Taxing Plastic Packaging in U.S. Soft Drinks

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1 Introduction

Plastic's strength, light weight, and moldability make it a marvel of the 20th century. However, pollution associated with plastic's production and waste may harm human health as well as pose a threat to numerous ecological systems. Packaging is one of plastic's most common use cases and is expected to grow rapidly in the coming decades. The proliferation of plastic and its potential harms have led some policymakers to look for ways to limit the use of single-use plastic applications, particularly in packaging. Spain and the United Kingdom have implemented weight-based taxes on single-use plastic packaging; Italy and Germany have also passed a plastic packaging tax, though their implementations have been delayed until 2027. In the U.S., there has been proposed legislation to implement an excise tax on virgin plastic, and a handful of U.S. states have passed extended producer responsibility (EPR) laws which aim to shift the burden of waste management to manufacturers; many of the states are still planning the implementation of these laws which could include taxes or fee collection from manufacturers. This paper aims to estimate the impacts of a national weight-based plastic packaging tax in the U.S. soft drinks industry, an appreciable user of plastic packaging.

While there have been a variety of estimates of the social cost of carbon, until recently there have been few estimates of the social cost of plastics. Lauer et al. (2025) estimate that the aggregate social cost of plastics in the U.S. is between $436 billion and $1.109 trillion annually, with the largest contributions attributed to increased disease and mortality and loss of ecosystem services. (The authors do not provide a marginal social cost of plastic, like one may find in the social cost of carbon literature.) A tax on plastic packaging could help internalize the external costs of plastic. A tax on plastic could encourage firms to shift from plastic to alternative packaging materials and package configurations, redesign packages to use less plastic, and to innovate other methods of delivering products to consumers. My analysis will focus on the first of these outcomes. My data and model allow researchers to observe how a price increase for plastic packaged products increases the demanded quantity of products packaged using other materials.

I use retail scanner data on soft drink sales since 2020, in combination with self-collected measure-

ments of plastic packaging weight, to study the potential effects of a plastic packaging tax on sales and consumer welfare. I first estimate a differentiated product demand system for the soft drinks industry. I then assess the impacts of different weight-based plastic packaging tax levels on the quantity demanded for different soft drink products. I use the predicted quantity demanded to estimate packaging material usage under the counterfactual tax rate. I make three main contributions to the existing literature. First, I provide one of the first estimates of the impacts of a weight-based plastic packaging tax applied to the entire U.S. market for a specific industry. The estimates of the impacts of such a tax give policymakers expected plastic use reductions, increases in the use of alternative packaging materials, and changes to consumer consumption. Second, my analysis is among the first to use retail scanner data post-Covid-19 to estimate soft drink demand; previous estimates of demand for soft drinks or other beverages have solely used data prior to 2020. Third, I quantify the plastic intensity of different configurations of soft drink packaging to demonstrate differential impacts of the tax on different sizes of containers.

Overall, I find that a \$1.00/kg tax on plastic packaging (equivalent to roughly \$0.015 to \$0.045 per container - 2% of the price of a typical \$2.00 2-L cola) would have resulted in an estimated 4.1% decline of plastic used by the soft drinks industry, equivalent to 13,000 metric tons of plastic over a three year period (2021-2023). The quantity of aluminum used by the industry would have increased by 1.3%. When consumers do purchase products in plastic packaging, I find that they shift to larger container sizes, which have a lower plastic intensity than smaller container sizes.

The remainder of the paper is organized as follows. First, I summarize some of the known issues with plastic use which motivate this research. Next, I review the current literature around excise taxes and fees, as well as other policies, to reduce specific products or components. Then, I describe the datasets that I use in my analysis before laying out my empirical framework. Finally, I present the results of my analysis and discuss implications for policymakers.

2 Background

2.1 Case of plastic reduction

A significant cause of concern around the single-use plastics is the large quantity of plastic waste generated. The amount of plastic waste generated annually is expected to increase 70% from about 435 million tons in 2019 to 736 million tons in 2040 (OECD, 2024) and to top one billion tons by 2060 (OECD, 2022). While most plastic waste is destined for landfills, recycling, or incineration (which is itself a contributor to greenhouse gas emissions), there is significant leakage of plastic waste into the environment. In 2019, 22 million tons of plastics were leaked from the waste management flow into adjacent ecosystems. Plastic waste is particularly likely to end up in aquatic environments because relatively light plastics are easily transported by the wind or water run-off. While plastic litter can be a human annoyance that reduces people's enjoyment of outdoor spaces, it can have detrimental effects on species inhabiting these spaces. Plastic products themselves or large fragments of plastics,

known as macroplastics, can cause significant injuries to wildlife. Unlike other organic materials, plastic does not fully biodegrade because there are few enzymes in nature capable of breaking down its polymers; however, photo-degradation will break down plastics into smaller pieces known as microplastics (smaller than 5 mm) and nanoplastics (smaller than 0.001 mm). Plastic waste at all sizes can cause problems for humans and other organisms.

The most well-documented impacts of plastic waste occur to natural ecosystems. Both aquatic and terrestrial wildlife can ingest or become entangled in macroplastics causing significant injury or even death to impacted animals (Blettler and Mitchell, 2021; Smith et al., 2025). Birds, mammals, reptiles, amphibians, and fish may become entangled with plastics that limit movement, may become strangled by pieces of plastic, or may ingest plastic leading to injury to internal organs or choking (Blettler and Mitchell, 2021). Recent research from Murphy et al. (2025) indicates that even relatively modest amounts of ingested macroplastics can drastically increase the risk of mortality of marine life, up to 90%. Smaller plastic particles may also be problematic. Microplastics are associated with inflammation and organ damage in animals (Rivers-Auty et al., 2023). Microplastics have become endemic in the environment; a meta-analysis found that over 80% of fish sampled for microplastics research in North America had ingested microplastics (Nina Wootton, 2021). Microplastics have been found in locations as remote as Antarctica (Pellegrino et al., 2025).

Increasing recycling could reduce the leakage of waste to the environment, one source of microplastic contamination, but the benefits of recycling may play a limited role in addressing the problems with plastics. As of 2024, only 24% of polyethylene terephthalate (PET), the primary plastic used in soft drink bottles, was recycled in the U.S.. While deposit programs could drive recycling rates even higher Basuhi et al., 2024, this may not be sufficient to provide the plastic the soft drinks industry needs not to address negative externalities associated with plastics. Unfortunately, unlike recycled aluminum, the properties of PET polymers degrade with subsequent recycling (Strakova et al., 2026; Alvarado Chacon et al., 2020). Both the clarity, strength and brittleness of the polymers can be compromised by additional recycling. Given the high pressures required to maintain carbonation in soft drinks, a high use of recycled PET in soft drink packaging is challenging. This is one reason why recycled PET is primarily used for other purposes such as in the creation of fabrics, like fleece for clothing or upholstery.

Even if it were possible to reduce plastic waste via recycling, the use of plastic may still pose problems. Plasticizers and other additives in plastics have been shown to cause problems in humans. For example, phthalates have been shown to disrupt the endocrine system and negatively impact reproduction, and perfluoroalkyl, and polyfluoroalkyl substances (PFAS) have been associated with a range of possible health issues in multiple organ systems (Mesquita et al., 2021; Fenton et al., 2021). Humans can be exposed to these additives through leaching of the chemicals into consumed products or into water reservoirs. People also likely inhale and ingest plastic particles, although scientists face challenges in accurately quantifying the amount of microplastics and nanoplastics in the human body (Kaushik et al., 2025; Xia and Wang, 2025; Monikh et al., 2025). Further studies

are needed for quantification and to understand the impact of micro and nanoplastics on human health, but early research suggests that exposure to the particles likely has some deleterious effects on health, including increased inflammation and cellular damage (Lamoree et al., 2025).

2.2 Policy landscape

To address the externalities associated with plastic packaging waste, some countries have implemented plastic packaging taxes, though their rates and structures differ by location. The European Union has levied a €0.80/kg ($0.94/kg) tax on non-recycled packaging waste in member states. The tax is collected directly from members, rather than from firms. Some EU members have designed their own taxation schemes to reduce plastic waste. Spain taxes non-reusable plastic packaging at a rate of €0.45/kg ($0.53/kg). In 2022, Germany implemented a refundable €0.25/container deposit on plastic beverage bottles and cans to encourage recycling; beginning in 2025, Germany required manufacturers to pay €0.18/kg for beverage containers not subject to the deposit. The plastic packaging tax in the United Kingdom is levied on plastic packaging with less than 30% recycled content at a rate of £228.82/ton, equivalent to $0.31/kg, as of April 2026, up from its initial rate of £200/ton in 2022.

In the U.S., the REDUCE Act House bill proposed in 2021, and again in 2023, would have taxed virgin plastic resin used in single-use packaging at $0.22/kg, increasing to $0.44/kg at a later date; no national plastic packaging tax legislation has been passed and enacted in the U.S. as of 2026. However, individual states have passed a variety of extended producer responsibility laws that aimed at reducing and financing waste processing across a variety of materials. The scope of the laws vary significantly across states, but common features of legislation include the establishment of a Producer Responsibility Organization (PRO), a listing of in-scope and/or excluded products/producers, planning and implementation timelines, and reporting requirements. The PROs propose most of the policies details, which are subsequently approved by their government department (Sustainable Packaging Coalition, 2026). I highlight some of the key provisions in California, Maine, Colorado, and Oregon, states in which a PRO has been established and has drafted an implementation plan. I focus on the program elements impacting plastic packaging, though it is worthwhile noting that increased costs of non-plastic materials reduce the relative cost differences between plastics and non-plastics, reducing potential substitution away from plastics.

California's EPR legislation Plastic Pollution Prevention and Packaging Producer Responsibility Act, Senate Bill 54, sets targets for the reduction of plastic and for the rates of recycling. It establishes a Producer Responsibility Organization (PRO) that will ensure that manufacturers meet the requirements of the legislation, including collecting fees manufacturers to cover material life cycles. California is targeting 25% less single-use plastic and 65% of single-use plastic being recycled. As of summer 2026, the PRO has defined a range of potential fee schedules for manufacturers based on the type of materials used (including, but not limited to, different plastics, metals, paper, and glass). For example, a clear PET bottle could be subject to fees as low as $0.11/pound plus 0.10per

container or as high as $0.35/pound plus 0.12per container . However, beverage containers are not subject to these fees since they are already subject to the California Refund Value (CRV) which was put in place in 2007. The CRV requires $0.05 refundable deposit per container less than 24 ounces, and $0.10 deposit per container 24 ounces or larger. While CRV containers are not subject to Senate Bill 54, CA Assembly Bill 793 requires beverage containers to contain 15%, 25%, and 50% of post-consumer recycled plastic by 2022, 2025, and 2030, respectively. Containers that fail to meet these requirements face a $0.20/pound fee based on the shortfall of recycled content.

Colorado passed HB 22-1355 in 2022 to require companies that sell packaging and paper products to cover the costs of recycling of these products. The state approved its PRO's plan at the end of 2025. The plan sets producer targets for post-consumer recycled content for plastic packaging (25% for rigid plastic and 10% for flexible plastic), as well as other materials by 2035. A clear PET bottle would be subject to $0.156/pound to $0.170/pound dues; colored PET bottles would be subject to $0.413/pound to $0.48/pound dues; aluminum and glass containers, on the other hand, would be subject to $0.021/pound and $0.042/pound dues, respectively. There is currently no deposit on beverage containers in Colorado.

Maine's LD 1423 in 2025 scaled back their initial EPR legislation LD 1541, passed in 2021. The Maine legislation targets 40% and 60% reductions in the weight of packaging material, by 2040 and 2050, respectively, but it does not set specific targets with respect to plastic waste. It requires 10%, 20% and 30% of packaging to be composed of post-consumer packaging material by 2030, 2040, and 2050, respectively, or face a fee. Litter audits will be verify packaging is below percentage targets. Producers must pay fees based on the packaging material they produce each year, but, as of summer 2026, the fee rates have not yet been defined. However, current rules state that low-volume producers (less than 15 tons of packaging material annually) will be required to pay no more $500/ton of packaging material (equivalent to $0.25/pound). (How are deposit bottles treated?)

Oregon's State Senate Bill 582B was passed in 2021, and its implementation plan was approved in 2025. Oregon excludes packaging covered under its deposit program, which sets a refundable deposit of $0.10 for most beverage containers. For covered materials not subject to the refundable deposit program, it collects producer fees set by material type, for example, $0.25/pound for clear PET bottles and jugs and $0.06/pound for aluminum containers.

Other states such as Maryland, Minnesota, and Washington have also passed EPR legislation, but they have not defined the fee schedules for their programs as of 2026. A half dozen other states in the U.S. are also considering EPR legislation. This paper could be a valuable input to the policymakers in these states.

3 Literature

Plastic packaging taxes have been suggested as a policy tool to reduce plastic use, but there has been little to evaluation of their effectiveness in reducing plastic use. Cela and Kaneko (2013) investigated Denmark's broad-based, weight-based packaging taxes on plastic boxes, cases, and crates; specifically, they model the imports of these packaging materials before and after implementation of the tax. They did not find that the tax significantly changed the quantity of imported packaging materials, which they attribute to price-inelasticity of plastic packaging. Afif et al. (2022) find similar impacts on plastic packaging use in their assessment of the weight-based, packaging taxes in Quebec, Canada. In both settings, all virgin packaging materials were taxed, rather than one material type being preferentially taxed, e.g., taxing only plastic packaging. A recent paper by Yoo (2025) uses 2019-2020 Nielsen data to assess an ad valorem tax on plastic packaging for 20 ounce bottles or less, in addition to other policy options to reduce plastic waste; the paper estimates the demand for a subset of 17 beverage products in five U.S. states. It predicts the ad-valorem tax would halve the plastic use on average across the state-month markets.

There have been analyses of policies that preferentially tax or ban specific single-use plastic items due to environmental concerns- from grocery bags to drinking straws and plastic eating utensils. Straws and utensils have primarily been subject to bans, whereas plastic shopping bags have been banned or taxed. Plastic carrier bag bans have had unintended effects, like increasing consumption of higher weight plastic bags (Taylor, 2019; Macintosh et al., 2020). Plastic bag taxes resulted in large decreases in disposable bag use in Chicago but resulted in fewer negative unintended consequences than bag bans (Homonoff et al., 2021). In Uruguay, Cabrera et al. (2021) also find a fee on bags resulted in a large decrease in the consumption of grocery bags.

Product-based CO_2 taxes are other environmental taxes that have been considered in the literature. Bonnet et al. (2018) simulates the impacts of a different tax rates on animal products in France to reduce greenhouse gas emissions; they find that even a high tax rate would fail to reduce emissions by the targeted amount. When only beef (or lamb) is subject to the tax, consumers shift their demand to other untaxed animal products. Yan and Eskeland (2018) estimate the impacts of Norway's vehicle registration tax tied to vehicle CO_2 emissions; they find that the tax led to a decrease in CO_2 intensity of vehicles in Norway.

In consumer packaged goods, taxing plastic packaging would be analogous to proposed or implemented excise taxes on sugar, salts, or fats. Excise taxes for these nutrients have been considered since excessive consumption of these nutrients is associated with increased health costs. Researchers have predicted the impacts of these taxes ex ante, as well as estimated ex post impacts. Taxes on sugar sweetened beverages are some of the most commonly studied nutrient excise taxes. Sugar sweetened beverage (SSB) taxes have been implemented country-wide in many countries, including the United Kingdom, France, Mexico, Peru, South Africa, and Thailand, as well as in a handful of U.S. cities (World Bank Group, 2023). Tax rates have ranged from less than \$0.01/ounce to

$0.06/ounce.

A summary of some of the key findings from literature on SSB taxes are shown in Table 1. The studies have been split into ex ante analyses that estimate demand and then simulate counterfactual impacts of a national tax and ex post analyses that estimate the impacts of implemented local or national taxes using quasi-experimental methods. All identified studies use data collected prior to the global Covid-19 pandemic in 2020. All referenced ex ante studies use household-level home-scan panel data, such as KANTAR Worldpanel and Nielsen Homescan, rather than retail scanner data as their primary data source.

Some ex ante analyses of SSB taxes assume 100% pass-through of taxes to consumers; other ex ante studies calculate theoretical pass-through rates between 105 to 133% (Bonnet and Réquillart, 2013; O'Connell and Smith, 2024). The ex ante pass-through estimates aren't vastly different than most ex post estimates, which are also close to 100%, with the exception of Thomas (2025) which finds pass-through as low as 24% for some uniform pricing firms (Seiler et al., 2021; S. Kaplan et al., 2024; Dickson et al., 2025). DellaVigna and Gentzkow (2019) and Hitsch et al. (2021) show uniform pricing by U.S. retail chains across geographic markets, which could dampen the effects of market shocks.) Demand for soft drinks is generally found to be elastic in both ex ante and ex post studies, but the magnitude may vary by geographic location and product aggregation (e.g., UPC versus Brand level). Some studies report individual price elasticities or the mean of individual price elasticities while other studies report the price elasticity of entire categories, like all of sugar sweetened beverages or all soft drinks.

An extensive meta-analysis of ex post studies of implemented sugar sweetened beverage tax and pricing policies by Andreyeva et al. (2022) estimated an average tax pass-through rate of 0.82 and price elasticity of -1.59.

Table 1: Summary of a selection of literature on sugar-sweetened beverage excise taxes

	Location	Years	Mean Own Price Elasticity	Calculated Pass-Through
Ex Ante				
Bonnet and Réquillart, 2013	France	2005	-3.52	107-133%
Allcott et al., 2019	US	2006-2016	-1.37 (all SD)	NA
Dubois et al., 2020	UK	2009-2014	-2.6 to -3.3 -1.29 (all SD)	105-108% (Ex Post)
Salgado Hernández and Ng, 2021	Mexico	2012-2015	-1.2 to -1.3 (all SD)	NA
O'Connell and Smith, 2024	UK	2008-2012	-2.1 -1.4 (all SD)	105-108%
Ex Post				
Seiler et al., 2021	Philadelphia	2015-2018	-1.37	97%
S. Kaplan et al., 2024	5 U.S. Cities	2012-2020	-1.00	92%
Dickson et al., 2025	UK	2014-2020	Not reported	100-127%
Knox and Jones-Smith, 2025	4 U.S. Cities	2016-2018	-1.6 to -2.1	Not reported
Thomas, 2025	6 U.S. Cities	2014-2020	-1.8 to -2.5	24%-109% (retailer dependent)

SD refers to soft drinks as a category.

4 Data

I use the Nielsen retail scanner dataset from 2021 to 2023 as the primary data source for this research. Nielsen retail scanner data are comprised of weekly pricing and sales volumes from over 90 retail parent chains within major markets across the US, starting from the year 2006; new data are released annually, with a two-year lag. Stores report units sold and average prices at the Universal Product Code (UPC) level across each week. The UPC codes can be matched to a product description, the brand name, the product size (e.g., 32 fluid ounces), the number of units offered within a package (e.g., single or multi-pack), as well as to other product attributes, which may include packaging material. Since product size and packaging material vary by UPC even within the same brand, I am unable to meaningfully aggregate the UPCs, which will result in a high computational burden. Therefore, I limit my tax analysis to a single product category rather than the full universe of products. In an industry analysis, I identify soft drinks as the product category on which I will estimate the impact of a plastic packaging tax.

In addition to retail scanner data, I create a plastic packaging weight dataset from manufacturer websites, as well as from samples collected by walking the aisle. I weigh a small sample of cleaned and empty bottles and caps to use as estimates of packaging weight for the soft drink products.

Finally, I use producer price indices for relevant product categories from the U.S. Bureau of Labor Statistics (BLS) to use as instruments for price, which is endogenous in the demand model. These

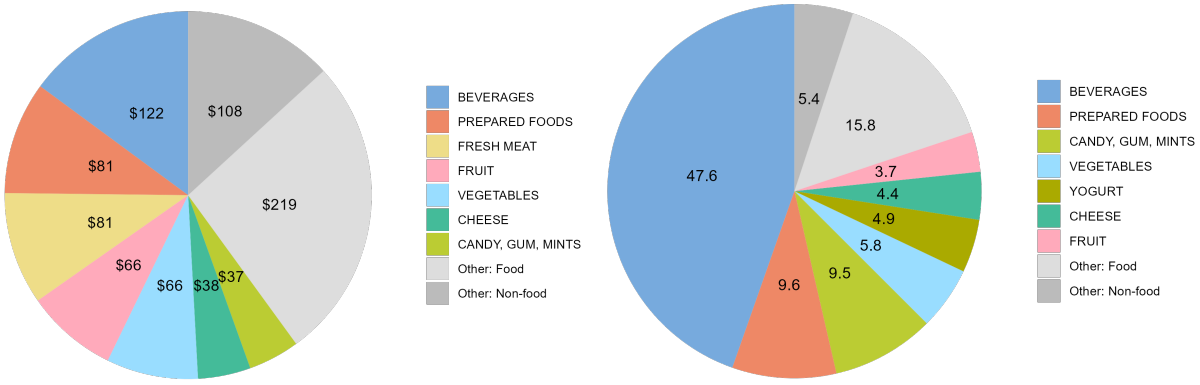


Figure 1: Super-category revenues (in billions of dollars) and percentage contribution to plastic packaging

national, monthly indices include the producer price indices for corn sweetener (a common ingredient in sugar-sweetened beverages) and aluminum and plastic resin, used in soft drink packaging. These indices when interacted with their respective product characteristics act as cost shifters. I also use monthly regional diesel prices from the U.S. Energy Information Administration (EIA) as another potential cost shifter.

4.1 Product Category Selection

A plastic packaging tax could impact a large proportion of products, since plastic packaging is used by nearly every consumer products industry. However, given the large size of datasets and sporadic packaging details, I have chosen to focus on one exemplar industry. An ideal industry for investigating the impacts of a plastic packaging tax would have 1) a meaningful economic significance, i.e., large revenue, 2) readily available packaging material data, 3) a relatively large volume of plastic in packaging, and 4) an existing mix of untaxed packaging materials to which consumers may substitute. To that end, I began by identifying super-categories in the Nielsen RMS which had large revenues and large proportions of identified plastic packaging units. Left side of Figure 1 shows that the beverages super-category generated $122 billion dollars at the Nielsen stores from 2021 to 2023, largest among the super-categories investigated; the right side of the figure also shows that almost 48% of the plastic packaging units identified in the Nielsen data were attributable to beverages. (It is worth noting that many UPCs are missing packaging material information in the Nielsen datasets; the beverage super-category has a relatively high percentage of UPCs with available packaging material type.)

The beverage super-category is comprised of 30 categories, including but not limited to soft drinks, water, sparkling water, fruit drinks, sport drinks, and energy beverages. Figure 2 shows that the two largest categories, by far, in terms of units sold are soft drinks and water. In the years of

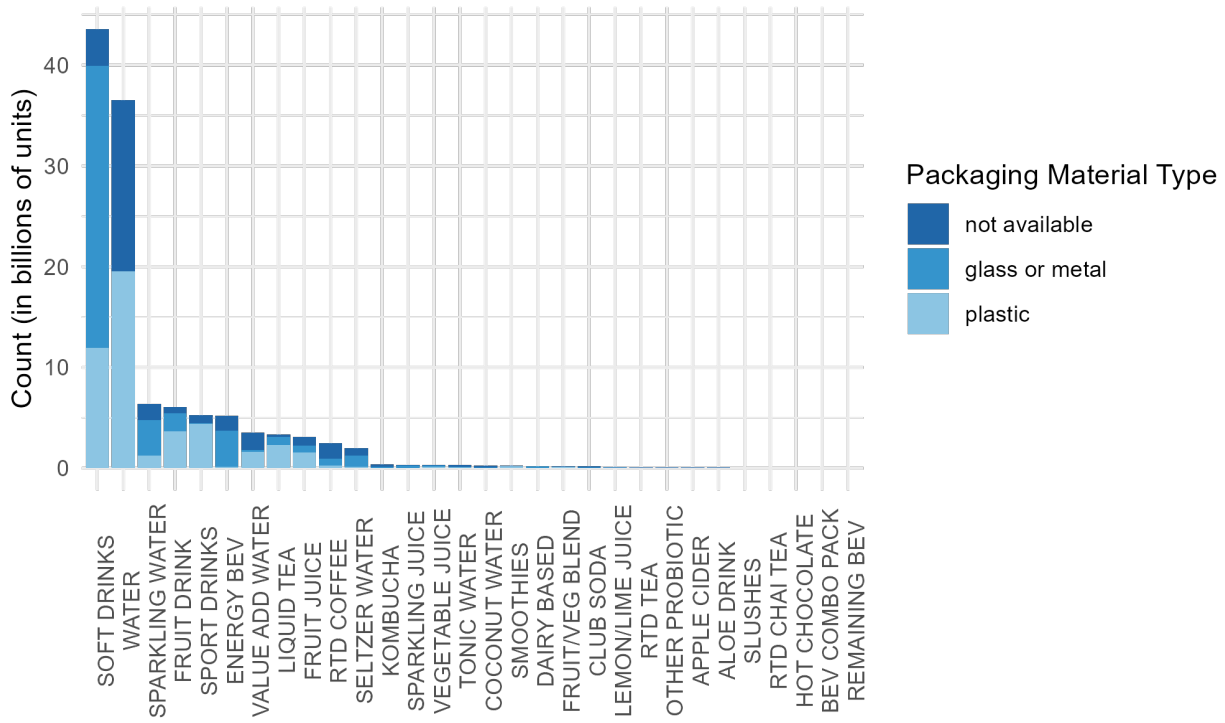


Figure 2: Beverage Units by Category and Packaging Material, 2021-2023

interest, over 40 billion containers of soft drinks were sold, and over 35 billion containers of water were sold making these both meaningful categories of interest. However, the figure also shows that many of the water products are either missing packaging material type or are packaged in plastic. Soft drinks, on the other hand, have fewer units with missing packaging information, as well as having a significant portion of glass or metal packaging. Soft drinks significant proportion of non-plastic packaging materials allows me to estimate preferences among different packaging types and allow me to see substitution between different packaging materials with the implementation of the tax. Given the economic significance and packaging material mix of the soft drink category, I choose to focus the remainder of my analysis on soft drinks.

4.2 Description of Retail Scanner Data

I initially aggregate to the UPC-store-month-year level using the UPC-store-weekly data to reduce computational burden. As shown in Table 2, the soft drink category is comprised of 9,446 individual UPCs across 484 brands sold in 56,295 stores within 2,740 counties; this results in 273,644,916 UPC-store-month observations; not all UPCs are sold in every store every month. Store location is defined by county, which I aggregate to Nielsen's Designated Market Areas ® (DMA), 205 non-overlapping geographic areas which receive similar advertising media. Stores are assigned to anonymized retail companies.

Table 2: RMS U.S. Soft Drink Sample Construction, 2021-2023

	Raw Sample	Final Sample
UPCs	9,446	3,645
Brands	484	303
Stores	56,295	45,395
Retailers	151	148
DMAs	205	205
UPC-store-month	273,644,916	241,250,051
Revenue	$37.221 B	$34.463 B

I limit the sample to products for which I have available information on brand, product size in ounces, packaging material type, multi-pack configurations, and store location, since these characteristics are used for demand estimation, and some of them are necessary for calculating the levied plastic packaging tax. I exclude in-store/deli soft drink purchases since packaging material is generally unknown. In addition to removing any implausible prices and sales quantities (possible data entry errors which may introduce noise in the model), I restrict to UPCs accounting for 99.99% of volume. I then restrict to stores with the top 99% of revenue and that offer a reasonable product selection, which I define as 30 or more distinct UPCs for sale. The final sample is comprised of 3,645 UPCs across 130 brands, sold in 45,395 stores. While the final sample has less than 40% of the raw sample's UPCs, I retain 241,250,051 UPC-store-month observations, which account for $34.463 billion in revenue across the three years, 2021-2023; my final sample covers over 90% of the revenue of the raw sample.

Defining a market as a combination of DMA-month-year, I calculate the UPC market share within each market. Table 3 summarizes the data across the 5,329,843 UPC-DMA-month observations. There is significant variation across the share outcome and the product characteristics, which is essential for identification. The number of UPCs available in each market varies widely, from 176 to 1377, with a mean of 722 UPCs. The price of soft drinks is about 6 cents per ounce but also has large variation; some of this variation in price per ounce is attributable to the volume in ounces, with larger packages generally having a lower price per ounce than smaller packages. Total size is the combined fluid ounces of soft drink sold under a single UPC unit, but I define the container size as being the fluid ounces held in the primary packaging, i.e., the can or bottle holding the soft drink. For example, the container size for a six-pack of 12-ounce cans is 12 ounces, while the total size is 72 ounces (6 times 12 ounces). On average, the share of soft drink ounces sold in plastic in a DMA-month market is 44%. Similar to Mariuzzo et al. (2003), I use diet soda and flavor as product characteristics in addition to product packaging. Regular soft drinks (versus diet soft drinks) account for an average 65.4% of soft drinks across all the markets. Cola is often the most commonly sold flavor, comprising an average 47.8% of soft drink volume sold in each market.

Table 3: Summary statistics for UPC-DMA-month observations (N=5,329,843)

	Mean	SD	Min	Max
UPCs per DMA-Month Market	722	191	176	1377
Share of DMA-Month Market	0.001	0.003	0.000	0.24
Price ($/sales unit)	3.70	2.70	0.20	67
Price ($/Oz)	0.072	0.056	0.002	1.4
Total Size (Oz)	75	63	5.8	480
Container Size (Oz)	23	21	2.7	432
Share per DMA-Month Market				
Plastic Share	0.444	0.085	0.204	0.686
Aluminum Share	0.548	0.083	0.306	0.794
Regular Soda	0.654	0.064	0.475	0.829
Flavor: Cola	0.478	0.049	0.355	0.723
Flavor: Citrus	0.129	0.061	0.015	0.317
Flavor: Pepper	0.118	0.059	0.023	0.331
Flavor: Lemon Lime	0.100	0.019	0.052	0.211
Flavor: Ginger	0.048	0.038	0.003	0.205
Flavor: Root Beer	0.037	0.013	0.005	0.081
Flavor: Orange	0.032	0.006	0.013	0.068

4.3 Packaging Material Weights

My proposed plastic packaging tax is levied on the mass of plastic used in the packaging, e.g., $1.00/kg of plastic. The increased price of taxed plastic-packaged soft drinks should lead consumers to substitute in one of two ways: 1) substitution to products packaged in metal or glass, or 2) substitution to products with a lower plastic intensity (for example, to a single larger container from many smaller containers). To calculate taxes on the amount of plastic used, I need the weight of the empty plastic soft drink bottles; unfortunately, this is not available in the Nielsen product data. Therefore, I generate a data set of plastic packaging weights for a subset of products. I collected samples of plastic soda bottles. Bottles were emptied and dried before being weighed on a calibrated scale. Bottles were weighed without caps or cap rings, and the caps were weighed separately. The scale was tared between each sample. Sample bottle volume ranged from 5.75 oz to 2 liters, across a range of brands. Becerril-Arreola and Bucklin (2021) also measured the mass of cleaned and empty PET bottles for carbonated soft drinks, without their caps; the paper's 2021 data do not take into account some of the reductions associated with recent bottle redesigns (Coca Cola Company, 2024).

Figure 3 shows the relationship between the bottle's fill volume in ounces and its unfilled mass in grams. The mass shown is for both the plastic bottle and its cap, since my proposed tax does not differentiate by the type of polymer. Generally, bottle mass increases with fill volume with the exception of some different volume bottles formed using the same mass preform; for example, 16.9-ounce and 20-ounce bottles tend to use the same preforms in bottle blow molding and, therefore, have the same unfilled mass. Cap mass consistently ranges from 1.9 g to 2.4 g and is not correlated

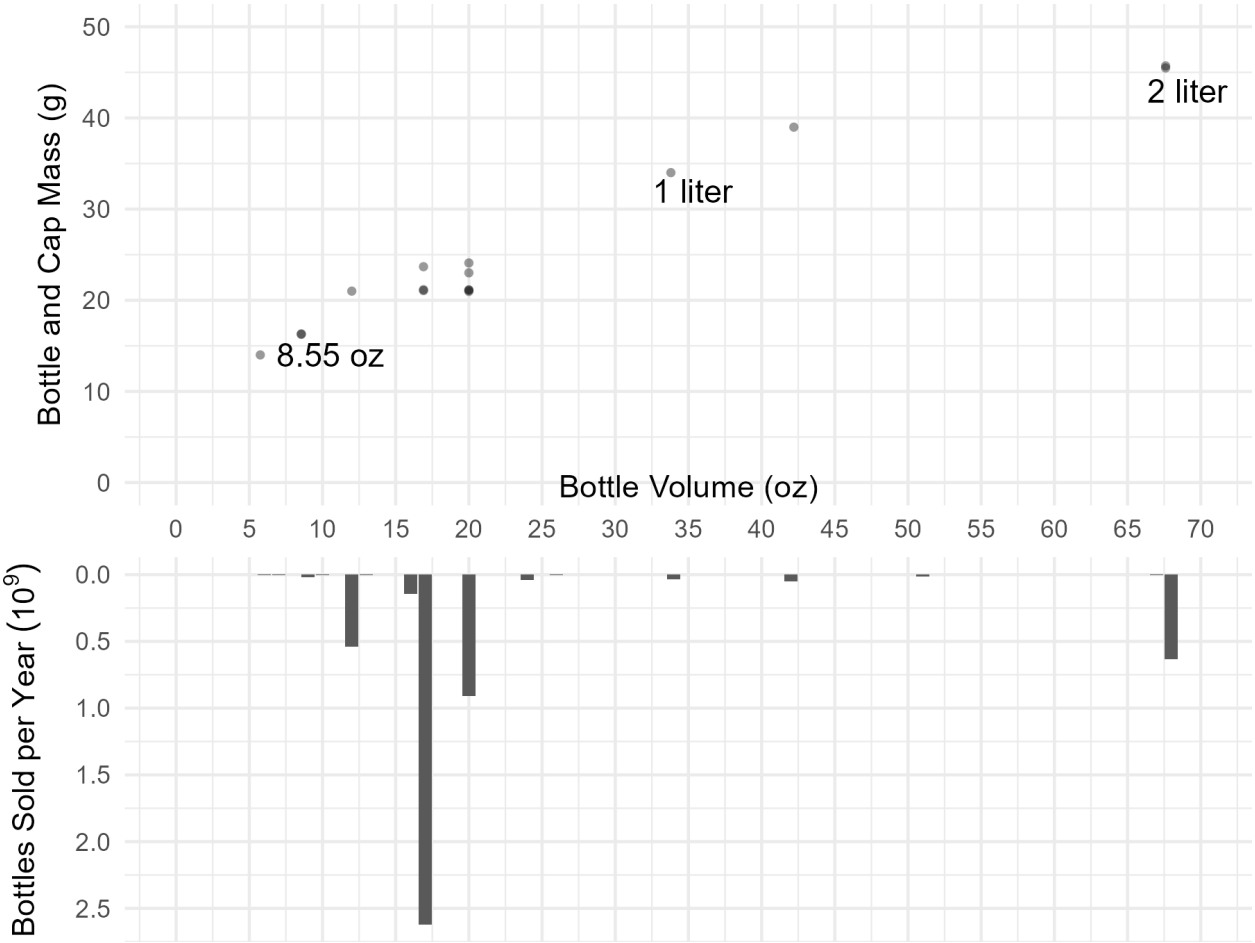


Figure 3: Plastic Soft Drink Bottle Mass versus Fill Volume

with bottle volume. The plastic intensity, defined as the number of grams of plastic used to hold each ounce of soft drink, decreases as bottle volume increases. Thus, eight 8.5-oz bottles or four 16.9-oz use 2.8 and 1.9 times as much plastic, respectively, as an volume-equivalent 2-L bottle. The lower panel of Figure 3 shows the average number of plastic bottles sold of each bottle size. The 16.9-oz bottles are the most commonly purchased bottle size in my dataset, accounting for over 2.5 billion bottles. The 16.9-oz bottles have a plastic intensity between 1.25 g/oz and 1.40 g/oz, double the plastic intensity of 2-L bottles.

A change that my model cannot account for is a reduction in the plastic mass used to fabricate a given bottle volume size by redesigning the bottles. While some companies have already undertaken a redesign of packaging to reduce their material usage, there are engineering constraints that make large reductions in plastic intensity for each bottle size challenging. A primary concern of the bottle design for a carbonated beverage is the large internal pressure - up to 55 pounds per square inch, required to keep the carbon dioxide dissolved. A reduction in mass without careful redesign would likely result in packaging failures and product loss.

5 Empirical Framework

In this section, I discuss how I estimate demand across all soft drink UPCs using a discrete choice model. I then impose a tax based on the weight of plastic packaging used in the product and then estimate the impact on sales and the weight of plastic packaging materials used within the industry. My preferred model is a nested logit model to elucidate the structure of consumer choices.

5.1 Demand Estimation

To estimate demand, I use share-based discrete choice models in which consumers choose among a set of N differentiated products. I borrow notation and explanations from Nevo (2000), Berry (1994), and Verboven (1996).

In a simple logit model, one assumes that consumer i's indirect utility V_{ijt} of product j in market t is given by

$$V_{ijt} = \underbrace{x_{jt}\beta - \alpha p_{jt} + \xi_{jt}}_{\nu_{jt}} + \epsilon_{ijt}$$

where p_{jt} is the price of product j in market t and x_j is a vector of product characteristics (e.g., size, flavor, caloric type, or packaging type) of j. Market t may be defined by geographic location and time; later notation will be more explicit as to the market definition. Assuming consumers maximize their utility across the product options and that ϵ_{ijt} is i.i.d. extreme value, then the mean utility ν_{jt} can be used to estimate the market share of product j in market t as

$$s_{jt} = e^{\nu_{jt}} / \sum_{k=0}^{N} e^{\nu_{jt}}$$

Mean level market share for the logit model may be estimated by the regression of $\ln s_{jlt} - \ln s_{0lt}$ on the product characteristics and price.

$$\ln s_{jlt} - \ln s_{0lt} = x_j\beta + \alpha p_{jlt} + \phi_{bl} + \phi_{lm} + \phi_{ly} + \epsilon_{jlt} \tag{1}$$

Product characteristics x_{jt} include the main packaging material (aluminum, plastic, or glass), container size, number of containers in a unit (multi pack count), whether the product is specially featured or displayed by the retail store, and whether the soft drink is full calorie or reduced/zero calorie. I use fixed effects to account for the unobserved product characteristics ξ_{jt}. Brand-location fixed effects ϕ_{bl} account for differences in brand quality and locational preferences for brands. Location-month and location-year, ϕ_{lm} and ϕ_{ly}, account for any trends in the location over time. The own-price elasticity of demand is calculated using $E_{jlt} = \alpha p_{jlt}(1 - s_{jlt})$.

Unfortunately, the logit model results in improbable substitution patterns driven by product market share rather than product similarity. A nested logit models creates more realistic substitution

patterns, in which substitution to products in the same nest is more likely than substitution outside the nest. Briefly, each consumer may choose among J products belonging to G distinct groups in the market. Consumer i's indirect utility from consuming product j belonging to group g in market t is defined as

$$V_{ijt} = \underbrace{x_{jt}\beta - \alpha p_{jt} + \xi_{jt}}_{\nu_{jt}} + \zeta_{ig[j]} + (1-\sigma)\epsilon_{ijt}$$

where $s_{j|glt}$ is product j's share of nest g in market lt and ζ_{ig} is a measure of utility common to all group g members that has distribution depending on σ. The σ term can be thought of as a measure of correlation within the groups. Assuming consumers maximize their utility across the product options, that ϵ_{ijt} is i.i.d. extreme value, then one can write the market share of product j in market t as

$$s_{jt} = \frac{e^{\nu_{jt}/(1-\sigma)}}{\left(\sum_{j\in J_g} e^{\nu_{jt}/(1-\sigma))}\right)^{\sigma}\left(\sum_{g\in G}\left(\sum_{j\in J_g} e^{\nu_{jt}/(1-\sigma))}\right)^{1-\sigma}\right)}$$

To facilitate estimation, one can linearize the equation to:

$$\ln s_{jlt} - \ln s_{0lt} = x_j\beta + \alpha p_{jlt} + \sigma \ln(s_{j|glt}) + \phi_{bl} + \phi_{lm} + \phi_{ly} + \epsilon_{jlt} \tag{2}$$

where the market is explicitly defined by both location l and time t, and s_{0lt} is the market share of an outside option.

One may allow for even more flexibility in substitution patterns by using multiple nesting levels. For the main specification, I use a two-level nested logit model with flavor f as the top level nest and caloric content c (defined by being regular or diet soda) as the lower level nest. Flavor is divided into eight broad flavor categories.

$$\ln\left(\frac{s_{jlt}}{s_{0lt}}\right) = X_{jlt}\beta + \alpha p_{jlt} + \sigma_1 \ln(s_{j|fclt}) + \sigma_2 \ln(s_{fc|flt}) + \phi_{bl} + \phi_{lm} + \phi_{ly} + \epsilon_{jlt} \tag{3}$$

In all cases of simple logit and nested logit, price is endogenous, such that exogenous variation from instrumental variables will be needed to estimate α. In the nested logit model, product j's share of the lower nest is also endogenous, so an additional instrument will be needed to estimate σ.

5.2 Tax Impact

O'Connell and Smith (2024), Seiler et al. (2021), and Dubois et al. (2020) estimate pass-through rates for sugar-sweetened beverage taxes to be around 100%. Therefore, given a similar product set to these papers, I assume that a plastic-packaging tax will be passed through to consumers at 100%. My proposed levied tax depends upon whether the packaging material is plastic, as well as the amount of plastic used in the packaging. The taxed price p^{τ} is the observed price p_{jlt} plus the product of a plastic container's mass m_j (in kilograms), $multi_j$ (the number of containers in the

sales unit), and the tax rate τ (\$/gram):

$$p^{\tau}_{jlt} = p_{jlt} + 1^{plastic}_{j} \times \tau \times m_j \times multi_j$$

The taxed price is fed back into the demand model to infer product shares under the tax, which is then used to determine the weight of plastic packaging used under the tax. It is expected that the tax will result in some substitution away from plastic products to products in aluminum and glass and to plastic-packaged products with lower plastic intensity such as larger bottle volumes.

6 Results

6.1 Demand

Table 4 shows the demand regression estimates from DMA-month-year market shares. The table includes estimates from an ordinary least squares (OLS) fixed effects regression, in addition to simple logistic regression and nested logistic regression with instrumental variables. While fixed effects have helped to account for some omitted variables bias, there is likely some remaining endogeneity in price, that needs to be addressed with instrumental variables.

IV logit model results in a significantly higher price coefficient than the OLS logit model; these models predict very different own price elasticities. The mean own price elasticity calculated using the IV logit model is -3.15, similar to the highly elastic individual product demand found by Dubois et al. (2020), Bonnet and Réquillart (2013), and O'Connell and Smith (2024). The OLS logit mean own price elasticity of -0.97, on the other hand, would indicate nearly unit elastic demand for individual drinks, which is unlikely given the high availability of substitutes in the soft drinks market.

While the substitution patterns predicted by the IV logit model are not realistic, the direction and magnitude product of characteristic coefficients is illuminating. The negative coefficient for container size and positive coefficient for multi indicates that consumers generally prefer smaller containers, purchased in multi packs to single containers with larger volume. This is particularly relevant since smaller containers are more plastic intensive than larger ones, as discussed in section 4.3. Furthermore, we can see that plastic packaging is more preferred to aluminum packaging. The preferences for these packaging configurations and materials may be rationalized by retaining soft drink carbonation - smaller volumes can be consumed in a single sitting while plastic containers are more likely to be resealable than aluminum ones. We can further see, by comparing coefficient magnitudes, that packaging material has a greater impact on share than calorie content.

The IV flavor-regular/diet nested logit is my preferred specification. The price coefficient is smaller than the IV logit model (-22.8731 versus -43.6248), but the magnitude of the mean own price elasticity, which takes into account both α and σ, is similar. If I limit to estimated own price

elasticities of just plastic packaged soft drinks, the mean own price elasticity is smaller, -2.566. The nesting parameter $\sigma_{j|flavor}$'s value of 0.5139 indicates significant similarity in products. The signs of other coefficients remain consistent between the IV logit and IV flavor nested logit model, although the magnitudes are smaller for the latter.

Table 4: Regression estimates of DMA-month share across individual UPCs, 2021-2023

Dependent variable: $\ln s_{jlt} - \ln s_{0lt}$	OLS LOGIT	IV LOGIT	IV FLAVOR NEST	IV FLAVOR REG/DIET NEST
Price ($/oz)	-13.4920 (0.3802)	-43.9517 (3.2498)	-21.9441 (2.1653)	-22.8731 (2.1679)
Container Size (oz)	-0.0013 (0.0009)	-0.0171 (0.0019)	-0.0083 (0.0011)	-0.0086 (0.0011)
Multi	0.0213 (0.0071)	0.1218 (0.0122)	0.0624 (0.0070)	0.0666 (0.0070)
Container Size × Multi	0.0048 (0.0006)	-0.0119 (0.0018)	-0.0061 (0.0010)	-.0066 (0.0010)
Features	2.6445 (0.2464)	0.9967 (0.2594)	0.3380 (0.1224)	0.3242 (0.1261)
Displays	4.1852 (0.3436)	4.0325 (0.3230)	2.0094 (0.1979)	2.0743 (0.1966)
Plastic (v Alum.)	0.5120 (0.0244)	0.8569 (0.0453)	0.4151 (0.03540)	0.4327 (0.0344)
Regular Soda (v Diet)	0.0543 (0.0118)	0.1245 (0.0138)	0.0264 (0.0097)	
$\sigma_{j\|Flavor}$			0.5139 (0.0299)	
$\sigma_{j\|FlavorRegDiet}$				0.50166 (0.0284)
$\sigma_{RegDietFlavor\|Flavor}$				0.4321 (0.0141)
Fixed Effects:				
DMA x month of year:	Y	Y	Y	Y
DMA x year:	Y	Y	Y	Y
Brand x DMA:	Y	Y	Y	Y
Observations	5,329,459	5,329,459	5,329,459	5,329,459
F-Stat	723.08	559.08	2372.89	2263.46
SE Clustering	DMA	DMA	DMA	DMA
KP Wald F-test stat		539.94	273.310	205.15
Hansen's J Statistic		5.457	0.542	1.003
RMSE (predicted shares)		0.0034	0.0028	
Own Price Elasticity	-0.968	-3.154	-3.234	-3.285

6.2 Impacts of Tax on Plastic Usage

Given pass-through estimates near 100% in the literature, I assume a 100% pass-through rate for the plastic packaging tax. I calculate the new taxed price for each product in each market according to the formula in section 5.2. I use the taxed price p^{τ}_{jlt} and the nested logit model to predict the counterfactual share of each UPC over the sample period (2021-2023). Using the new shares, I then calculate the packaging material quantity. Table 5 shows the sales volume (in ounces) predicted by the demand model with non tax and at three taxes levels: $0.50/kg, $1.00/kg, and $5.00/kg of plastic. As shown in the second column, the total sales of soft drinks over the three years declines from 824.6 billion ounces (about 24.4 billion liters) to 685.2 billion ounces (about 20.3 billion liters) at the highest tax rate. The third and fourth columns split the sales among sales in plastic bottles and sales in aluminum cans (glass is a small fraction of sales and is not shown). The material's

Table 5: Predicted Impact of Tax Rates on Soft Drink Sales, 2021-2023

Tax Rate	Total Sales (oz)	Sales in Plastic (oz)	Sales in Aluminum (oz)	Sales in Plastic in 16 oz or less	Sales in Plastic in 16-50 oz	Sales in Plastic in 50 oz or more
Baseline	824.6×10^9	377.8×10^9 (45.8%)	443.1×10^9 (53.7%)	28.8×10^9 (7.6%)	241.2×10^9 (63.8%)	107.9×10^9 (28.6%)
\$0.50/kg	820.3×10^9	370.7×10^9 (45.2%)	445.9×10^9 (54.4%)	27.9×10^9 (7.5%)	235.8×10^9 (63.6%)	106.9×10^9 (28.8%)
\$1.00/kg	816.1×10^9	363.6×10^9 (44.6%)	448.7×10^9 (55.0%)	27.1×10^9 (7.5%)	230.6×10^9 (63.4%)	105.9×10^9 (29.1%)
\$5.00/kg	785.2×10^9	311.2×10^9 (39.6%)	470.1×10^9 (59.9%)	21.3×10^9 (6.8%)	191.9×10^9 (61.7%)	98.1×10^9 (31.5%)

Table 6: Predicted Impact of Tax Rates on Packaging Material Usage, Revenue and Changes to Consumer Surplus, 2021-2023

	Packaging Material Predicted Weight (kg)		Tax Revenue	Δ CS
Tax Rate	Plastic	Aluminum	($\times 10^6$)	($\times 10^6$)
No Tax	437.8×10^6	523.9×10^6	\$0	
\$0.50/kg	428.7×10^6	527.2×10^6	\$214.3	-\$216.6
\$1.00/kg	419.7×10^6	530.5×10^6	\$419.7	-\$428.7
\$5.00/kg	353.3×10^6	555.8×10^6	\$1766.5	-\$1971.3

proportion of total sales are shown underneath in parentheses. The percentage of sales in plastic decreases from almost 46% to under 40% at the highest tax rate. The last three columns show a breakdown of the plastic sales by bottle sizes: 16 ounces or less, between 16 and 50 ounces, and 50 ounces or more. A small shift from smaller containers to larger containers can be observed with an increase in the tax rate, but the shifts are not as pronounced as the shifts from plastic to aluminum.

Table 6 shows the predicted quantities of packaging material weights at each tax rate. The \$0.50/kg, \$1.00/kg, \$5.00/kg tax rates result in 2.1%, 4.1%, and 19.3% declines in overall plastic weight, respectively; they also lead to increases of 0.6%, 1.3%, and 6.1% in aluminum, respectively. The two final columns of the table show the expected collected tax revenue, which is the tax rate times the weight of plastic, and the change in consumer surplus. One can see that the decline in consumer surplus is larger than the tax revenue, which implies a decline in overall welfare. However, these calculations do not take into account any social costs of plastic. If the social costs of plastic use are large, then welfare will be improved by the tax.

7 Discussion

Using the 2021-2023 Nielsen Retail Scanner Data, I find similar own price elasticities as previous studies using data prior to 2020, before the Covid-19 pandemic, which confirms that the demands for individual soft drinks remain elastic. Despite price elastic demand for soft drinks, the tax rates I investigate have only modest impacts on the aggregate amount of plastic packaging used by the

soft drinks industry. This is likely driven by a consumer preference for plastic consumed in small containers. A tax rate of $0.50/kg, equivalent to the largest proposed rates in the U.S., results in a 2.1% decrease in plastic packaging used for soft drinks. Even a large tax rate of $5.00/kg, more than five times the rate proposed by the E.U., reduces plastic use by only 19%. I also find that, at all tax rates, the decrease in consumer surplus from the tax outweighs the tax revenue collected from the tax. However, the changes in welfare do not account for any reductions in social costs associated with the tax. Those social costs can include costs associated with plastic use as well as possible social costs associated with health from overall lower consumption of soft drinks.

This paper considers the short- to medium-term impacts of a plastic packaging tax to current product mix. In the long-run, soft drink firms can adapt by redesigning products and their packaging to use less plastic. Firms may be able to create new formulations using less packaging overall or more sustainable. For example, firms may offer more products compatible with at home soda makers, such as offered by SodaStream, DrinkMate, and SMEG.

A Supplementary Data Tables

Table 7: Summary of U.S. State Relevant EPR Legislation

State	Legislation	Plan Status	Plastic Reduction Targets	Plastic Recycling Rate Targets	Beverage Container Deposit	Example material fees
California	SB 54	Implementation in 2027	25% by 2032	65% by 2032	Exempt	Clear PET: 11¢/lb + 0.10¢/unit Aluminum[1]: 7¢/lb
Colorado	HB 22-1355	Approved	None	55% by 2035 (all materials)	NA	Clear PET: 15.0¢/lb Aluminum: 2.0¢/lb
Maine	LD 1541	RFP for SO	40% by 2040 (all materials)	75% by 2045	Exempt	TBD
Maryland	SB 222 SB 901	Fee collection in 2029	None TBD	50%	NA	TBD
Minnesota	HF 3911	Draft by 2028	None	75% by 2030 (all materials)	NA	TBD
Oregon	SB 582B	Approved	None	25% by 2028 50% by 2040	Exempt	Clear PET: 25¢/lb Aluminum: 6/lb
Washington	SB 5284	Draft by 2028	TBD	TBD	Not applicable	TBD

Reference Sustainable Packaging EPR summaries; CAA: Circular Action Alliance; CA Illustrative Fees Note that California has CRV (California Refund Value) fees on beverage containers since 2007, so are exempt Beverage Container Recycling Program. https://circularactionalliance.org/california [1] CA Aluminum - foil molded container w/o plastic component (using low scenario). In Maine, PRO is referred to as Stewardship Organization (SO).

B Quantile Regression

Unlike standard linear regression which estimates the conditional mean of a dependent variable, median regression estimates that conditional median of a dependent variable. Median regression is more robust to outliers (like the extreme values I observe in product market shares) than mean regression. Median regression is a special case of quantile regression in which the conditional 0.50-quantile is estimated. Quantile regression may use the same linear equation as ordinary least squares regression, but, rather than minimizing the square of the residuals, the quantile regression estimator β_q for quantile q minimizes the following objective function:

$$\sum_{i:y_i \geq x_i\beta}^{N} q\,|y_i - x_i\beta_q| + \sum_{i:y_i < \beta}^{N} (1-q)\,|y_i - x_i\beta_q| \tag{B.1}$$

For median regression, equation B.1 simplifies to

$$\sum_{i}^{N} |y_i - x_i\beta_{med}|$$

In demand estimation, price is an endogenous variable requiring the use of instrumental variables. Chernozhukov and Hansen (2005)'s instrumental variable quantile regression (IVQR) model and D. M. Kaplan and Sun (2017)'s smoothing of the IVQR's smoothing of the moment conditions allows me to estimate a quantile regression for the logit model of equation (1). While a STATA function has been created to implement a smoothed IVQR, it does not take into account fixed effects, which require the data to be manually demeaned (D. M. Kaplan (2022)). Estimate precisions need to be determined via bootstrapping, taking the demeaning into account in each bootstrap iteration. Given the large size of the dataset, rough estimate precision was determined using 300 bootstrap iterations. The logit demand model is used for comparison since the nested logit models failed to converge. The results are shared in Table 8 in the next section.

C Alternative Models

This section covers alternative regression models used for demand. My preferred dataset uses prices winsorized at the 0.1% level, but I also calculate the IV models using prices that have not been winsorized. These are shown in columns two, three, and six. I find similar regression coefficient estimates to the models estimated using the winsorized prices, but the range of individual elasticities are more reasonable.

I also calculate a nested logit model using simplified flavor groupings. Rather than the eight flavor groupings in my original model, I have four flavor groupings. The model appears to be mis-specified since nest coefficient is negative, but should be between 0 and 1; I could find no instrumental variables that would lead to a feasible σ value. I also tried using an unrestricted nested logit model with the simpler flavor categories where there is a separate coefficient for each nest; this again resulted in at least one infeasible, negative $\sigma value$.

I also tried a different double nesting structure with flavor as the top nest and packaging material as the bottom nest. In this case, the price coefficient was positive, indicating mis-specification or unaddressed endogeneity.

Finally, as mentioned in section B, I ran an IV median regression on the logit demand model. I wanted to verify that the regression estimates were not being driven by extreme values. The median regression coefficient for price is fairly similar to the logit regression based on means rather than medians.

Table 8: Alternative regression demand models

Dependent variable: $\ln s_{jlt} - \ln s_{0lt}$	IV LOGIT	IV FLAVOR NEST	IV SIMPLER FLAVOR NEST	UNRESTRICTED IV SIMPLER FLAV	IV FLAVOR REG/DIET NEST	IV FLAVOR PKG MAT NEST	IV LOGIT (Median Reg)
Price ($/oz)	-43.6248 (3.2457)	-21.9441 (2.1653)	-92.5555 (7.4977)	-42.2234 (3.8489)	-22.8731 (2.1679)	11.9487 (0.9251)	-32.0759 (2.6218)
Plastic (v Alum.)	0.8430 (0.0446)	0.4151 (0.03540)	1.7557 (0.1061)	0.8178 (0.0593)	0.4327 (0.0344)		0.4330 (0.0331)
Regular Soda (v Diet)	0.1186 (0.0135)	0.0264 (0.0097)	0.2679 (0.0282)	0.1002 (0.0129)		-0.0518 (0.0060)	0.0417 (0.0142)
$\sigma_{j\|Flavor}$		0.5139 (0.0299)	-1.0095 (0.1416)				
$\sigma_{j\|CITRUS_LL}$				-0.0072 (.0450)			
$\sigma_{j\|COLA}$				0.0142 (0.0412)			
$\sigma_{j\|OTHER}$				0.0444 (0.0491)			
$\sigma_{j\|PEPPER_RB}$				0.0031 (0.0480)			
$\sigma_{j\|RegDietFlav}$					0.5017 (0.0284)		
$\sigma_{RegDiet\|Flav}$					0.4321 (0.0141)		
$\sigma_{j\|PkgMtFlav}$						0.6483 (0.0283)	
$\sigma_{PkgMat\|Flav}$						0.8834 (0.0293)	
F-Stat	538.24	2372.89	170.42	560.73	2263.46	1693.32	
KP Wald F-test stat	508.259	273.310	38.338	69.179	205.146	63.264	
Hansen's J Statistic	4.693	0.542	7.536	3.331	1.003	9.919	

Though not shown, product characteristics include features, display, and interaction container size and multipack. Flavor is either a covariate or part of nesting. All columns included fuel intensity & aluminum ppi as instrumental variables. Additional IVs by column: (2) Rival products of same flavor (3) Rival products of same flavor and rival products of same flavor and reg/diet, 4) Rival products of same flavor and rival products of same flavor and package material. SE clustering at DMA level. Fixed effects include DMA x month, DMA x year, and Brand x DMA. There is no winsorization of prices.

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