
Notice $CS^{a,Uniform} > 0 = CS^{m,Uniform}$, for $\theta \in (0, 0.5)$. For $\theta \in (0.5, 1)$, the difference in consumer surplus is depicted as in this graph.

Figure 1.2 graphs an example of the difference in consumer surplus between the APR scheme and the MPR scheme based on the relation (1.64). We can see that low type benefits from APR in two points. First, there are some low types can consume the goods under APR but not under MPR (the type θ between $c-1$ and $c/2$). Second, among the consumers that buy the goods ($\theta \geq c/2$), the low types get higher surplus under APR than MPR while the high types get smaller surplus under APR. Therefore, even though the expected social welfare under the two price response cases are the same, the high types in fact subsidize the low types under APR case.

That story can also be captured in figure 1.3. Figure 1.3 shows the optimal price schedules under APR

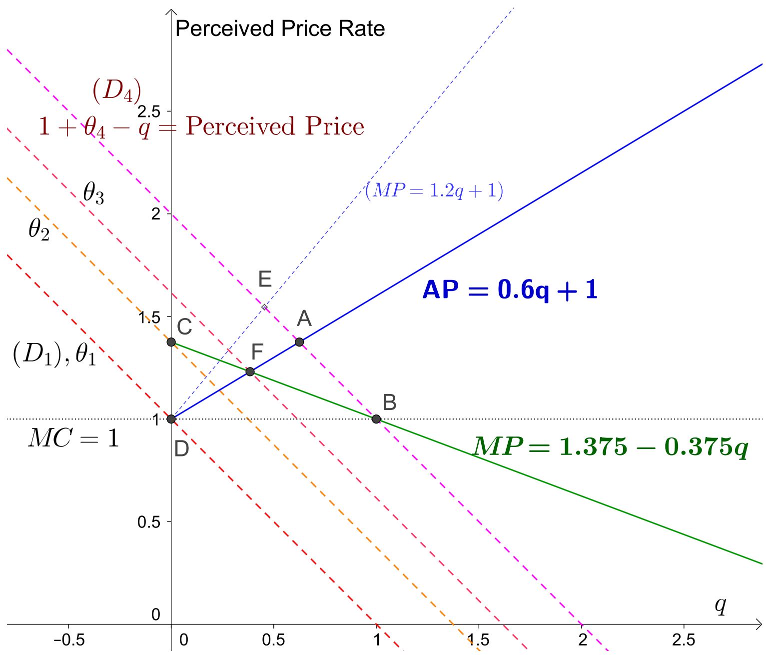


FIGURE 1.3: The regulated price design under APR and MPR in the case of uniform distribution and linear demands
Note: There are two optimal price schedules corresponding to two price response behaviors. When consumers respond to marginal price, the regulator opts to design $MP = 1.375 - 0.375q$. When consumers respond to average price, the regulator opts to design $AP = 0.6q + 1$. Under the quadratic utility function and uniform distribution of consumer type, the APR price schedule is IUP while the MPR price schedule is DUP.

and MPR in the case of $\mathcal{R} = 0.6$ and $c = 1$. We can see that those consumer types between θ_1 to θ_2 could not pay for the goods under MPR price schedule though they can under APR price schedule. That is because the price rate under MPR price schedule is much higher than the price rate under APR price schedule. Such price rate gap remains until the intersection quantity point F in the graph. This, therefore, implies that among consumers who can pay for the goods under both price response cases, there still exists the low types – between θ_2 and θ_3 – who enjoy larger surplus under APR price schedule than under MPR price schedule (while the high types from θ_3 to θ_4 experience a contrary situation).

1.5.2 Suboptimal Behavior May Increase Social Welfare Compared To Standard Optimal Behavior

Remark. In the monopoly pricing solution, the firm may get better off and consumers are worse off for the APR of the consumers.

In the regulated firm pricing solution, APR price schedule may lead to an increase in welfare compared to MPR pricing.

To formally verify the above remark, we will work with a quadratic utility function that leads to linear demands, and the Pareto distribution of the consumer type. Specifically, let $U(q,\theta) = (1+\theta)q - 1/2q^2$; $C(q) = cq$, and a fixed cost F. The consumer type follows Pareto distribution with scale $s > 0$ and shape $\alpha > 0$ that has the following probability density function (PDF) and the cumulative distribution function (CDF) respectively:

$$f(x) = \frac{\alpha s^\alpha}{x^{\alpha+1}} \tag{1.65}$$

$$F(x) = 1 - \frac{s^\alpha}{x^\alpha} \tag{1.66}$$

The hazard rate $\frac{f(\theta)}{1-F(\theta)} = \frac{\alpha}{\theta}$. See figure 1.4 for the density shape of Pareto distribution under different values of parameters. An important note is the support of Pareto distribution is (s,∞). If we think the type is represented by income, Pareto distribution is appropriate to depict an economy where everyone has a definitely positive income amount and there is no restriction on the highest income amount someone can earn.

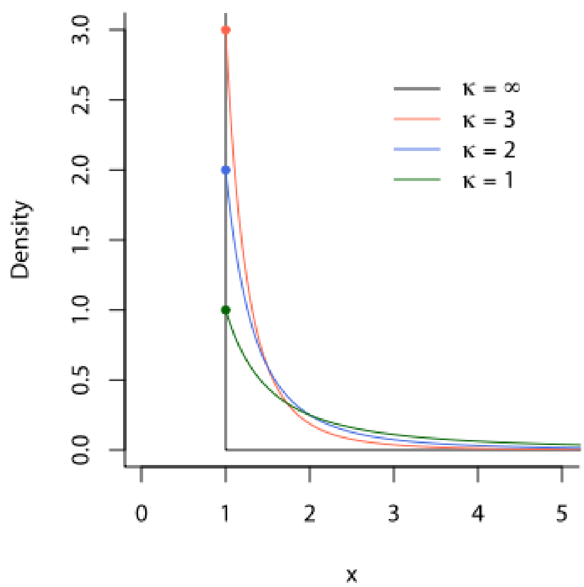


FIGURE 1.4: Pareto density with scale $s = 1$ and different shape κ.

We first present the main results in MPR case and APR case then discuss the results under monopoly pricing and regulated firm pricing. Recall that the monopoly pricing and regulated firm pricing share the similar pricing form using the policy number $\mathcal{R}$ in the mark-up ratio. The monopoly pricing corresponds to the case $\mathcal{R} = 1$ and the regulated firm pricing corresponds to the case $\mathcal{R} \in (0,1)$. We have the following results:

Marginal Price Response With Pareto Distributed Type

The cutoff type above which consumers can consume a positive amount of goods is:

$$\theta \geq \frac{c-1}{1-\mathcal{R}^m/\alpha} \tag{1.67}$$

The optimal consumption is

$$Q^{m,Pareto}(\theta) = \begin{cases} \left(1-\frac{\mathcal{R}^m}{\alpha}\right)\theta + 1 - c, & \theta \geq \frac{c-1}{1-\mathcal{R}^m/\alpha} \\ 0, & \text{otherwise} \end{cases} \tag{1.68}$$

The optimal pricing schedule satisfies

$$MP^{m,Pareto} = P_q^{m,Pareto} = \left(\frac{1}{1-\frac{\mathcal{R}^m}{\alpha}} - 1\right) q + \frac{c-1}{1-\frac{\mathcal{R}^m}{\alpha}} + 1 \tag{1.69}$$

Expected before-the-fixed-cost profits:

$$\mathbf{E}\pi^{m,Pareto} = \frac{\left(1-\frac{\mathcal{R}^m}{\alpha}\right)^{\alpha} \mathcal{R}^m (c-1)^{2-\alpha} s^{\alpha}}{(\alpha-\mathcal{R}^m)(\alpha-2)}, \text{ for } \alpha > 2 \text{ and } c-1 \geq s \tag{1.70}$$

Expected consumer surplus:

$$\mathbf{E}[CS^{m,Pareto}] = \frac{(c-1)^{2-\alpha}\alpha^2 s^{\alpha}\left(1-\frac{\mathcal{R}^m}{\alpha}\right)^{\alpha+1}}{(\alpha-\mathcal{R}^m)^2(\alpha-1)(\alpha-2)}, \text{ for } \alpha > 2 \text{ and } c-1 \geq s \tag{1.71}$$

Average Price Response with Pareto Distributed Type

The cutoff type above which consumers can consume positive amounts of goods is:

$$\theta \geq c-1 \tag{1.72}$$

The optimal consumption is

$$Q^{a,Pareto}(\theta) = \begin{cases} \frac{\theta+1-c}{1+\mathcal{R}^a}, & \theta \geq c-1 \\ 0, & \theta < c-1 \end{cases} \tag{1.73}$$

The optimal pricing schedule satisfies

$$AP^{a,Pareto} = \mathcal{R}^a q + c, \ \theta \geq c-1 \tag{1.74}$$

Expected before-the-fixed-cost profits:

$$\mathbf{E}\pi^{a,Pareto} = \frac{2\mathcal{R}^a (c-1)^{2-\alpha} s^{\alpha}}{(\mathcal{R}^a+1)^2(\alpha-2)(\alpha-1)}, \text{ for } \alpha > 2 \text{ and } c-1 \geq s \tag{1.75}$$

Expected consumer surplus:

$$\mathbf{E}[CS^{a,Pareto}] = \frac{s^{\alpha}(c-1)^{2-\alpha}}{(\mathcal{R}^a+1)^2(\alpha-2)(\alpha-1)},, \text{ for } \alpha > 2 \text{ and } c-1 \geq s \tag{1.76}$$

Welfare Implication Under Monopoly Pricing

Under monopoly pricing solution ($\mathcal{R}^m = \mathcal{R}^a = 1$), we see that

$$\mathbf{E}\pi^{m,Pareto} < \mathbf{E}\pi^{a,Pareto} \tag{1.77}$$

This means that the monopolist gets better off due to the inattention to the price of consumers. When consumers respond to average price, they would face a higher increasing slope of the average rate price schedule than under MPR scenario. The steeper increasing unit rate price schedule would bring higher before-the-fixed-cost profits to the monopolist. This also implies that consumers in general would get worse off for their biased behaviors and indeed, we have:

$$\mathbf{E}[CS^{a,Pareto}] - \mathbf{E}[CS^{m,Pareto}] = -\frac{\left(1-\frac{1}{4}\left(1-\frac{1}{\alpha}\right)^{1-\alpha}\right)\alpha^2 s^{\alpha}(c-1)^3}{(\alpha-2)(\alpha-1)^3(c-1)^{\alpha+1}\left(1-\frac{1}{\alpha}\right)^{1-\alpha}} < 0 \tag{1.78}$$

Welfare Implication Under Regulated Firm Pricing

We are interested in the existence of the situation in which the regulated firm can covers fixed costs to break even while the social welfare is higher under APR than MPR. We will show that such situation exists under appropriate policy parameters $\mathcal{R}^a, \mathcal{R}^m$ and distribution parameter α.

The monopolist's before-the-fixed-cost profits are regulated to a fixed return to cover just enough the same fixed costs under both APR and MPR. That is, the constant Ramsey numbers $\mathcal{R}^m$ and $\mathcal{R}^a$ satisfy:

$$\frac{\left(1-\frac{\mathcal{R}^m}{\alpha}\right)^{\alpha}\mathcal{R}^m(c-1)^{2-\alpha}s^{\alpha}}{(\alpha-\mathcal{R}^m)(\alpha-2)} = FC = \frac{2\mathcal{R}^a(c-1)^{2-\alpha}s^{\alpha}}{(\mathcal{R}^a+1)^2(\alpha-2)(\alpha-1)}, \text{ for } \alpha > 2 \text{ and } c-1 \geq s \tag{1.79}$$

$$\Rightarrow \left(1-\frac{\mathcal{R}^m}{\alpha}\right)^{\alpha-1}\frac{\mathcal{R}^m}{\alpha} = \frac{2\mathcal{R}^a}{(\mathcal{R}^a+1)^2}(\alpha-1) \tag{1.80}$$

Notice the difference in expected consumer surplus (same as in expected social welfare since the expected variable profits equal to the fixed cost F) between the two price response cases is:

$$\mathbf{E}[CS^{a,Pareto}] - \mathbf{E}[CS^{m,Pareto}] = \frac{s^{\alpha}(c-1)^{2-\alpha}}{(\alpha-1)(\alpha-2)}\left((\mathcal{R}^a+1)^{-2} - \left(1-\frac{\mathcal{R}^m}{\alpha}\right)^{\alpha-1}\right) \tag{1.81}$$

Using the equation 1.80, we have

$$\mathbf{E}[CS^{a,Pareto}] - \mathbf{E}[CS^{m,Pareto}] = \frac{s^{\alpha}(c-1)^{2-\alpha}}{(\alpha-1)(\alpha-2)}(\mathcal{R}^a+1)^{-2}\left(1-2\cdot\frac{\mathcal{R}^a}{\mathcal{R}^m}\cdot\frac{\alpha}{\alpha-1}\right) \tag{1.82}$$

Hence, the regulated monopoly pricing under APR will lead to higher social welfare than under MPR as long as the policy allows parameters $\mathcal{R}^m, \mathcal{R}^a$ appropriately to demand distribution environment α such that the relation (1.80) holds and $\frac{\mathcal{R}^a}{\mathcal{R}^m} < \frac{\alpha-1}{2\alpha}$. An example is the policy that induces $\mathcal{R}^m = 0.5$ when $\alpha = 3$, which leads to $\mathcal{R}^a = 0.154$.

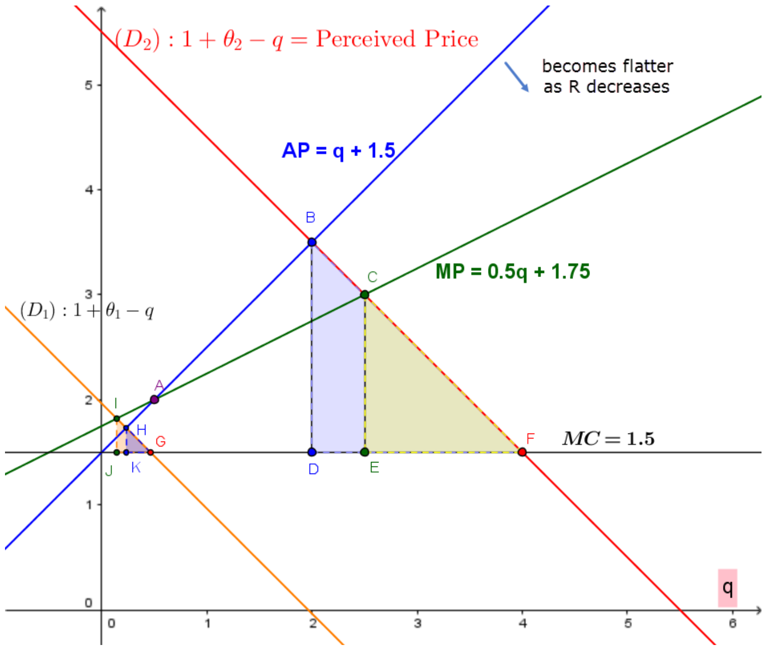
Figure 1.5 shows the change in optimal price schedules when changing from monopoly pricing to regulated firm pricing and from MPR to APR. In monopoly pricing scheme, a steeper unit rate and lower starting point price schedule is charged under APR. This generates larger variable profits for the monopolist while makes consumers worse off overall. A small number of low type consumers can purchase at a lower price leading to a smaller deadweight loss compared to the MPR (deadweight loss HKG smaller than IJG). However, most of the consumers are worse off for paying a higher price at B rather than at C due to the biased APR.

Once restricted by the profit constraint, the monopolist is forced to charged at a lower mark up ratios: Both price schedules under APR and MPR become flatter. Interestingly, the policy may induce a higher unit rate price schedule under MPR than under APR (since both optimal unit rate price schedules are increasing, the marginal rate should be above the average rate to allow the same generated variable profits). The welfare under APR schedule, hence, would be higher than under MPR (for smaller deadweight loss is arised).

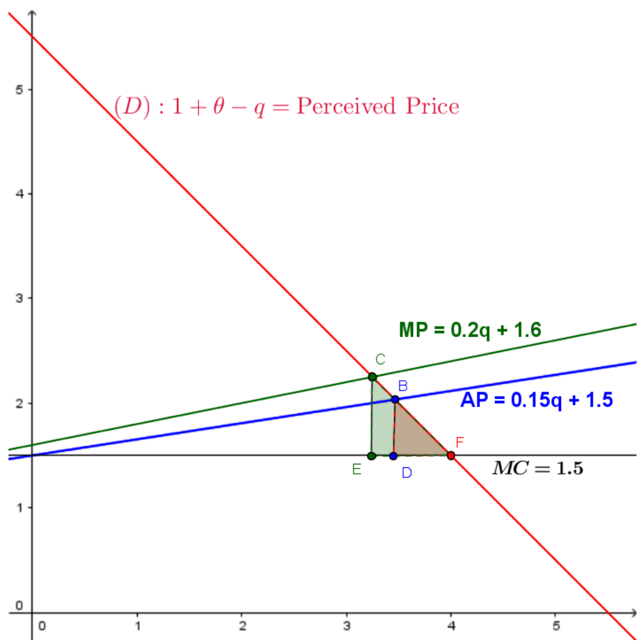
1.6 Conclusion

From an economic efficiency standpoint, increasing marginal price schedule for a monopolist and for a regulated firm is a puzzle since the literature of nonlinear pricing implies the optimal price schedule has decreasing marginal prices. However, recent evidence points out that electricity consumers respond to changes in average prices rather than to changes in marginal prices due to the complexity of nonlinear price schedules, see Ito (2014). We characterize optimal nonlinear prices in the world of APR consumers. We show that the optimal nonlinear price schedule may have increasing marginal prices, thereby implying that the increase block tariffs used by regulators may achieve the double goals of efficiency and equity.

In the world of APR, under price regulation, the new nonlinear price schedule may lead to a higher social welfare than the price schedule in the world of MPR. It should be noticed that the social welfare in the world of APR under unregulated firm pricing schedules is lower than in the world of MPR. This implies that consumers get worse off due to their biased APR and the monopolist can exploit it under unregulated prices. However, the regulated pricing can mitigate the deadweight loss due to the bias and improve efficiency.



(A) Deadweight loss in monopoly pricing



(B) Deadweight loss in regulated firm pricing

FIGURE 1.5: Deadweight loss in optimal monopoly pricing and regulated firm pricing.

Note: The horizontal axis is for quantity q, the vertical axis is for the responding (perceived) price p. Parameter values are $c = 1.5, \alpha = 3$. In monopoly pricing, $\mathcal{R}^m = 1 = \mathcal{R}^a$. In regulated firm pricing, $\mathcal{R}^m = 0.5, \mathcal{R}^a = 0.15$.

The binding profit constraint in regulated firm pricing makes both the optimal marginal price and average price schedules flatter. However, their slopes have changed at different speed, leading to the regulated marginal price schedule above the regulated average price in the end. Therefore, the deadweight loss under APR is smaller then under MPR, in regulated firm pricing scheme.

Chapter 2

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

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.

2.1 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

[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.

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 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

[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.

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 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

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

using solid waste data. Kamita (2001) analyzes the market structure consequences of merger. Salz (2017) studies the role of intermediaries between businesses and private institutions and private waste carters in New York trade waste collection market. Kawai (2011) studies auction design when sellers have incentive to invest for quality improvement in municipal plastic recycling auctions in Japan.

The paper also complements studies that address interstate waste flow controls. In the hazardous waste market, Levinson (1999a,b) find that interstate waste taxes decrease shipments of waste to states enacting high taxes, and provided an estimate of the magnitude of tax elasticities. In the solid waste market, Ley et al. (2000, 2002) find that limitations on the size of shipments can perversely increase interstate waste shipments since states export smaller volumes to more destinations. They use the aggregate data at the state level and consider state planners' problem assuming the demand for waste disposal services is linear and a competitive equilibrium. My model, however, considers the haulers' decisions about where to deposit waste from each county. This accounts for the fact that disposal landfills are differentiated in prices, distances, and quality, thereby explaining the impacts of environmental protection 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 2.2 provides legislative background of interjurisdiction waste restrictions. Section 2.3 shows general picture of waste disposals in California and the current distribution of waste flows by demographics. I emphasize that the inequitable distribution of waste flows by race and ethnicity is not fully explained by economic factors, namely, income, disposal prices, and transport distance to a facility. Hence, when modeling the waste flows to study distribution impacts by race, it is important to include facility fixed effects. Section 2.4 presents the structural model of haulers' decisions about where to deposit waste from each county, which is the demand for waste disposal. Section 2.5 reports results of counterfactual policy experiments. Section 2.6 concludes.

2.2 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 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.

[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.

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.

2.3 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 (B.1).

2.3.1 Waste Disposal In California

Figure (2.1) 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 (2.1d) 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 (2.1e). Closures of nearby disposal facilities also result in an increase in shipping distance. Figure (2.1c) 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 (2.1f) 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.

2.3.2 Market Boundary of Waste Flows

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

$$q_{cjt} = \beta_d f_d(Distance_{cj}) + \beta_p f_p(Price_{jt}) + \gamma_{ct} + \eta_j + \epsilon_{cjt} \tag{2.1}$$

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 (2.2) 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 (2.1)). Table (2.1) 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 (2.1a) show the market boundaries for counties San Francisco and Los Angeles.

Table (2.2) 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.

2.3.3 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.

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 (2.3) 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.

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.

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

$$\text{Affected Level}_j = \beta_0 + \beta_1 Waste_j + \beta_2 Income_j + \epsilon_j \tag{2.2}$$

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 (2.3) 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.

The Distribution of Waste Flows By Race in Affected Communities

Table (2.4) reports mean demographics for generating counties and receiving communities (3-mile nearby communities and receiving counties). The table also contrasts the numbers to the California state level. For 3-mile nearby communities, the average population is 26,000 persons of which 49.4% are white, 2.7% are black, 8.1% are Asian, and 35.3% are Hispanic. When weighted by trash amount at a facility, percentages of 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. The disparity becomes more apparent when contrasting waste weighted demographics in receiving community to generating county. While the percentage of white is higher in generating county than receiving community, the percentages of Asian and Hispanic people are lower.

Since waste flows are 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:

$$q_{cj} = \beta_0 + \beta_1 \% Race_j + \beta_2 Income_j + \beta_3 Price_j + \beta_4 Distance_{cj} + \beta_5 Nonlocal_{cj} + \delta_c + \epsilon_{cj} \quad (2.3)$$

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 (2.5) 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 become 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 (2.6) reports results using intercounty and local observations separately. As seen from column (1) in table (2.5), waste is sent more to minority communities. However, there is substantial heterogeneity in intercounty flows and local flows. Columns (1) and (4) in table (2.6) 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.

2.4 A Model of Waste Flows

2.4.1 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

$$U_{ijct} = \beta X_{jct} + \epsilon_{ijct} \equiv \beta_p \text{price}_{jt} + \beta_d \text{distance}_{cj} * \text{fuel price}_t + \gamma_j + \epsilon_{ijct} \tag{2.4}$$

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

$$P_{ijct} = \frac{\exp(\beta X_{jct})}{\sum_{k \in C_{ct}} \exp(\beta X_{kct})} \equiv P_{jct} \tag{2.5}$$

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.

2.4.2 Model Likelihood

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

$$f(Y_{ict};\beta) = \prod_{j=1}^{J} P_{ijct}^{y_{ijct}} \tag{2.6}$$

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

$$L(\beta) = \sum_{c,t}\sum_{i}\sum_{j} y_{ijct}\log P_{jct} \tag{2.7}$$

$$L(\beta) = \sum_{c,t}\sum_{j}\log P_{jct}\sum_{i} y_{ijct} \tag{2.8}$$

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

$$s_{jct} \equiv \frac{\sum_i q_{ict}y_{ijct}}{Q_{ct}} = \frac{q_{ct}\sum_i y_{ijct}}{Q_{ct}} \tag{2.9}$$

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

$$L(\beta) = \sum_{c,t}\sum_{j}\log P_{jct}\cdot s_{jct}\cdot \underbrace{Q_{ct}/q_{ct}}_{N_{ct}} \tag{2.10}$$

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

$$L(\beta) = \frac{1}{N}\sum_{c,t}\sum_{j}\log P_{jct}\cdot s_{jct} \tag{2.11}$$

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

$$L(\beta) = \frac{1}{q}\sum_{c,t}\sum_{j}\log P_{jct}\cdot s_{jct}\cdot Q_{ct} \tag{2.12}$$

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 (2.12). I cannot identify the truck size, but I can identify the haulers' preference parameters.

2.4.3 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.

2.4.4 Model Results

Table (2.7) 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

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

facility fixed effects specification does not resolve all bias in price coefficient estimate. Although its estimate of price coefficient has the correct sign, it is extremely small and statistically insignificant, and the resulted price elasticity is -0.03. Using market sizes of the other relevant markets to instrument price, the upward bias is mitigated. The magnitude of price coefficient becomes two order of magnitude bigger; price elasticity is -4.20. The positive sign of the first coefficient of control function confirms the upward bias is corrected.

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

The ratio between transport cost coefficient and price coefficient captures hauler's willingness to pay for proximity to the disposal facility. This is the cost of transportation. The estimates imply that transportation costs $\$0.43$ per ton-mile given diesel prices at the 2000 level (\$1.672/gal). This agrees with the estimates from several publications. First, Miller and Osborne (2014) report the transportation costs $\$0.46$ per ton mile for shipping cement. Second, the 20th edition of Transportation in American (2007) reports that revenues per ton mile for Class I general freight common carriers (basic truck transport) ranged from roughly \$0.29–\$0.35 over 1983–2003. Third, previous studies in waste transportation in 1990 and 1992 report transport costs from \$0.16 to \$0.36 per ton mile; see Fischer et al. (1993).

2.4.5 Model Fit

Figure (2.4) 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.

2.4.6 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 (2.12), we can use the unweighted estimator (2.11). 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 (2.12).

Table (2.8) 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.

2.5 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 (2.3.3), 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.

2.5.1 Intercounty Waste Transport and Economic Impacts

Panel A in table (2.9) 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.

2.5.2 Demographic Distribution of Waste Flows

Panel B in table (2.9) 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

$$\%\text{ trash to white} = \frac{\sum_{j\in J_c} q_{cj} \times \text{Number of whites in j's 3-mile buffer}_j}{\text{Total population in j's 3-mile buffer}_j} \cdot \frac{1}{\sum_{j\in J_c} q_{cj}} \times 100 \qquad (2.13)$$

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 (2.3.3), 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 (2.3.3) 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.

2.6 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.

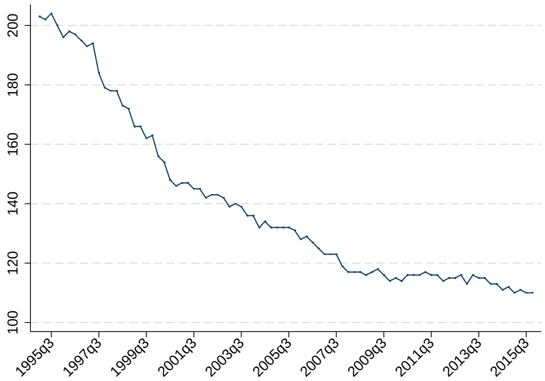
Using a structural model to estimate the demand for waste disposal, I find that policies that limit interjurisdictional waste flows would not generally lead to a more equitable distribution of trash. Making intercounty waste transport costlier by taxing gasoline prices, taxing out-of-county waste, or 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)?

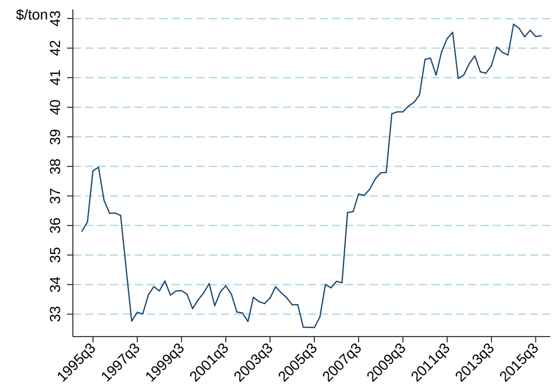
A second extension is to consider the equilibrium effects. Adding the supply side to the structural model is useful to account for the fact that disposal facilities may change their prices upon a counterfactual policy. This relaxes the current assumption that haulers bear the full costs of policies. 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.

FIGURE 2.1: Overview of solid waste disposal in California from Jan 1995 to Dec 2015

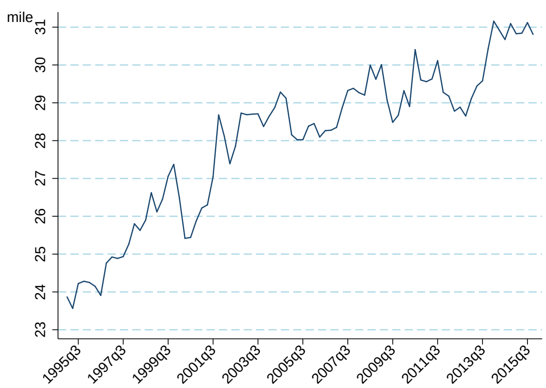
(A) Number of disposal facilities



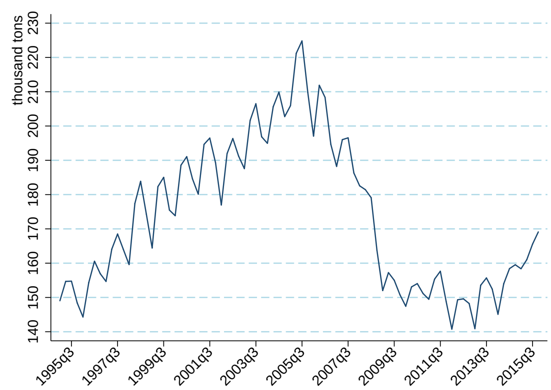
(B) (Waste weighted) average disposal price (in 2000 dollars) haulers in a county pay



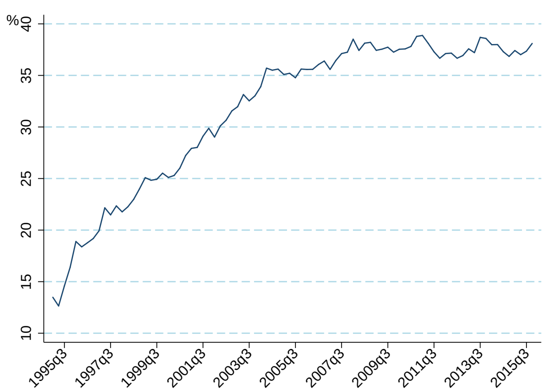
(C) (Waste weighted) average distance haulers in a county travel



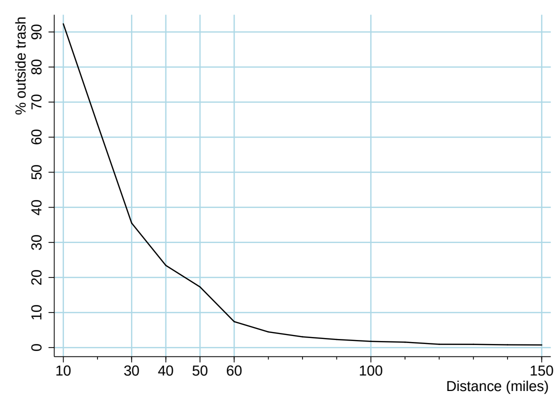
(D) Total waste amount generated by the average county



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



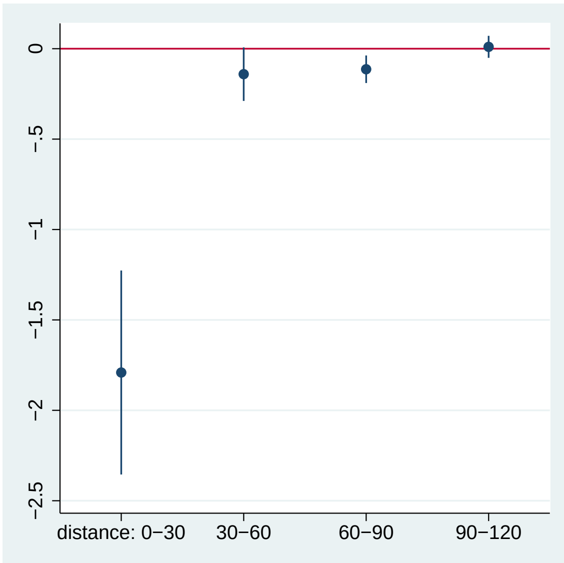
(F) Percentage of waste that travels beyond a given distance



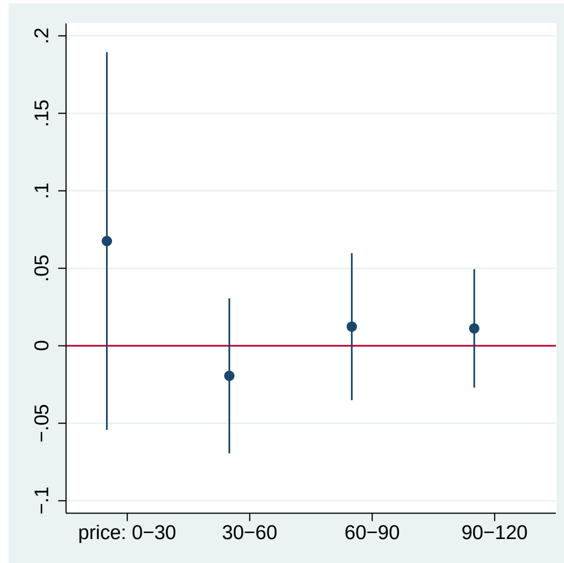
Note: The graph shows several features in California waste disposal industry over time. Distance is driving distance from population weighted coordinate of origin county to destination facility. Figure (2.1f) shows the percentage of waste that is transported farther than a given distance from origin county in a recent year, 2015.

FIGURE 2.2: Price response and distance response by distance

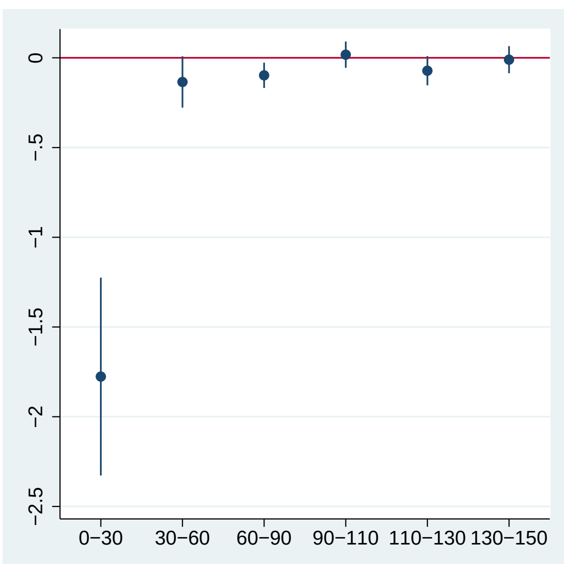
(A) Distance response at different knots of distance using analysis of waste flows within 120 miles



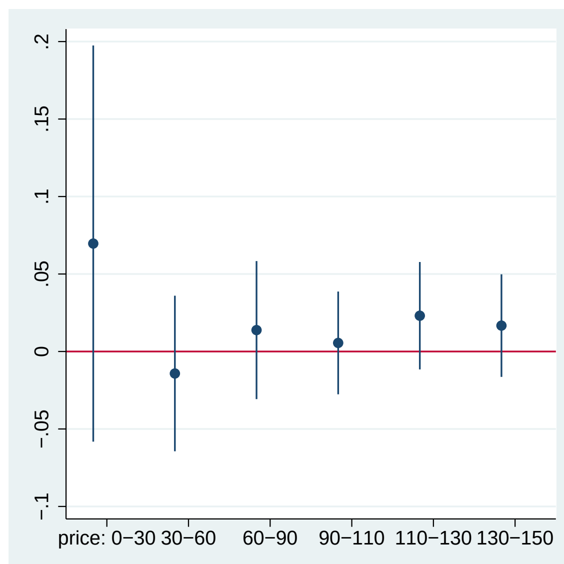
(B) Price response at different knots of distance using analysis of waste flows within 120 miles



(C) Distance response at different knots of distance using analysis of waste flows within 150 miles

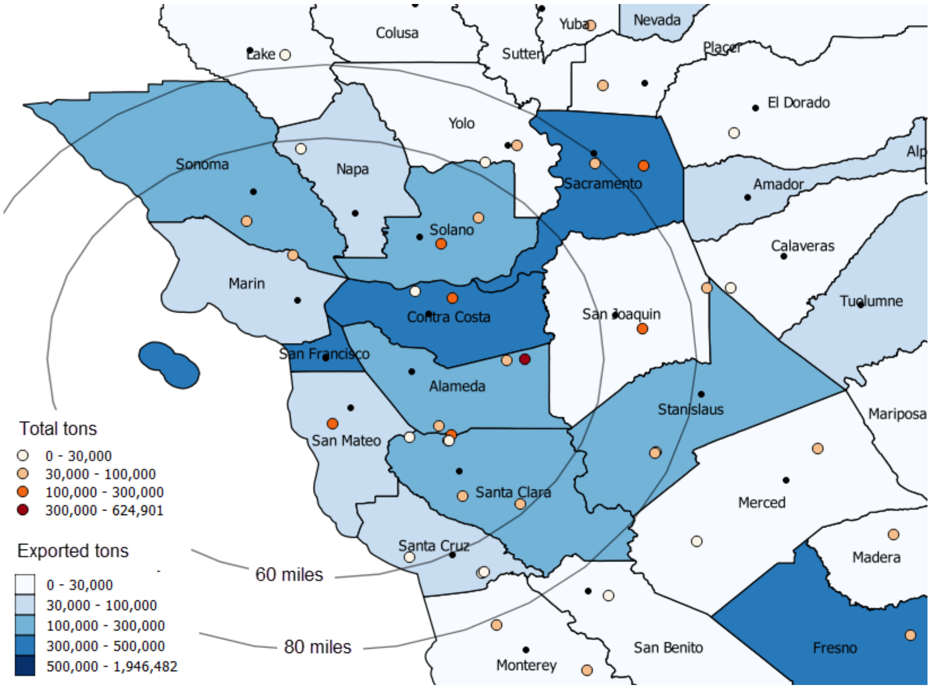


(D) Price response at different knots of distance using analysis of waste flows within 150 miles

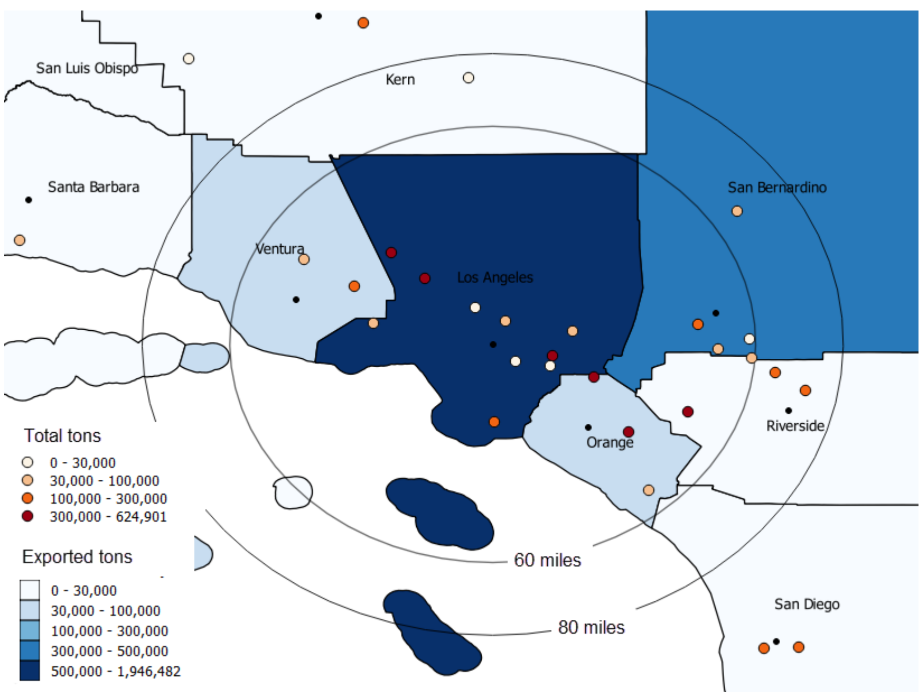


Note: Figure shows the coefficients on distance and price at different knots of distance (linear splines) from the quarter by origin county fixed effect regression, where dependent variable is trash amount from a county to a facility. Figures (2.2a) and (2.2b) use the sample of all combinations of flows by a county and a facility within 120 miles. Figures (2.2c) and (2.2d) 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 2.3: Illustrate sizes of choice sets



(A) Choice set of San Francisco market

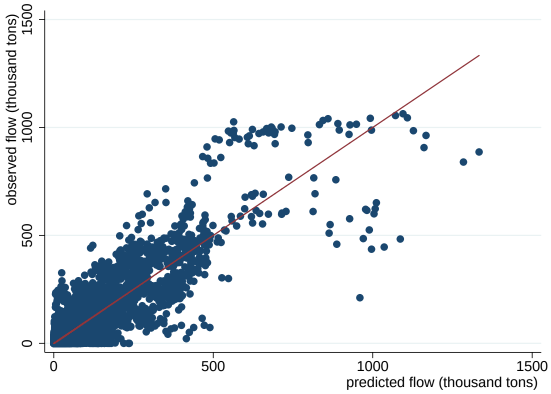


(B) Choice set of Los Angeles market

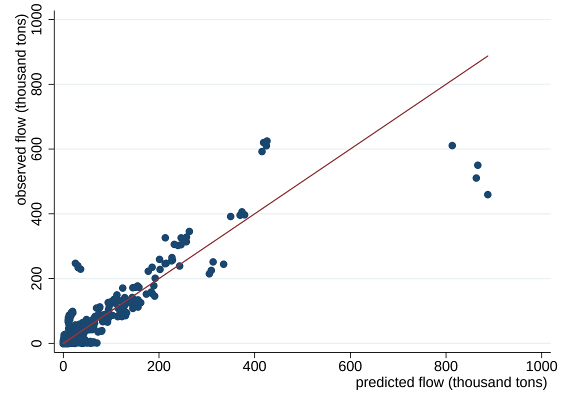
Note: The graph shows how wide 60-mile and 80-mile markets are from the population center of San Francisco and Los Angeles. Black dots represent population center coordinates of counties. Counties are blue colorized by out-of-county exports of waste. Facilities are red colorized by total waste amount.

FIGURE 2.4: Model fit

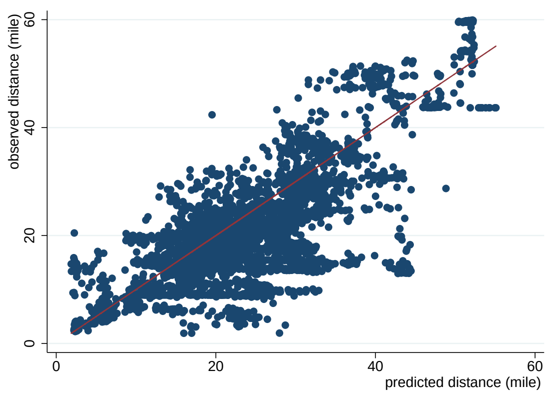
(A) Correlation between observed waste flows and predicted flows ($= 0.8965$)



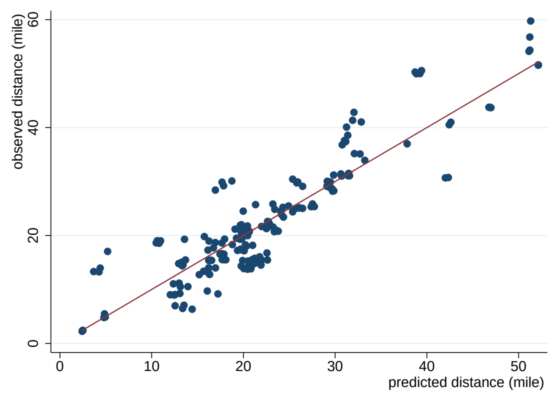
(B) Correlation between observed waste flows and predicted flows in 2010 ($= 0.9128$)



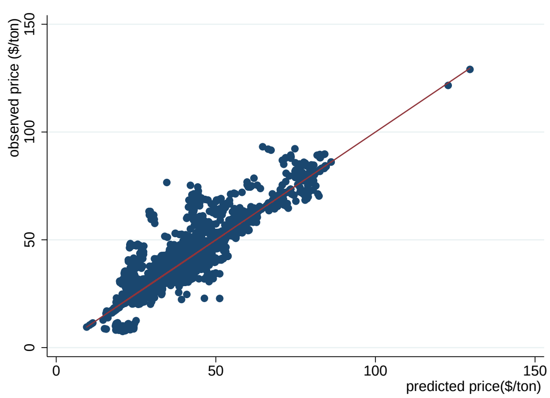
(C) Correlation between observed distance and predicted distance ($= 0.8175$)



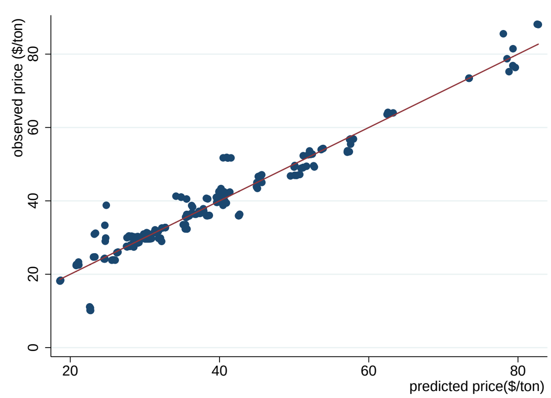
(D) Correlation between observed distance and predicted distance in 2010 ($= 0.9205$)



(E) Correlation between observed price and predicted price ($= 0.9268$)



(F) Correlation between observed price and predicted price in 2010 ($= 0.9712$)



Note: The graph shows the correlation coefficient between observed values and predicted (model implied) values of key variables. Panels (2.4a) and (2.4b) show the correlation in trash flows (trash amount generated from a county to a facility in a quarter). Panels (2.4c) and (2.4d) show the correlation in (waste weighted) average distance shipped by a county in a quarter. Panels (2.4e) and (2.4f) show the correlation in (waste weighted) average tipping fee by a county in a quarter. Panels (2.4b), (2.4d), and (2.4f) show the correlation for observations in year 2010.

TABLE 2.1: 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 2.2: Summary statistics of panels of waste flows

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

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

TABLE 2.3: 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 2.4: Summary statistics of demographics at waste generating county vs. receiving community

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

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

TABLE 2.5: 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 (2.6) below. Standard errors are clustered by destination county. Significant level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE 2.6: 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 reports 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 (2.5). Standard errors are clustered by destination county. Significant level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE 2.7: 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 2.8: 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 2.9: 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.

Chapter 3

Residential Sorting: Evidence from Openings and Closings of Municipal Solid Waste Facilities in California

Forming sound environmental justice policy involves understanding whether the correlation between race and environmental bads results from the disproportionate siting of locally unwanted land uses or nuisance-driven residential mobility. This paper presents evidence of residential sorting using a difference-in-difference strategy. Specifically, I compare changes in population after an opening (and closing) of a trash site between blocks within one mile to faraway blocks. Results show a 11 percent decrease in white population and a 44 percent increase in Hispanic population in a block after a trash site opened within one mile. Closing the site does not change white population immediately while inducing a 11 percent fall in Hispanic population, relative to the period during which the site was operating.

3.1 Introduction

Environmental justice (EJ) has long been considered important in the agenda of the U.S. Environmental Protection Agency since the 1994 Executive Order of President Bill Clinton.[1] Evidences of environmental injustice are first formally shown by the U.S. General Accounting Office (1983) and United Church of Christ's Commission on Racial Justice (1987) (UCC). They report the disproportionate distribution of facilities for treatment, storage, and disposal of hazardous waste (TSDFs) among demographic groups by race/ethnicity, and income.[2] Two decades later, the revised report by UCC (Bullard et al., 2007) showed that the disparity is still an issue: African American and Hispanic residents occupied 43.7% of residents within one kilometer (0.6 mile) of a hazardous waste facility, while just 19% outside of a 5-km buffer. Given the persistence of the disparity, researchers have continued to unravel the explanations for the correlations between race, ethnicity, and hazards. Some studies argue that environmental inequality emerges

[1] See the details of the EPA's "Plan EJ 2020" at www.epa.gov/environmentaljustice/about-ej-2020

[2] UCC reported the percentage minority population in zip code areas with an operating hazardous waste facility, on average, was twice as great as in areas that did not contain a site.

because environmental hazards are disproportionately sited in minority neighborhoods. Others show that environmental injustice may develop and persist, since minority residents are more likely to move into areas containing hazards. Such evidence of residential mobility is important, because it suggests that some EJ policies (e.g. Superfund remediation) may not help the households that were originally exposed to the environmental hazards, but instead benefit the richer households that migrate into the area (Sieg et al., 2004).

This paper tests the residential sorting hypothesis using a panel data of block-level demographics. Using a difference-in-difference model, I identify the impact of entry and exit of municipal solid waste (MSW) facilities on population of each demographic groups in affected communities. Specifically, I compare the population change after an opening/closing of the site between affected blocks that contain a facility within one mile and faraway blocks, after controlling for time-invariant characteristics of blocks and year fixed effects. The identification assumption is that the demographic trends between blocks within a block group are likely to be similar apart from their proximity to an entry (or exit).

I find evidence of migration correlated with openings and closings of MSW facilities at a block. Opening leads to white exit of about 11 percent and Hispanic move-ins of 44 percent. Closing the site would not induce white mobility but a significant fall of 11 percent in Hispanic population, relative to the operating period. In fact, relative to the period before the site were opened, closing induces white exit of about 13 percent and Hispanic move-ins of 32 percent.

There are several factors that contribute to the migration resulted from openings and closings of waste facilities. The first is green preference or willingness to avoid pollution of residents in the neighborhoods of facilities. The second is job preference. Economic activities of MSW facilities may create job opportunities. With a weak green preference, one may prefer to move in the MSW neighborhood because of a job offer. The third is credit constraints. Closing an MSW facility may gentrify its neighborhood, resulting an increase in housing values. This will induce out-migration of people who have credit constraints and cannot afford high costs of living.

While this paper does not disentangle the effects of those above channels, it presents evidence of their effects. Specifically, I show that closing an MSW facility does not gentrify its neighborhood toward white taste but destroy job opportunities for Hispanic residents. I exploit the closing events that resulted from the 1992 Resource Conservation and Recovery Act (RCRA) to decompose the effect of closings into the effect of closings started in 1992–1996 and the effect of closings that began after 1996. The results show that closures of MSW facilities under the 1992 RCRA resulted in much higher white exit than post-1997 closures. The reason is because the closed sites during 1992–1996 were heavily polluted. Closures of MSW facilities under 1992 RCRA did not receive any special treatment, contrasting to sites under the Superfund program that received special cleanup. MSW facilities were forced to close because they did not meet new environmental regulations, such as requirements to install methane and water monitoring. On the other hand, post-1997 closures, which resulted from the downturns in the operation of a facility, led to a larger job loss, resulting in significant move-outs of Hispanic residents, relative to the move-ins during the operating period of trash sites.

Evidence of non-gentrification and job loss effects of MSW site closures is also implied by the results that show decreases in median household income and median housing values in the site neighborhoods.

Specifically, closing an MSW site led to 6.7 percent fall in median household income and 3.6 percent fall in median housing values in 1-mile nearby blocks, relative to the period during which the site was operating.

The paper builds upon studies of residential sorting in response to changes in an environmental amenity, by Banzhaf and Walsh (2008), and Gamper-Rabindran and Timmins (2011). Banzhaf and Walsh (2008) predict increased population density in neighborhoods that experience exogenous improvements in air quality, suggesting that households vote with their feet for environmental quality. Gamper-Rabindran and Timmins (2011) present evidence of residential sorting after Superfund remediation programs. Their method is less prone to the endogeneity problems than Banzhaf and Walsh (2008)'s method because they exploit the risk assessment under the Superfund program to compare neighborhoods of similar-risk toxic sites that received cleanup treatment to those that did not. My paper exploits the spatial and temporal variations in the openings and closings of MSW facilities to compare the change in population after these events between nearby blocks within 1 mile of the sites and faraway blocks beyond 1 mile.

In addition to studies on residential sorting, the literature discusses the evidence of neighborhood gentrification and the effects of environmental bads on human health. Currie et al. (2015) also exploit the spatial variation and temporal variation in openings and closings of industrial plants to study their effects on housing values and infant's health. Davis (2011) study the effects of operating power plants on local housing values and rents. Greenstone and Gallagher (2008), and Gamper-Rabindran and Timmins (2013) document the effects of Superfund cleanups on housing values.

Those papers and the literature on environmental justice have studied the distribution of industrial plants in the toxic release inventory database and the distribution of treatment, storage, and disposal facilities for hazardous waste. I, on the other hand, focus on the impacts of municipal solid waste facilities. This is important because closure of an MSW facility does not necessarily lead to in-migration. A closed MSW facility stops receiving trash, but it does not receive any special treatment. Hence, the closed facility must have both accumulated pollution over its operating period and the loss of jobs opportunities, thereby inducing move-outs in local communities.

3.2 Data

3.2.1 Facility Data

MSW facility data come from surveys by an industry survey company. The data survey quarterly volume and price by facility from 1992 to 2016. I focus on the list from January 1992 to December 2010 that contain a facility that ever operated in this period. The status of operating versus closing are based on annual price value rather than volume value. Specifically, a facility is considered "operating" if it has a positive price value. Yet, a few facilities continued receiving a small amount of trash for a few years after its price was zero. There are three facilities that re-opened after closing for some years. Since those closing periods were less than five years, I assume these facilities were active. I do not observe the facilities that closed before 1992.

Figure (3.1) shows the number of sites by type during the period 1992–2010. Most opening sites are transfer stations and composting sites; only four opening sites are landfills. By contrast, most closing sites are landfills and demolition landfills. While most openings happened in 1995–1996, most closings appear to continuously happen during 1990s. Figure (3.2) shows the map of closings and openings in California between 1992 and 2000.

3.2.2 Demographic Data

Residency data come from aggregate data at the block level from the decennial census (accessed via IPUMS NHGIS) for three years, 1990, 2000, and 2010. These data are available publicly and at the smallest geographic unit the Census Bureau uses. Information at the block level includes total population, race, ethnicity, gender, age, number of house units, occupied houses, occupied-by-owner houses, number of householders by race and ethnicity. Some economic variables are available only at the block group level, such as education, median household income, median housing value, median gross rent, housing occupancy, housing tenure, population below poverty, household receiving public assistance income, household receiving social security income. For these block-group variables, I assign count variables to block values based on population shares.

Because US Census Bureau redesign census units from 1990 to 2010, I construct the panel of block by year for years 1990, 2000, and 2010 by fixing the 2010 blocks and calculating the 1990 and 2000 information for these blocks using NHGIS crosswalks. NHGIS crosswalks are similar to the US Census Bureau relationship files, but NHGIS crosswalks provide interpolation weights to support the allocation of summary data from 2000 blocks to a 2010 block. Each interpolation weight identifies approximately what portion of the 2000 block's population and housing units were located in its intersection with a 2010 block. So, for each 2000 block, a share of each demographic count is assigned to a 2010 block based on the interpolation weight.

I drop blocks that do not have any land areas. Due to missing values of demographic characteristics for 1990 blocks, the final sample of block by year include $565,468$ block observations in 1990 and $691,487$ observations in each of 2000 and 2010. Table (3.1) reports summary statistics of the characteristics of these blocks by year.

To examine the change in residency due to exposure to a nearby MSW facility, I define the exposure status of a block based on the distance from the block's geographic centroid to the nearest facility. The literature has suggested radii from one to three miles for TSDFs and toxic plants to capture the local effects of environmental hazards. In this paper, I use one mile as the base line, and conduct sensitivity checks for larger distances such as two miles and three miles. Using the status of MSW facilities, I can define the exposure status of blocks *at a point in time*. For example, an "active" block is the block that is near to an active facility; a "closed" block is the block that is near to a closed facility. Because the one-mile buffer of a block may include several facilities, a "mixed" block is the block that is near to an active facility and also to a closed facility. To ensure the mutual exclusivity of these categories, an "active" block is, hence, the block that is near to *only* active facilities. Similarly, a "closed" block is the block that is near to only closed facilities.

To estimate effects of openings and closings of MSW facilities, comparing a block that contains a facility to a block that does not requires that these blocks must be similar in unobserved characteristics that could determine residential mobility. Rather than relying on similarity of levels, my approach uses difference-in-difference strategy. This strategy relies on the assumption that trends in the unobserved determinants of residential mobility are evolving similarly.

3.3 Evidence of Residential Sorting Using Panel Data

Given the panel data of blocks in three time periods, 1990, 2000, and 2010, and different timing of openings and closings of MSW facilities, my difference-in-difference strategy exploits the variation in geographical and temporal exposure to a facility. Specifically, I compare the change in block outcome after an opening/closing of a facility in exposed blocks, relative to unexposed blocks. Formally, the regression model is:

$$Y_{bt} = \alpha_1 \mathbf{1}[\text{Active}]_{bt} + \alpha_2 \mathbf{1}[\text{Closed}]_{bt} + \alpha_3 \mathbf{1}[\text{Mixed}]_{bt} + \eta_b + \tilde{\eta}_t + \epsilon_{bt} \tag{3.1}$$

where Y_{bt} is the resident level (by race and ethnicity) of block b in year t. Indicator $\mathbf{1}[\text{Active}]_b$ equals 1 if block b contains only active facilities within its one mile buffer of its centroid in year t. Indicator $\mathbf{1}[\text{Closed}]_{bt}$ equals 1 if block b contains only closed facilities within its one mile buffer of its centroid in year t. Indicator $\mathbf{1}[\text{Mixed}]_{bt}$ equals 1 if block b contains an active facility and another closed facility within its one mile buffer of its centroid in year t. The left-out category is blocks with no facility at all, within one mile.

The regression includes block fixed effects η_b to control for all time-invariant determinants of residency in a block, and year fixed effects $\tilde{\eta}_t$ to control for factors that are common across blocks in the same year. The inclusion of these fixed effects ensures that identification comes from facility openings and closings. The year fixed effects are also important since they provide model flexibility to capture the fact that different blocks may be exposed to an operating facility at different times. The standard errors are clustered by tract to allow each tract to have different economic and demographic structure, and blocks within the tract to share similar activities. An alternative is to cluster by block group. However, even block groups may be small units and share similar economic conditions within a tract. Additionally, facilities may locate on block and block group borders, which makes clustering by tract more appropriate. Of course, one can also cluster by adjacent group of block groups and/or adjacent group of tracts to fully account for spatial correlation resulted from near-border facility siting.

The parameters of interest are α_1 and α_2, which measure the effects of openings and closings of MSW facilities, relative to the period before opening, respectively. Specifically, parameter α_1 measures the effect on population level in nearby blocks, relative to faraway blocks, during the period that the facility is operating, relative to the period before it opened. Parameter α_2 measures the effect on population level in nearby blocks, relative to faraway blocks, during the period that the facility is closing, relative to the period before it opened. Variable $\mathbf{1}[\text{Mixed}]_{bt}$ is mainly to control for blocks that have multiple facilities and that have an active facility and a closing facility. Parameter α_3 is not the main interest, although it captures the effect of having both an active facility and a closing facility relative to the period before operating.

To test the effect of closing relative to the operating period, I use the following regression:

$$Y_{bt} = \beta_1 \mathbf{1}[\text{Near}]_{bt} + \beta_2 \mathbf{1}[\text{Closed}]_{bt} + \eta_b + \tilde{\eta}_t + \epsilon_{bt} \tag{3.2}$$

where $\mathbf{1}[\text{Near}]_{bt}$ equals 1 if block b contains any facility, either closing or opening, within its one mile buffer of its centroid in year t. The parameter of interest is β_2, which measure the effect of closing relative to operating period. Parameter β_1 measures the effect of openings, which is in fact equal to α_1.

There are several channels for the effects of closing an MSW facility. To relate the effects of closings to causes by pollution versus job loss, I decompose the effect of closings into the effect of closings due to environmental regulation and the effect of closings due to economic condition and the operation of a facility itself. Specifically, I decompose the effect of closings into the effect of closings that began in 1992–1996 and the effect of closings that began afterward. Due to the 1992 RCRA regulation, the closings happening during 1992–1996 should have resulted from the strict regulation, while the closures started from 1997 should be accounted by the operation process of facilities. This pattern can be supported in figure (3.1), which shows a sharp increase in closures from 1992 to 1996 and a jump in openings of transfer stations (which were not subject to RCRA regulation).

I hypothesize that closings resulting from environmental regulation would affect population by pollution channels. Sites that are forced to close by regulation are more heavily polluted than other sites, and hence induce more out-migration. Although one may argue that sites that are forced to close by regulation would receive environmental remediation and hence attract new move-ins, this is not likely the case for MSW facilities. Closures of MSW facilities under 1992 RCRA did not receive any special treatment from the Superfund program for hazardous waste sites. MSW facilities were forced to close under 1992 RCRA because these sites did not meet new environmental regulations such as installing methane and water monitoring. Hence, closed sites under 1992 RCRA are likely to irritate their neighborhoods more than other sites. This would result in greater out-migration at these sites for those who have high preferences to avoid living near a trash site. On the other hand, closures resulted from the downturn operation of a facility are highly associated with large job loss. As a result, there would be exits for those who had preferences to move into neighborhoods of trash sites for employment.

The control group I have used so far is the group of blocks beyond one mile from the facility location. If there is any impact on neighborhoods within two miles, for example, this would result in bias against my findings using one-mile neighborhoods. To explore the effects of openings and closings by distance to the environmental bads, I use the following regression:

$$\begin{aligned} Y_{bt} = &\sum_{d=1}^{6} \delta_d \mathbf{1}[\text{Active from } (d-1) \text{ to } d \text{ miles}]_{bt} \\ &+ \sum_{d=1}^{6} \gamma_d \mathbf{1}[\text{Closed from } (d-1) \text{ to } d \text{ miles}]_{bt} \\ &+ \sum_{d=1}^{6} \omega_d \mathbf{1}[\text{Mixed from } (d-1) \text{ to } d \text{ miles}]_{bt} + \eta_b + \tilde{\eta}_t + \epsilon_{bt} \end{aligned} \tag{3.3}$$

where $\mathbf{1}[\text{Active from } (d-1) \text{ to } d \text{ miles}]_{bt}$ equals 1 if the distance from the centroid of block b to the nearest active facility is between $(d-1)$ miles to d miles and there is no closed facility in that range. Indicator $\mathbf{1}[\text{Closed from } (d-1) \text{ to } d \text{ miles}]_{bt}$ equals 1 if the distance from the centroid of block b to the nearest closed facility is between $(d-1)$ miles to d miles and there is no active facility in that range. Indicator $\mathbf{1}[\text{Mixed from } (d-1) \text{ to } d \text{ miles}]_{bt}$ equals 1 if the distances from the centroid of block b to the nearest active facility and the nearest closed facility are between $(d-1)$ miles to d miles. Parameters of interest are δs and γs, which measure the effects of opening and closing of a trash facility by distance, relative to the areas beyond 6 miles, respectively.

Before turning to the results, I consider some of potential limitations associated with the data and the empirical design. First, I do not have information on closings that happened before 1992. The control group in my analysis potentially include blocks that have closed facilities that I did not observe. This information missing, however, is not a problem because it would create bias against my findings. Second, I do not have more frequent data on population by year to distinguish the short-run and long-run effects of openings and closings and do event analysis. Missing yearly data also prevents me from conducting a parallel trend test (to test the identification assumption of difference-in-difference model) and Granger causality test (to test whether causes happen before consequences and not vice versa). Third, I do not have additional regressors to control for time variant characteristics. Conventional methods would use block characteristics before 1990, interacted with a time trend, to control for block-by-time specific characteristics. However, the Census Bureau completely redesigned census geography with the 1990 Census, and nothing comparable between 1980 blocks and 1990 blocks. Our results, however, show that block fixed effects and year fixed effects already do a good job in explaining the block population, evident by high values of R squared.

3.4 Results

Table (3.2) reports estimates for the effects of openings and closings on residency by race and ethnicity. Panel A shows the effects on population. Panel B shows the effects on number of households by race and ethnicity of householder. The estimates are the coefficients of regression model (3.1), columns (1)–(4), and model (3.2), columns (5)–(8). I estimate these models on a unbalanced panel of block-by-year observations for years 1990, 2000, and 2010. The panel is unbalanced due to missing values of some blocks in 1990.

The estimates in panel A show that an operating MSW facility within one mile is associated with significant decreases in white population and black population, but a significant increase in Hispanic residents. Using the block mean population in 1990, this implies a decrease of 11 percent in the white population, a decrease of 32 percent in black population, and an increase of 44 percent in Hispanic population in a block. Closures of MSW facility result in a further significant decrease of 14 percent in black population, and a significant fall of 11 percent in Hispanic population, relative to operating period.

Results in panel B show effects of openings and closings on the number of households that are consistent with results in panel A. Specifically, using the block mean household in 1990, an opening of an MSW facility within one mile is associated with a 13 percent decrease in white-head households, a 26 percent decrease in black-head households, and a 39 percent in Hispanic-head households. Relative to the operating period, closings result in a further 3 percent decrease in white-head households, a 10 percent in black-head household, but a 24 percent increase in Asian-head households, and negligible effect on Hispanic households.

These estimates suggest a significant pattern of white and black exits and Hispanic move-ins in neighborhoods of operating MSW facilities. The white exit can be explained by two reasons. First, white residents may have higher willingness to avoid unpleasant surroundings of trash sites. Second, white residents may have more resources to move away from the sites than Hispanic residents. Meanwhile, Hispanic residents may find job opportunities in neighborhoods of operating MSW facilities to move in. Alternatively, Hispanic people may find affordable housing and living options in these affected areas due to income constraints.

The negative effects of closing, relative to operating period, on all three racial groups suggest that closing sites may be more heavily polluted than operating sites or destroy job opportunities. Although time-variant characteristics are not controlled in the regressions, several important determinants of block residency have been controlled by block fixed effects and year fixed effects. High values of adjusted R squared helps increase our confidence in the validity of the estimates.

To relate the effects of closings to reasons of pollution and job loss, I decompose the effect of closings into the effect of closings due to environmental regulation and the effect of closings as an organization and operation process of a facility. Specifically, table (3.3) decomposes the effect of closings into the effect of closings happening since 1992–1996 (due to RCRA regulation) and the effect of closings from 1997 (due to volunteer operation process of facilities). The estimates show that regulation-forced closures result in much bigger exit by white residents and bigger move-ins by Hispanic people. This verifies the conjecture that sites that are forced to close by regulation are more heavily polluted than operating sites, resulting bigger exit by white residents. On the other hand, closures resulted from the downturn operation of a facility lead to larger job loss, resulting in significant move-outs of those Hispanic residents that had moved in during the operating period of trash sites.

I also examine the effects of openings and closings on other outcomes. Since these variables are interpolated from block group levels, the estimates are much less robust than the effects on residency level. Table (3.4) reports the effects on median household income, median housing values, and median gross rent. Four interesting facts emerge. First, neighborhoods of MSW facilities earn less than faraway areas. Second, neighborhoods of closed facilities earn much less. This suggests that closures of MSW facilities result in job loss for their neighborhoods. Third, neighborhoods of closed facilities have much lower value after closure than during the operating period before the facility closed. This verifies the above conjecture that a closed facility is associated with high pollution level, and that closing does not remedy the environmental hazards, at least for the 10-year period. Additionally, the low housing values after closures suggest that facilities do not close because of high land costs, if closing decisions reflect expected future costs. Fourth, post-1997 closures are associated with higher decrease in income and house values, which again suggests these closures are highly likely to destroy jobs.

In all regressions the comparison group is blocks that do not contain any facilities within one mile from the blocks' centroids. To examine the sensitivity of the results on the definition of affected communities, I explore the spatial effects of openings and closings by distance to hazards. Examining the effects of facility operation in distance is helpful because channels of unwanted elements from MSW facilities such as smells, toxic emissions, water pollution have geographical affects, and dwindle in distance. Figure (3.3) plots the coefficients δ's, γs and their 95th percentile confidence intervals. It shows the marginal effect of an operating facility on resident level with respect to distance to the nearest MSW facility. Overall, the marginal effect of an opening of a trash site fades with distance. Point estimates for the effects of white exit and Hispanic move-ins are significant for blocks within 4 miles of an opening of a trash site and fade away beyond 4 miles. Closing a trash site does not result in a significant improvement of amenities to recover to the period before opening. Since trash is cumulated into a site over time, closure reflects an end after many years of operations. Hence, we can see residential mobility due to an opening of a trash site has spread into larger areas surrounding the site. The Hispanic move-ins and the white exit patterns are still highest in the nearest neighborhoods of the sites.

Tables (C.1) and (C.2) in the appendix reestimate the effects of opening and closing in 2-mile neighborhoods and 3-mile neighborhoods, respectively. Results confirm smaller effects in extended neighborhoods than the 1-mile neighborhoods.

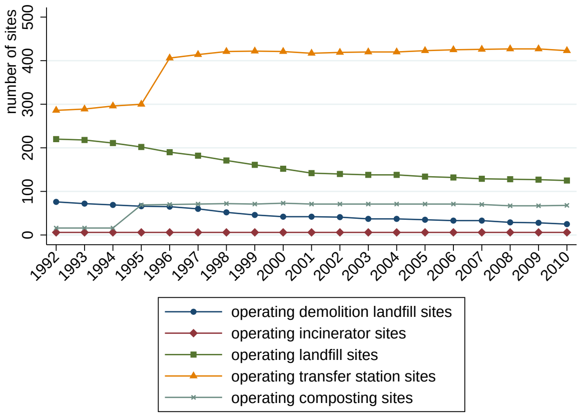
3.5 Conclusion

This paper presents evidence of residential mobility in the surroundings of MSW facilities. Opening a trash site induces a significant decrease in white residents, but an increase in Hispanic residents in 1-mile nearby blocks. While the literature has documented sizable in-migration after Superfund cleanup (18 percent increase in population density, Gamper-Rabindran and Timmins (2011)) or reduced exposure to TRI pollution (5–7 percent increase in population, Banzhaf and Walsh (2008)), this paper shows that there is no significant in-migration after closing an MSW facility. Closure, however, results in out-migration. A reason is that waste has been accumulated over time into a site. A closed MSW facility only stops receiving trash, but it does not receive any special treatment. The closed facility must have accumulated pollution over its operating periods, and hence induce a higher white exit and a larger area of affection by distance. Closure also reduces Hispanic move-ins considerably due to job destructions.

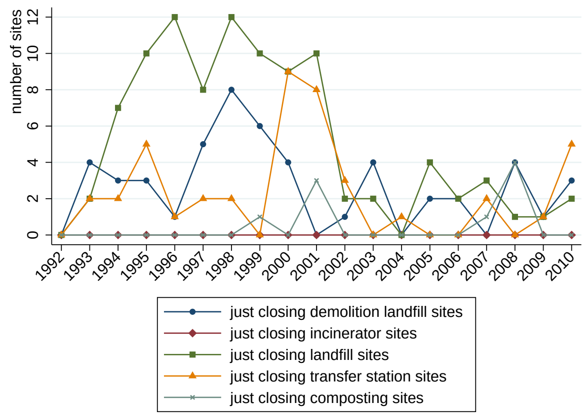
Figures and Tables

FIGURE 3.1: Overview of municipal solid waste facilities in CA from Jan 1992 to Dec 2010

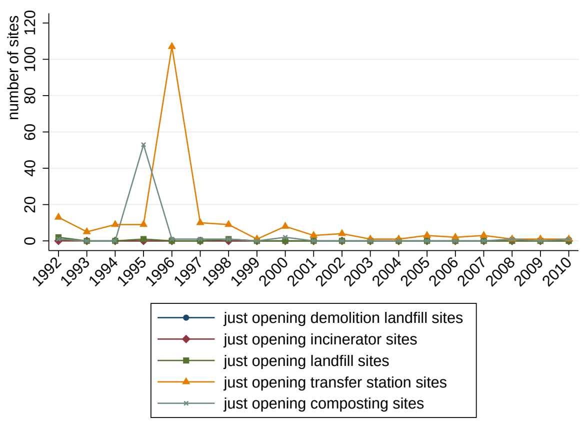
(A) Number of operating sites



(B) Number of new closings



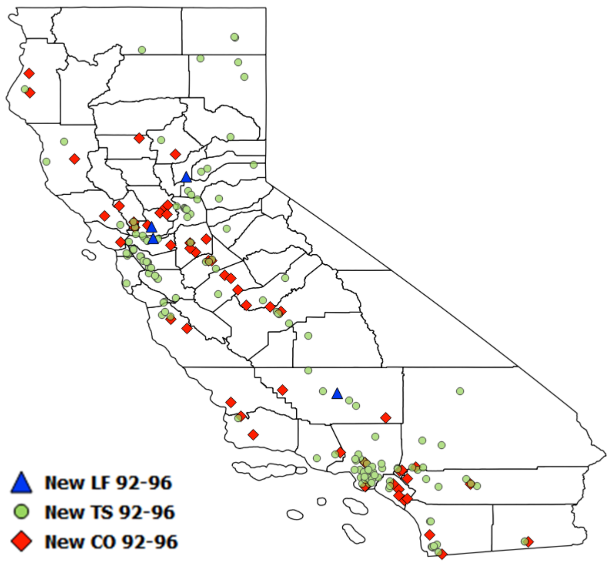
(C) Number of new openings



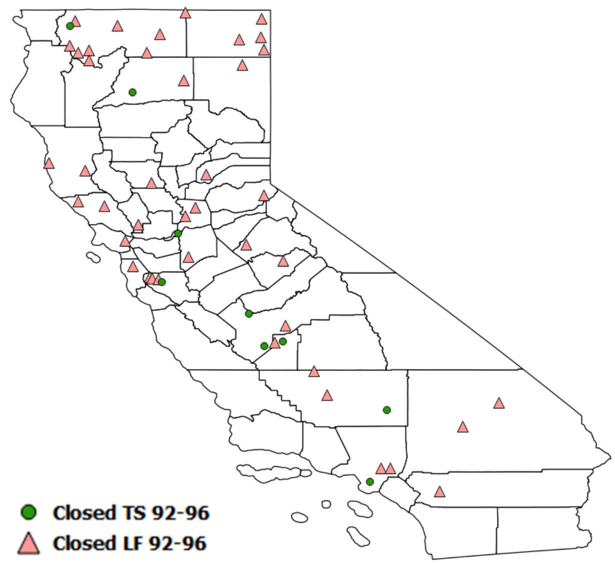
Note: The graph shows the number of MSW sites by type and year. Operating sites are active sites that have positive price values. New closings refer to sites that have just closed in that year. New openings refer to sites that have just opened in that year. Demolition landfills are basically landfills that accept construction and demolition waste.

FIGURE 3.2: Map of new openings and closings of MSW facilities in CA from Jan 1992 to Dec 2010

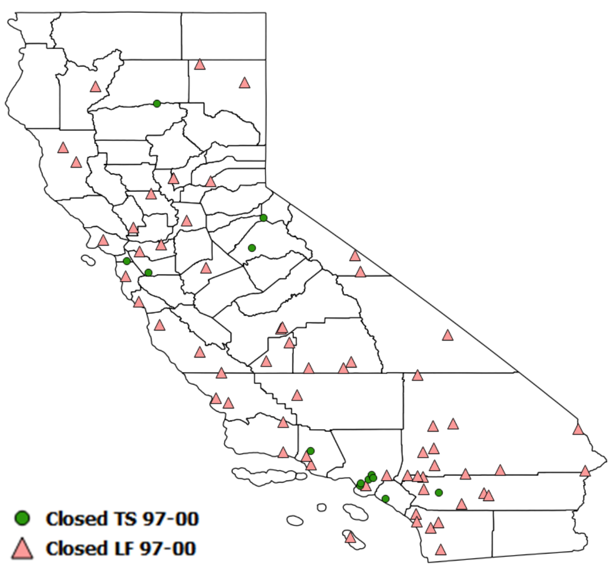
(A) New openings during 1992–1996



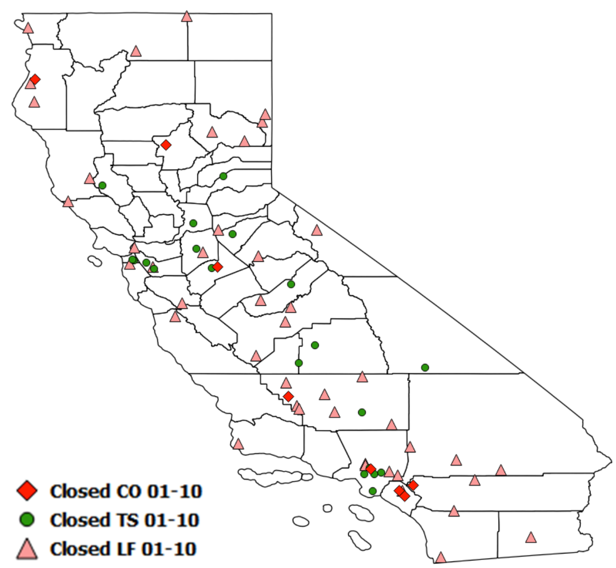
(B) New closings during 1992–1996



(C) New closings during 1997–2000



(D) New closings during 2001–2010

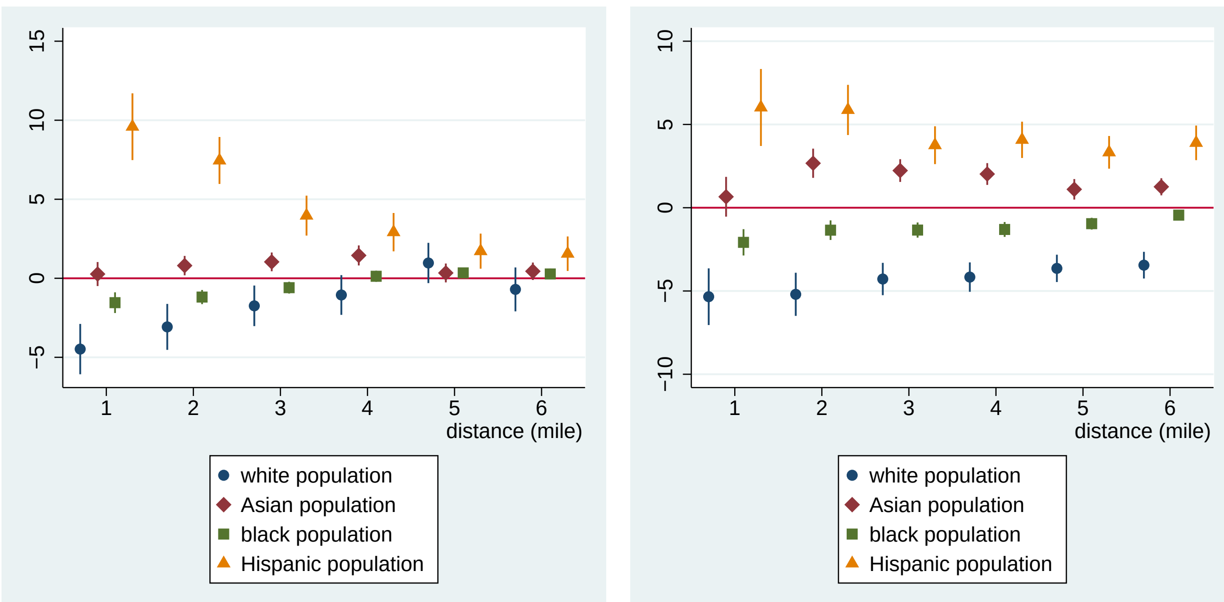


Note: The graph shows the locations of new openings and new closings of MSW facilities in California from January 1992 to December 2010. MSW facilities are divided into three categories: LF, TS, and CO. LF denotes a landfill that includes an MSW landfill, an incinerator, or a demolition site. TS implies a transfer station that includes a transfer station or a material recovery site. CO implies a composting site.

FIGURE 3.3: The effects of openings and closings on population by distance

(A) The effects of being near to an active facility

(B) The effects of being near to a closed facility



Note: The graph shows the effects of living near an opening and closing of an MSW facility by distance. The figures were constructed by regressing population level on indicators for the distances to the nearest opening/closing MSW site, and block and year fixed effects. Standard errors are clustered by tract. Reported are the coefficients and their 95% confidence intervals for the opening/closing events happening between $d-1$ miles and d miles to the block's centroid. These are the marginal effects on population level in the blocks that are near to an opening/closing site, relative to blocks that are beyond 6 miles away.

TABLE 3.1: Characteristics of blocks by year

	1990		2000		2010	
	count	percentage	count	percentage	mean	percentage
total blocks	565,468		691,487		691,487	
active blocks	42,805	7.57%	60,667	8.77%	52,432	7.58%
closed blocks	0	0%	10,148	1.47%	16,942	2.45%
mixed blocks	0	0%	3,686	0.01%	5,859	0.01%
	mean	sd	mean	sd	mean	sd
population	52.63	108.51	48.98	113.84	53.88	121.89
white	30.11	64.13	22.87	55.27	21.63	52.96
Asian	4.79	19.46	5.28	23.46	6.91	28.81
black	3.70	20.42	3.16	18.94	3.13	18.43
Hispanic	13.60	46.31	15.86	55.00	20.27	61.60
household	18.36	38.46	16.63	38.66	18.19	41.37
white household	12.37	28.08	9.69	24.58	9.41	23.80
Asian household	1.32	5.52	1.59	7.51	2.18	9.75
black household	1.28	6.74	1.12	6.07	1.17	5.93
Hispanic household	3.25	10.16	3.71	12.21	4.90	14.39
median household income	39425.17	30255.36	45437.47	29269.67	50424.88	26446.30
median housing value	52866.52	40570.41	46979.29	30262.88	39814.08	20881.26
median gross rent	642.63	443.18	715.51	436.88	850.18	421.48

Note: This table reports characteristics of blocks by year, after reassigning 1990 values and 2000 values to 2010 blocks, using NHGIS crosswalk links and weights. Year 1990 has a smaller number of blocks due to missing values.

TABLE 3.2: Effects of openings and closings of MSW facilities on 1-mile neighborhoods

	(1) white	(2) Asian	(3) black	(4) Hispanic	(5) white	(6) Asian	(7) black	(8) Hispanic
Panel A: Effects on resident population								
active	-3.328***	-0.352	-1.205***	5.959***				
	(0.610)	(0.347)	(0.324)	(0.888)				
closed	-3.977***	0.068	-1.737***	4.416***	-0.630	0.443	-0.531**	-1.518**
	(0.857)	(0.610)	(0.401)	(1.138)	(0.563)	(0.496)	(0.260)	(0.758)
mixed	-4.232***	-1.466**	-1.247***	4.800***				
	(1.118)	(0.637)	(0.438)	(1.334)				
near					-3.342***	-0.369	-1.206***	5.941***
					(0.612)	(0.347)	(0.324)	(0.888)
adj. R^2	0.841	0.745	0.743	0.823	0.841	0.745	0.743	0.823
Panel B: Effects on resident households								
active	-1.584***	-0.051	-0.329***	1.268***				
	(0.245)	(0.108)	(0.106)	(0.190)				
closed	-2.022***	0.256	-0.451***	0.994***	-0.428*	0.315*	-0.123*	-0.267
	(0.366)	(0.217)	(0.123)	(0.252)	(0.257)	(0.187)	(0.073)	(0.175)
mixed	-2.052***	-0.451**	-0.306**	0.963***				
	(0.419)	(0.184)	(0.140)	(0.290)				
near					-1.592***	-0.057	-0.328***	1.263***
					(0.246)	(0.108)	(0.106)	(0.190)
adj. R^2	0.883	0.742	0.864	0.852	0.883	0.742	0.864	0.852
N	1948442	1948442	1948442	1948442	1948442	1948442	1948442	1948442

Note: This table reports estimates for the effects of openings and closings on residency by race and ethnicity. Panel A shows the effects on population. Panel B shows the effects on number of households by race and ethnicity of householder. The estimates are the coefficients of regression models (3.1) and (3.2). I estimate these models on a unbalanced panel of block-by-year observations for years 1990, 2000, and 2010. The panel is unbalanced due to missing values of some blocks in 1990. All models include block and year fixed effects. Standard errors are clustered by tract.

TABLE 3.3: Effects of pre-1997 and post-1997 closings of MSW facilities on 1-mile neighborhoods

	(1) white	(2) Asian	(3) black	(4) Hispanic	(5) white	(6) Asian	(7) black	(8) Hispanic
active	-3.409***	-0.376	-1.194***	5.913***	-3.382***	-0.282	-1.201***	5.966***
	(0.610)	(0.349)	(0.322)	(0.885)	(0.610)	(0.345)	(0.324)	(0.889)
pre-1997 closed	-6.066***	1.952	-1.623***	4.530***	-6.036***	2.052	-1.630***	4.587***
	(1.175)	(1.370)	(0.522)	(1.559)	(1.176)	(1.379)	(0.523)	(1.568)
post-1997 closed	-3.479***	-0.731	-1.771***	4.289***	-3.454***	-0.645	-1.777***	4.338***
	(0.916)	(0.589)	(0.435)	(1.215)	(0.917)	(0.592)	(0.437)	(1.219)
multi-closed					3.584	12.207**	-0.933*	6.964
					(11.043)	(5.487)	(0.546)	(9.963)
mixed	-4.284***	-1.492**	-1.224***	4.723***	-4.231***	-1.312**	-1.238***	4.825***
	(1.106)	(0.627)	(0.435)	(1.318)	(1.127)	(0.654)	(0.440)	(1.345)
adj. R^2	0.841	0.745	0.743	0.823	0.841	0.745	0.743	0.823

Note: This table decompose the effect of closings into the effect of closings happening since 1992–1996 and the effect of closings from 1997. "Multi-closed" indicates multi-site blocks that contain a site that closed in pre-1997 period and a site that closed in post-1997 period. I estimate these models on a unbalanced panel of block-by-year observations for years 1990, 2000, and 2010. The panel is unbalanced due to missing values of some blocks in 1990. All models include block and year fixed effects. Standard errors are clustered by tract.

TABLE 3.4: Effects of openings and closings economic conditions of 1-mile neighborhoods

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	median household income			median housing value			median gross rent		
active	-4505.3***		-4403.5***	-2045.4***		-1935.2**	-69.5***		-68.5***
	(612.5)		(609.1)	(765.9)		(763.8)	(10.0)		(10.0)
closed	-7215.6***	-2646.6***		-3965.5***	-1925.1*		-84.6***	-13.4	
	(1112.4)	(886.4)		(1349.4)	(1067.5)		(17.6)	(13.7)	
mixed	-7507.0***		-7354.4***	-1811.8		-1674.1	-147.0***		-145.4***
	(1961.6)		(1950.4)	(1835.5)		(1821.6)	(24.6)		(24.5)
near		-4552.3***			-2041.7***			-70.7***	
		(619.2)			(772.1)			(10.1)	
pre-97 closed			-5750.3***			-1550.6			-87.7***
			(1744.0)			(1733.9)			(23.4)
post-97 closed			-7560.9***			-4606.1***			-81.4***
			(1236.1)			(1523.1)			(19.9)
adj. R^2	0.649	0.649	0.649	0.605	0.605	0.605	0.471	0.471	0.471

Note: This table reports estimates for the effects of openings and closings on median household income and housing values in blocks that contain an exposed facility within 1 miles from the blocks' centroids. I estimate these models on a unbalanced panel of block-by-year observations for years 1990, 2000, and 2010. The panel is unbalanced due to missing values of some blocks in 1990. All models include block and year fixed effects. Standard errors are clustered by tract.

Appendix A

Chapter 1 Appendix

A.1 Monopoly Pricing Under Marginal Price Response

Let the indirect utility from the IC constraint be $V(\theta) \equiv max_q U(q,\theta) - P^m(q)$. Following the standard literature results, the IC constraint requires that $Q^m(\theta)$ weakly increases in θ and that the marginal surplus $V_\theta > 0$. The IR constraint is satisfied if and only if $V(\theta_0) \geq 0$ (the utility of the lowest type is nonnegative), given that $V_\theta > 0$. The expected profits can be written in terms of expected total surplus minus consumer surplus:

$$\begin{aligned}
&\int_{\theta_0}^{\theta_1} (P(Q^m(\theta)) - C(Q^m(\theta)))dF(\theta) \\
=& \int_{\theta_0}^{\theta_1} (U(Q^m(\theta),\theta) - C(Q^m(\theta)) - V(\theta))dF(\theta) \\
=& \int_{\theta_0}^{\theta_1} \left((U(Q^m(\theta)),\theta) - C(Q^m(\theta)) - \frac{1-F(\theta)}{f(\theta)} \cdot U(Q^m(\theta),\theta) - V(\theta_0) \right) dF(\theta)
\end{aligned} \tag{A.1}$$

The last equation is obtained by using integration by parts. Hence, the firm's pricing problem is transformed to the problem of choosing $Q^m(\theta)$ to maximize A.1 subject to $Q(\theta)$ nondecreasing and $V(\theta_0) \geq 0$. The optimal price schedule is recovered from $U(Q^m(\theta),\theta) - P(Q(\theta)) = V(\theta)$, where $V(\theta) = V(\theta_0) + \int_{\theta_0}^{\theta_1} U_\theta(Q^m(\theta),\theta)d\theta$. Solving these gives the following results.

Result 1. When the consumer responds to marginal price, the optimal consumption $q^m = \max\{Q^m(\theta), 0\}$ where $q^m = Q^m(\theta)$ satisfies:

$$U_q - C_q = \frac{1-F}{f} \cdot U_{q\theta} \tag{A.2}$$

The optimal price schedule $P^m(q)$ satisfies:

$$U_q(Q^m(\theta),\theta) - P_q^m(Q^m(\theta)) = 0 \tag{A.3}$$

We also have

$$Q^m_\theta \text{ is nondecreasing} \tag{A.4}$$

$$V(\theta_0) = U(Q^m(\theta_0), \theta_0) - P^m(Q(\theta_0)) \geq 0 \tag{A.5}$$

A.2 Regulated Firm Pricing Under Marginal Price Response

Similar to the monopoly pricing framework, the optimization problem can be transformed into

$$\max_q \int_{\theta_0}^{\theta_1} U(q,\theta) - C(q) d\theta \tag{A.6}$$

$$\text{s.t.} \int_{\theta_0}^{\theta_1} \left((U(Q^m(\theta)), \theta) - C(Q^m(\theta)) - \frac{1 - F(\theta)}{f(\theta)} \cdot U(Q^m(\theta), \theta) - V(\theta_0) \right) dF(\theta) = FC \tag{A.7}$$

$$q \text{ increasing in } \theta \tag{A.8}$$

$$U(q(\theta_0), \theta_0) \geq 0 \tag{A.9}$$

Using the Lagrangian function and its first order condition, we get

Result 2. When the consumer responds to marginal price, the optimal consumption $q^m = \max\{Q^m(\theta), 0\}$ where $q = Q^m(\theta)$ satisfies:

$$U_q - C_q = \left(\frac{\lambda}{1 + \lambda} \right) \cdot \left(\frac{1 - F}{f} \cdot U_{q\theta} \right) \tag{A.10}$$

The optimal price schedule $P^m(q)$ satisfies:

$$U_q(Q^m(\theta), \theta) - P^m_q(Q^m(\theta)) = 0 \tag{A.11}$$

We also have

$$Q^m_\theta \text{ is nondecreasing} \tag{A.12}$$

$$V(\theta_0) = U(Q^m(\theta_0), \theta_0) - P^m(Q(\theta_0)) \geq 0 \tag{A.13}$$

Notice this means

$$\frac{MP - MC}{MP} = \frac{\mathcal{R}}{\epsilon} \tag{A.14}$$

where $\mathcal{R} \in [0, 1]$ is Ramsey number and ϵ is price elasticity of demand for qth unit across all types.

$$\epsilon = \frac{f}{1 - F} \cdot \frac{U_q}{U_{q\theta}} \tag{A.15}$$

A.3 Omitted Proofs

Demonstration of Corollary . Remind that under MP response, we have:

$$\frac{MP - MC}{AP} = \frac{\mathcal{R}^m}{\epsilon} \tag{A.16}$$
$$\Leftrightarrow 1 - \frac{MC}{MP} = \frac{\mathcal{R}^m}{\epsilon} \tag{A.17}$$

Hence if ϵ is constant (and the cost is strictly convex) or increasing in q then the marginal price is decreasing. □

Demonstration of Corollary . We have

$$\frac{AP - MC}{AP} = \frac{\mathcal{R}^a}{\eta} \tag{A.18}$$
$$\Leftrightarrow 1 - \frac{MC}{AP} = \frac{\mathcal{R}^a}{\eta} \tag{A.19}$$

Hence if η is constant (and the cost is strictly convex) or increasing in q then the average price is increasing. □

Demonstration of Corollary . When consumers respond to marginal price, the optimal pricing scheme satisfies

$$\frac{U_q - C_q}{U_q} = \mathcal{R}^m \cdot \frac{1-F}{f} \cdot \frac{U_{q\theta}}{U_q} \tag{A.20}$$
$$\Rightarrow \frac{MP - MC}{MP} = \frac{\mathcal{R}^m}{\epsilon} = \frac{\mathcal{R}^m}{\frac{f}{1-F} \cdot \theta} \tag{A.21}$$

Notice that $\frac{d\epsilon}{dq} = \frac{d\epsilon}{d\theta}\frac{d\theta}{dq} = (\frac{dh}{d\theta}\theta + h(\theta))\frac{d\theta}{dq}$ where $h(\theta)$ is the hazard rate $\frac{f}{1-F}$. Since we have $\frac{d\theta}{dq} > 0$, the increasing hazard rate implies the increasing elasticity, thus decreasing marginal price, and decreasing average rate.

When consumers respond to average price, the optimal pricing scheme satisfies

$$\frac{U_q - C_q}{U_q} = \mathcal{R}^a \cdot \frac{-qU_{qq}}{U_q} \tag{A.22}$$
$$\Rightarrow \frac{AP - MC}{AP} = \mathcal{R}^a \cdot \frac{-qV_{qq}}{V_q} \tag{A.23}$$

Therefore, the increasing curvature implies the increasing average price. □

Appendix B

Chapter 2 Appendix

B.1 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.[1] 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.

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

B.2 Test of Market Boundaries Using 2SLS Models

TABLE B.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.

Appendix C

Chapter 3 Appendix

C.1 Redefine the Areas of Affected Communities

TABLE C.1: Effects of openings and closings of MSW facilities on 2-mile neighborhoods

	(1) white	(2) Asian	(3) black	(4) Hispanic	(5) white	(6) Asian	(7) black	(8) Hispanic
Panel A: Effects on resident population								
active	-3.450***	0.339	-1.391***	6.511***				
	(0.537)	(0.270)	(0.221)	(0.663)				
closed	-5.004***	2.271***	-1.559***	6.005***	-1.415***	1.940***	-0.139	-0.597
	(0.757)	(0.488)	(0.289)	(0.864)	(0.502)	(0.398)	(0.197)	(0.567)
mixed	-5.469***	0.205	-1.811***	7.832***				
	(0.745)	(0.424)	(0.322)	(0.913)				
near					-3.443***	0.340	-1.390***	6.506***
					(0.537)	(0.270)	(0.220)	(0.662)
adj. R^2	0.842	0.745	0.743	0.823	0.842	0.745	0.743	0.823
Panel B: Effects on resident households								
active	-1.388***	0.266***	-0.382***	1.455***				
	(0.201)	(0.090)	(0.076)	(0.141)				
closed	-2.132***	1.139***	-0.423***	1.413***	-0.672***	0.869***	-0.039	-0.067
	(0.307)	(0.180)	(0.099)	(0.192)	(0.215)	(0.151)	(0.059)	(0.130)
mixed	-2.422***	0.326**	-0.419***	1.829***				
	(0.279)	(0.136)	(0.105)	(0.198)				
near					-1.385***	0.266***	-0.382***	1.454***
					(0.201)	(0.090)	(0.076)	(0.141)
adj. R^2	0.883	0.742	0.864	0.852	0.883	0.742	0.864	0.852
N	1948442	1948442	1948442	1948442	1948442	1948442	1948442	1948442

Note: This table reports estimates for the effects of openings and closings on residency by race and ethnicity in blocks that contain an exposed facility within 2 miles from the blocks' centroids. Panel A shows the effects on population. Panel B shows the effects on number of households by race and ethnicity of householder. The estimates are the coefficients of regression models (3.1) and (3.2). I estimate these models on a unbalanced panel of block-by-year observations for years 1990, 2000, and 2010. The panel is unbalanced due to missing values of some blocks in 1990. All models include block and year fixed effects. Standard errors are clustered by tract.

TABLE C.2: Effects of openings and closings of MSW facilities on 3-mile neighborhoods

	(1) white	(2) Asian	(3) black	(4) Hispanic	(5) white	(6) Asian	(7) black	(8) Hispanic
Panel A: Effects on resident population								
active	-2.559***	0.854***	-1.042***	4.817***				
	(0.532)	(0.271)	(0.186)	(0.586)				
closed	-3.655***	3.154***	-0.929***	4.240***	-0.690	2.165***	0.227	-0.899*
	(0.766)	(0.476)	(0.252)	(0.784)	(0.520)	(0.383)	(0.170)	(0.517)
mixed	-5.652***	1.880***	-1.912***	7.270***				
	(0.662)	(0.390)	(0.239)	(0.747)				
near					-2.392***	0.799***	-0.995***	4.685***
					(0.533)	(0.271)	(0.186)	(0.585)
adj. R^2	0.842	0.745	0.743	0.823	0.841	0.745	0.743	0.823
Panel B: Effects on resident households								
active	-0.856***	0.475***	-0.311***	1.100***				
	(0.197)	(0.091)	(0.064)	(0.126)				
closed	-1.453***	1.448***	-0.296***	1.064***	-0.408*	0.910***	0.039	-0.121
	(0.300)	(0.170)	(0.089)	(0.177)	(0.212)	(0.138)	(0.053)	(0.121)
mixed	-2.295***	0.953***	-0.495***	1.745***				
	(0.249)	(0.130)	(0.079)	(0.164)				
near					-0.778***	0.449***	-0.301***	1.065***
					(0.197)	(0.092)	(0.064)	(0.126)
adj. R^2	0.883	0.743	0.864	0.852	0.883	0.743	0.864	0.852
N	1948442	1948442	1948442	1948442	1948442	1948442	1948442	1948442

Note: This table reports estimates for the effects of openings and closings on residency by race and ethnicity in blocks that contain an exposed facility within 3 miles from the blocks' centroids. Panel A shows the effects on population. Panel B shows the effects on number of households by race and ethnicity of householder. The estimates are the coefficients of regression models (3.1) and (3.2). I estimate these models on a unbalanced panel of block-by-year observations for years 1990, 2000, and 2010. The panel is unbalanced due to missing values of some blocks in 1990. All models include block and year fixed effects. Standard errors are clustered by tract.

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