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Bag leakage: The effect of disposable carryout bag regulations on unregulated bags☆

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ABSTRACT

Leakage occurs when partial regulation of consumer products results in increased consumption of these products in unregulated domains. This article quantifies plastic leakage from the banning of plastic carryout bags. Using quasi-random policy variation in California, I find the elimination of 40 million pounds of plastic carryout bags is offset by a 12 million pound increase in trash bag purchases—with small, medium, and tall trash bag sales increasing by 120%, 64%, and 6%, respectively. The results further reveal 12–22% of plastic carryout bags were reused as trash bags pre-regulation and show bag bans shift consumers towards fewer but heavier bags. With a substantial proportion of carryout bags already reused in a way that avoided the manufacture and purchase of another plastic bag, policy evaluations that ignore leakage effects overstate the regulation's welfare gains.

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1. Introduction

Governments often regulate or tax the consumption of products with negative externalities (e.g., alcohol, tobacco, sugar, and gasoline). However, policies are not always complete in their coverage, applying to only a subset of jurisdictions or products contributing negative externalities. Leakage occurs when partial regulation directly results in increased consumption of these products in unregulated parts of the economy (Fowlie, 2009). If unregulated consumption is easily substituted for regulated con-

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sumption, basing the success of a regulation solely on reduced consumption in the regulated market overstates the regulation's welfare gains.

In this article, I quantify leakage from the regulation of plastic in consumer goods. The United Nations Environmental Program estimates that 10 to 20 million tonnes of plastic enters the world's oceans each year, costing $13 billion in environmental damage to marine ecosystems, including losses incurred by fisheries and tourism (UNEP, 2014). With growing concern about the costs of plastic waste, governments are turning to economic incentives and command-and-control regulations to curb the use of consumer plastics. An increasingly popular environmental policy has been the regulation of disposable carryout bags (DCB).[1] Approximately 242 local governments in the U.S. adopted DCB policies between 2007 and 2016, across 20 states and the District of Columbia.[2] Most DCB policies in the U.S. prohibit retail food stores from providing customers with thin plastic carryout bags at checkout and require stores to charge a minimum fee for paper and other reusable carryout bags. However, all remaining types of disposable bags are left unregulated (e.g., trash bags and waste bin liners). Given DCBs can be reused as trash bags before they are disposed,[3] this article asks the empirical question: Do bans on plastic carryout bags cause consumers to increase their purchases of unregulated plastic trash bags?

The answer to this question is not only relevant for quantifying leakage; it also provides a key variable for evaluating the environmental effectiveness of DCB policies. Life-cycle assessments (LCAs)—studies that estimate a product's cradle-to-grave environmental impact—are used, and often required, by governments around the world in designing environmental legislation (Ehrenfeld, 1997; Rebitzer et al., 2004).[4] LCAs of plastic, paper, and reusable carryout bags have been shown to be sensitive to assumptions made about the weight and number of trash bags displaced by the secondary use of plastic carryout bag, with the reuse of plastic carryout bags as bin liners substantially improving their environmental performance (Mattila et al., 2011). According to a UK Environmental Agency (2011) study, a shopper needs to reuse a cotton carryout bag 131 times to have the same global warming potential (measured in kilograms of CO2 equivalent) as plastic carryout bags with zero reuse, while that same cotton bag needs to be reused 327 times if all plastic carryout bags are reused as bin liners. Thus, a contribution of this paper is to provide an estimate for the *reuse* of plastic carryout bags that policymakers can use as a benchmark for calculating and interpreting LCA results.

Determining the causal relationship between regulations and leakage is challenging because one must construct a credible counterfactual for consumption in the absence of the regulation, both for regulated and unregulated goods. To understand the causal effect of DCB policies on regulated and unregulated bag consumption, I take advantage of quasi-random variation in local government DCB policy adoption in California—where 139 policies were implemented over nine years. Having more than one policy change over time allows me to separate the causal effect of the policies from other time-varying factors. The second challenge I address is that of limited data. I bring together two data sources: (i) weekly retail scanner data with store-level price and quantity information on trash bag sales, and (ii) observational transaction-level data collected in-store for the number and types of carryout bags used at checkout. Leakage, in this case, is quantified by comparing changes in trash bag sales (from the scanner data) to changes in carryout bag use (from the observational data). While data on trash bags sales are readily available to researchers in retail scanner datasets, such as the one used in this paper, transaction-level data on carryout bag use (for both bags obtained in the store and those brought from outside) are more challenging to obtain, due to their manual, time-consuming nature to collect.[5] Thus, another contribution of this paper is the combination of scanner and observational data, which does not rely on consumers self-reporting their bag use.[6]

Using quasi-random variation in policy adoption and bag use data over time, I employ an event study design to quantify the effect of DCB policies on the use of plastic, paper, reusable carryout bags, as well as the sale of four types of trash bags. The results show that a 40 million pound reduction of plastic per year from the elimination of plastic carryout bags is offset by an additional 12 million pounds of plastic from increased purchases of trash bags. In particular, sales of small, medium, and tall trash bags increase by 120%, 64%, and 6%, respectively. This means that 28.5 percent of the plastic reduction from DCB policies is lost due to consumption shifting towards unregulated trash bags. The results also provide a lower bound for the reuse of plastic carryout bags, with 12–22% of plastic carryout bags reused as trash bags pre-regulation. In other words, a substantial proportion of carryout bags were already reused in a way that avoided the manufacture and purchase of another plastic bag.

[1] Disposable carryout bag (DCB) refers to either plastic or paper carryout bags provided by retailers at checkout for "free." In fact, retailers pass the cost of DCBs on to their customers in the overall price of goods purchased.

[2] For lists of disposable bag policies in the U.S., see Californians Against Waste, www.cawrecycles.org/list-of-national-bans, *accessed 21 May 2018*.

[3] Surveys conducted in 2007 found that 51 percent of households report reusing their plastic carryout bags, and of those that reuse, 55 percent report reusing their plastic carryout bags as trash bags and waste bin liners (AECOM, 2010).

[4] International standards for LCAs (referred to as the ISO 14040 series) have been developed to provide a consensus framework for industries and policymakers to incorporate LCAs in their guidelines and/or laws (ISO 14040, 2006).

[5] Rigorous in-store data collection and analysis of carryout bag use pre- and post- DCB policy change have been conducted in the Washington D.C. metropolitan area (Homonoff, 2018), California (Taylor and Villas-Boas, 2016), and Chicago (Source: "Chicagoans Reduce Disposable Bag Use by Over Forty Percent Since Implementation of Checkout Bag Tax," *ideas42, New York University, and the University of Chicago Energy and Environment Lab*, 24 Apr. 2017, www.ideas42.org/cbdt, *accessed 22 May 2018*).

[6] Food retailers—such as grocery stores—are often used as laboratories to test economic theory. For instance, grocery store scanner data has been used to test the effects of tax salience on consumer demand (Chetty et al., 2009), income effects from sharp changes in fuel prices (Gicheva et al., 2010), and avoidance behavior from negative environmental shocks (Graff Zivin et al., 2011).

These results provide an estimate of the share of consumers already behaving in a manner that reduces waste and carbon emissions. This is akin to the economic debate over how many recipients of environmental subsidies are "non-additional"—i.e., getting paid to do what they would have done anyway (Joskow and Marron, 1992; Chandra et al., 2010; Gallagher and Muehlegger, 2011; Boomhower and Davis, 2014; Ito, 2015).[7] For instance, Boomhower and Davis (2014) find that half of all study participants that received an energy-efficiency subsidy would have replaced their appliances with no subsidy. The concern is that a subsidy will not be cost-effective if a large enough fraction of consumers is non-additional. In the case of DCB policies, instead of rewarding too many consumers for the green behavior they would have done anyway, DCB policies restrict the choice set of green behaviors available, preventing green behaviors that would have been done anyway. Therefore, this paper empirically addresses the critical question of "subtractionality"—i.e., how many consumers would have reused their plastic carryout bags as trash bags, had they not been banned. Moreover, this paper examines *who* are the subtractional customers. Supplemental heterogeneity analyses reveal that plastic bag reuse is correlated with having a pet or a baby (i.e., having dependents whose waste must be collected and disposed of), spending less per item (i.e., bargain shopping), purchasing more items per trip, and having a college degree.

This article also extends the literature on pollution leakage and spillover effects. While numerous studies analyze leakage related to regulating production-driven externalities (such as greenhouse gas emissions),[8] the empirical literature examining leakage from regulating consumption-driven externalities is limited. Adda and Cornaglia (2010) analyze the effect of smoking bans in public places on exposure to second-hand smoke. The authors find that bans displace smokers to private places where they contaminate non-smokers, especially young children. Davis (2008) studies a policy in Mexico City where drivers are prohibited from using their vehicles one weekday per week on the basis of the last digit of their vehicle's license plate. The author finds no change in air quality due to the policy; instead, drivers circumvent the restriction by increasing the total number of vehicles in circulation. Similar to these studies, I find that DCB policies are circumvented by consumers substituting towards unregulated plastic bags.

Finally, this paper contributes to the literature by examining the persistent effects of behavioral interventions. Do interventions set a new behavioral status quo (or default) which lasts indefinitely, or do behaviors drift as people re-optimize? Cronqvist et al. (2018) argue that this question has not received enough attention, and as it is inevitably an empirical question, we should expect variability across contexts. Cronqvist et al. (2018) find that the effects of defaults in pension plan selection are remarkably persistent, lasting nearly two decades. Allcott and Rogers (2014) study the short-run and long-run effects of monthly social comparison reports on energy use and find the average treatment effect increases at a declining rate over the first four reports and then persists for the remainder of the reports. Conversely, Jacobsen (2011) found that the release of Al Gore's documentary *An Inconvenient Truth* led to a temporary increase in household purchases of voluntary carbon offsets—the effect only lasting a couple of months. Similar to these studies, this paper is able to analyze the persistent effects of DCB regulations on bag use. The results reveal that increased sales of trash bags persist at least four years after policy implementation (the entire length of the post-policy sample period).

Policy-induced changes in plastic bag use have implications for greenhouse gas emissions, marine debris, and landfilling. I conclude this article by discussing the benefits of reduced litter and marine debris from thin plastic carryout bags, the costs of greater emissions from the production of thicker bags, and the costs of thicker bags taking up more space in landfills. If carbon footprint was the only metric of environmental success, the results in this paper suggest DCB policies are having an adverse effect. However, if the unmeasured benefits with respect to marine debris, toxicity, and wildlife are great enough, they could outweigh the greenhouse gas costs. While the upstream relationship between plastic production and carbon footprint is well understood, the downstream relationship between plastic litter and marine ecosystems is less established, making it challenging to evaluate the environmental success of DCB policies. However, it is clear that ignoring leakage overstates the regulation's welfare gains.

The remainder of the article is organized as follows. Section 2 describes the policy implementation variation and catalogs the data. Section 3 presents the event study empirical design. Section 4 reports the event study results, as well as robustness checks. Section 5 quantifies the leakage effect and discusses the environmental implications of changes in the composition of plastic bags, with respect to carbon footprint, landfilling, and marine pollution. Section 6 presents heterogeneity analyses, introducing supplemental data at the customer-level. Section 7 concludes with policy implications and future research.

2. Data

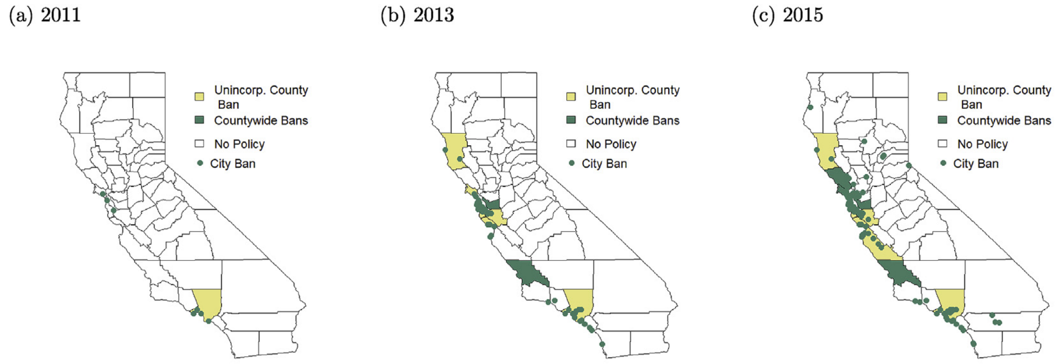
2.1. Adoption of disposable carryout bag regulations

With variation in policy adoption across time and space, California provides an exceptional quasi-experiment for analyzing the effects of DCB policies. From 2007 through 2015, 139 Californian cities and counties implemented DCB policies, affecting over one third of California's population.[9] This local legislative momentum continued and culminated with the nation's first statewide

[7] There is a large literature on non-additionality and "free-riders" in energy efficiency programs, for which Boomhower and Davis (2014) provide a thorough discussion.

[8] See Fowlie (2009) and Fowlie et al. (2016a,b) for a review of this literature.

[9] Author's calculations. See Online Appendix Table A.1 for a list of California DCB policies and implementation dates from 2007 to 2015.



Note: The local governments of unincorporated counties and incorporated cities can pass ordinances to regulate disposable carryout bags. City-level policies are depicted with dark green circles. Unincorporated county policies are shaded in light yellow. Countywide policies—where all unincorporated areas and all cities in a county implement DCB regulations—are shaded in dark green.

Fig. 1. California disposable carryout bag (DCB) policies over time.

plastic carryout bag ban, which was voted into law on November 8, 2016. Fig. 1 maps the implementation of DCB policies in California at three points in time. Similar to other local government waste regulations, DCB policies may be implemented by city councils (for incorporated areas), county boards of supervisors (for unincorporated areas), and county waste management authorities (for entire counties with opt-out options for incorporated areas). This figure shows that DCB policies have varied greatly in both their implementation dates and locations.

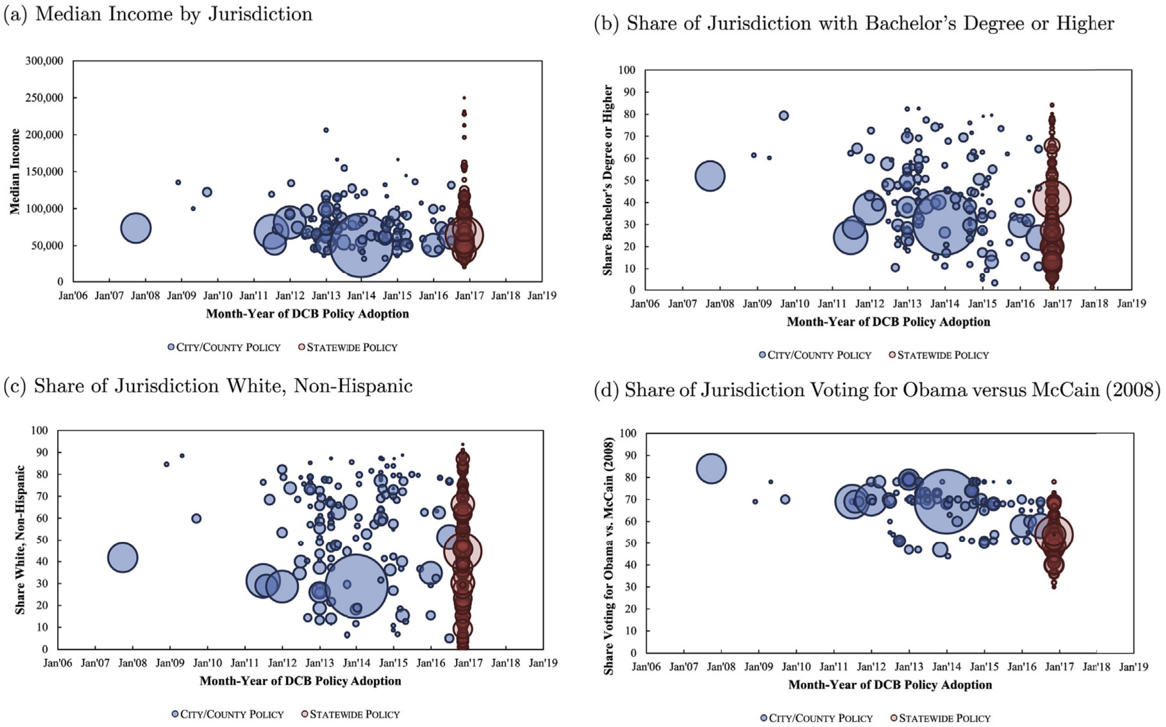
It is important to note that local jurisdictions decide when DCB policies will be operative; the stores within a jurisdiction do not make this decision. The start date is specified in a jurisdiction's ordinance document (i.e., bill). Examining the ordinance documents of all 111 jurisdictions in California that implemented DCB policies between 2007 and 2014, I find that 21% of jurisdictions specified January 1 as their start date, 30% specified the first of a month that was not January, 14% chose Earth Day (April 22), 11% chose a specific date other than the first of the month, and 23% did not specify a specific date and instead wrote to be operative 1, 3, or 6 months after adoption. Start dates vary across all days of the week. Importantly, while start dates were not randomly chosen, the dates were also not selected in a systematic way across all jurisdictions. The event study empirical strategy exploits this quasi-random variation in DCB policies across time and space to explore how DCB policies influence the use of plastic bags.

Fig. 1 also shows that, before the statewide DCB policy in 2016, the majority of local DCB policies were adopted in coastal counties—where nearly 70% of California's population lives (Wilson and Fischetti, 2010). To further understand whether and how early adopting jurisdictions differ from late adopting jurisdictions, Fig. 2 plots jurisdictions by their implementation dates (x-axis) and four population characteristics (y-axis): (a) median income, (b) education attainment, (c) racial composition, and (d) voting behavior. Panels (a), (b), and (c) demonstrate that early adopting jurisdictions are not systematically more or less affluent, educated, or white than later adopting jurisdictions, with substantial variation and overlap in these measures amongst both early and late adopters. Conversely, panel (d) shows that voting for the Democratic presidential candidate in 2008 is a strong predictor of being an earlier implementor of a DCB policy. Early adopters had Democratic vote shares between 44 and 84 percent while late adopters had vote shares between 30 and 78 percent.

Even though early and late adopting jurisdictions may have different characteristics (such as political leaning), this will not lead to biased estimates as long as there is no trend in the difference between early and late adopters' bag sales in the pre-policy period. With the variation in policy implementation shown in Figs. 1 and 2, I will estimate the causal effect of DCB policies on bag sales using an event study design. The identifying assumption of the event study model is that, absent the DCB policies, outcomes (i.e., bag sales) in treated jurisdictions (i.e., early adopters) would have remained similar to the control jurisdictions (i.e., late adopters). Underlying trends in the outcome variable correlated with DCB policy enactment are the most likely violation of this assumption. Yet part of the appeal of an event study model—especially one with several treatment units and dates—is that it provides a way to investigate this possible violation. Event study models align the treatment events so that the differences in outcomes between early and late adopters can be plotted and tested over event-time, both *before* and after the policy change.

2.2. Retail scanner data

To measure trash bag sales, I use the Retail Scanner Database collected by AC Nielsen and made available through the Kilts Center at The University of Chicago Booth School of Business. The retail scanner data consist of weekly price and quantity



Note: This figure plots California jurisdictions by their DCB policy implementation dates (x-axis) and population characteristics (y-axis). Each circle in each panel represents one of the 539 jurisdictions in California and the size of the circle corresponds to the population size of the jurisdiction in 2010 (e.g., the largest circle is Los Angeles city, with a 2010 population of 3.8 million). Blue circles represent jurisdictions that adopt regulations before the statewide policy is implemented while red circles represent jurisdictions covered by the statewide policy. *Sources*: Author's calculation. Population, median household income, education, and race statistics come from U.S. Census Bureau, 2010 Census of Population and 2008-2012 American Community Survey. 2008 U.S. Presidential election results were compiled by the New York Times

Fig. 2. Jurisdiction characteristics by implementation date.

information generated by point-of-sale systems for participating retail chains across the United States.[10] I use a subset of retail scanner data from participating stores in California between January 2009 and December 2015. While this database contains a wide variety of store formats and types, I focus my analysis on food stores (i.e., supermarkets, grocery stores, and specialty food stores), mass merchandising stores (e.g., supercenters and big-box stores), and drug stores because these stores formats regularly sell non-food grocery items, such as trash bags.

I design a sample of participating stores ideal for the event study model which I present in Section 3. I include stores in jurisdictions (i.e., counties or cities) that meet the following criteria: (1) the jurisdiction is located in California and is no more than 50 miles from the coast, and (2) the jurisdiction is either an entire county or can be uniquely identified based on its 3-digit zip code. The second criteria is due to a limitation of the Nielsen scanner data—the exact location of each store is not provided—making it challenging to match stores to DCB policies. I only know in which county and 3-digit zip code each store is located. Thus I limit the sample to the stores in 11 counties and 8 cities uniquely identified by their 3-digit zip code. This gives me a total of 546 stores. Table 1 presents characteristics of the 19 jurisdictions in my sample, organized by order of DCB policy implementation. Twelve jurisdictions implemented DCB polices before 2016 (during the sample period) while the remaining 7 jurisdictions did not implement DCB policies until the statewide policy (after the sample period). In addition to the jurisdiction name, implementation date, and store-sample count, Table 1 also reports the 2016 estimated population and median household income for each jurisdiction.

Next, I aggregate the raw microdata to the store-by-month-by-product-group level. With respect to garbage bags, there are 4 product categories: Small Trash Bags (≈4 gallons), Medium Trash Bags (≈8 gallons), Tall Kitchen Trash Bags (≈13 gallons), and Large Trash Bags (≈30 gallons). Table 2 presents the summary statistics for the quantity and price variables by product group from 2009 to 2010, which is in the pre-policy for all jurisdictions and stores in my sample. While I am interested in the total number of bags sold, bags are generally sold grouped in boxes. Thus I report summary statistics for both boxes and individual bags. Bag product groups vary in their quantities sold and in their prices. For example, the average store in my sample sells

[10] When a retail chain agrees to share their data, all of their stores enter the database. As a result, the database includes more than 50,000 individual stores.

Table 1
Jurisdiction and store-sample characteristics.

Jurisdiction	Implementation Month	Stores (#)	Pop. (2016)	Med. HH Inc. (2016)
City of Long Beach	August 2011	26	470,130	$55,151
City of Santa Monica	September 2011	8	92,478	$82,123
City of San Jose	January 2012	53	1,025,350	$90,303
City of Pasadena	July 2012	15	142,059	$73,029
San Luis Obispo County	October 2012	19	282,887	$64,014
Alameda County	January 2013	92	1,647,704	$79,831
Mendocino County	January 2013	9	87,628	$43,510
San Mateo County	April 2013	39	764,797	$98,546
City of San Mateo	June 2013	10	103,959	$95,667
City of Glendale	July 2013	10	200,831	$56,069
City of Richmond	January 2014	6	109,813	$57,107
Sonoma County	September 2014	31	503,070	$66,833
City of San Diego	November 2016	65	1,406,630	$68,117
Del Norte County	November 2016	2	27,540	$42,363
Lake County	November 2016	4	64,116	$36,132
San Benito County	November 2016	5	59,414	$73,814
San Diego County	November 2016	85	3,317,749	$66,529
Solano County	November 2016	22	440,207	$69,227
Ventura County	November 2016	45	849,738	$78,593

Note: Jurisdictions were chosen based on meeting the following criteria: (1) jurisdiction is located in California and is no more than 50 miles from the coast, and (2) jurisdiction is either an entire county or can be uniquely identified based on its 3-digit zip code. The statewide DCB policy was voted into law on November 8, 2016. *Sources*: Author's calculation. Population and median household income statistics come from U.S. Census Bureau, Population Estimates Program (PEP) and American Community Survey (ACS).

Table 2
Scanner data summary statistics (store-by-month, pre-policy, 2009–2010).

Variable	Mean	Std. Dev	Min	Max	Obs.
Small Trash Bags (4 gal.)					
Boxes sold per month	33.49	54.76	0.00	654.00	13,104
Bags sold per month	1,538.75	3,255.21	0.00	33,740.00	13,104
Bags per box	36.30	13.23	21.50	85.00	7,963
Price per box	2.83	0.70	0.99	5.49	7,963
Price per bag	0.09	0.03	0.02	0.22	7,963
Medium Trash Bags (8 gal.)					
Boxes sold per month	21.17	26.51	0.00	281.00	13,104
Bags sold per month	799.63	1,545.59	0.00	19,812.00	13,104
Bags per box	40.94	72.34	20.00	400.00	10,852
Price per box	3.24	1.59	0.01	10.99	10,852
Price per bag	0.13	0.04	0.00	0.22	10,852
Tall Kitchen Bags (13 gal.)					
Boxes sold per month	301.61	349.28	6.00	3,304.00	13,104
Bags sold per month	15,467.03	21,246.23	151.00	193,049.00	13,104
Bags per box	46.46	8.93	18.75	77.57	13,104
Price per box	6.49	0.72	3.15	8.76	13,104
Price per bag	0.16	0.02	0.10	0.24	13,104
Large Trash Bags (30 gal.)					
Boxes sold per month	99.17	81.81	0.00	652.00	13,104
Bags sold per month	2,484.40	2,293.75	0.00	20,534.00	13,104
Bags per box	25.52	3.98	10.00	45.43	13,103
Price per box	6.21	0.82	2.44	9.99	13,103
Price per bag	0.27	0.03	0.16	0.39	13,103

Source: Author's calculations from retail scanner data.

15,467 tall kitchen bags and 800 medium trash bags per month; the average box of 26 large trash bags costs $6.21 and the average box of 36 small trash bags costs $2.83.

2.3. Observational data

The second data source I employ is in-store data measuring the number and types of carryout bags used at checkout. These data were obtained through direct observation of transactions by enumerators stationed inside grocery stores near checkout lanes. The enumerators made bi-weekly visits to a set of 7 stores during the months before and after a DCB policy change in the

Table 3
Observational data summary statistics.

Variable	Mean	Std. Dev	Min	Max	Obs.
Without DCB Policies					
Plastic bags per txn.	3.77	3.78	0.00	30.00	1,715
Paper bags per txn.	0.05	0.43	0.00	8.00	1,715
Reusable bags per txn.	0.16	0.66	0.00	7.00	1,715
With DCB Policies					
Plastic bags per txn.	0.00	0.00	0.00	0.00	2,323
Paper bags per txn.	0.51	1.20	0.00	14.00	2,323
Reusable bags per txn.	1.00	1.41	0.00	10.00	2,323

Source: Author's calculations from in-store observational data.

San Francisco Bay Area. Three of the stores visited experienced a DCB policy change mid-sample period, 2 of the stores had a DCB policy in place for the entire sample period, and 2 of the stores had no policy for the entire sample period. These visits were made over five months—one month before (December 2013) and four months after (January–April 2014) the policy change.[11] For a highly detailed discussion of the in-store data and the data collection methodology, please see Taylor and Villas-Boas (2016).

For each observed transaction, data was collected on the number and types of checkout bags used, whether a bagger was present,[12] the length of the transaction in minutes, and basic demographic characteristics of the person paying, such as gender and race. This type of transaction specific information can only be gained from in-store observations, and is not included in the scanner datasets from these stores.

Table 3 provides summary statistics for these data with respect to the number of carryout bags used per transaction—by bag type (i.e., plastic, paper, and reusable) and by whether or not the transaction occurred at a store with a DCB policy in effect. First, the average transaction at stores *without* a DCB policy used 3.77 plastic bags, 0.05 paper bags, and 0.16 reusable bags. These numbers are quite similar to a study conducted in Los Angeles County grocery stores, which found the average transaction pre-policy used 4.00 plastic bags, 0.06 paper bags, and 0.10 reusable bags (AECOM, 2010).[13] Second, the average transaction at stores *with* a DCB policy used 0.00 plastic bags, 0.51 paper bags, and 1.00 reusable bags. Therefore, as shown in Taylor and Villas-Boas (2016), plastic carryout bag bans are effective in eliminating the use of plastic carryout bags.

2.4. Bag product group by weight

In order to compare the environmental impacts of the various types of bags people use, I convert all bag product groups into their weight in pounds. Table 4 describes the material, weight, and volume capacity for the four categories of garbage bags from the scanner data and for six categories of common carryout bags. Unless otherwise indicated, I calculate bag weights using material densities and standard bag dimensions. Among the trash bags, small trash bags are the lightest and carry the least volume (0.0101 lb; 4 gal) and large trash bags are the heaviest and carry the greatest volume (0.0555 lb; 30 gal). Among the carryout bags, plastic carryout bags are the lightest and carry the least volume (0.0077 lb; 4 gal) while the various reusable bags are heavier and carry greater volumes (0.0606–0.5051 lb; 5–9 gal). It is important to note that small trash bags are most similar to plastic carryout bags (i.e., the bags banned under Californian DCB policies) with respect to material, weight, and volume capacity.

3. Empirical design

3.1. Scanner data event studies

I estimate the causal effect of DCB policies on bag purchases using an event study design. I aggregate the raw retail scanner data to the store-by-month-by-product-group level and employ the following event study regression model:

$$Y^B_{sjm} = \sum_{l=-12}^{12} \beta_l D_{l,jm} + \theta_{sj} + \delta_m + \epsilon_{sjm} \tag{1}$$

where Y^B_{sjm} is the outcome variable for store s in jurisdiction j and month-of-sample m with respect to bag product group B, θ_{sj} is a vector of store fixed effects, and δ_m is a vector of month-of-sample fixed effects. $D_{l,jm}$ is a dummy variable equaling one

[11] Each visit lasted 1–2 hours and was made on either Saturday or Sunday between 11:00am and 7:00pm. To prevent potential biases, the order in which the stores were visited on each observation date was randomized.

[12] Baggers are courtesy clerks that work at supermarkets and other retail outlets. Their primary duties are to put purchased groceries into bags for customers, to put filled bags back into shopping carts, and sometimes to help customers to their vehicles.

[13] As a comparison from a different state, Homonoff (2018) finds that the average transaction at supermarkets in Maryland used 1.90 disposable bags and 0.26 reusable bags before a DCB policy was enacted.

Table 4
Bag product group characteristics.

Bag Product Group	Material	Weight (lb/bag)	Volume Capacity (gal/bag)
Trash & Storage Bags			
Small trash bag	LDPE; 18 in × 17 in × 0.5 mil	0.0101	4
Medium trash bag	LDPE; $20\frac{1}{2}$ in × 20 in × 0.69 mil	0.0187	8
Tall kitchen bag	LDPE; 24 in × $28\frac{3}{8}$ in × 0.78 mil	0.0351	13
Large trash bag	LDPE; 30 in × 33 in × 0.85 mil	0.0555	30
Carryout Bags			
Plastic carryout bag[a]	HDPE	0.0077	4
Paper carryout bag[b]	Kraft Paper; Flat Handles	0.1267	5
Reusable carryout bag	Woven PP[c]	0.3086	6
–	Non-woven PP[d]	0.2372–0.2736	5–6
–	Cotton[d]	0.1735–0.5051	5–9
–	Heavy duty LDPE[d]	0.0606–0.0937	5–6

Note: LDPE = low-density polyethylene. HDPE = high-density polyethylene. PP = polypropylene. LDPE has a density of 0.0330 lb/in^3 (Sterling Plastics, Inc.). HDPE has a density of 0.0347 lb/in^3 (Plastics International.). mil = a thousandth of an inch. Unless otherwise indicated, bag weights are calculated by author using material densities and standard bag dimensions.
[a] *Source*: CalRecycle. "Diversion Study Guide, Appendix I; Conversion Factors: Glass, Plastic, Paper, and Cardboard." www.calrecycle.ca.gov, *accessed Apr. 25, 2017*.
[b] *Source*: Uline. "Paper Grocery Bags – 12 × 7 × 14", 17 Barrel, Flat Handle, Kraft" www.uline.com, *accessed Apr. 25, 2017*.
[c] *Source*: Reuse This Bag, "Woven Polypropylene Grocery Bag." reusethisbag.com, *accessed Apr. 25, 2017*.
[d] *Source*: UK Environmental Agency (2011).

if jurisdiction j in month m implemented a DCB policy l months ago, with $l = 0$ denoting the month of implementation. The endpoints are binned, with $D_{12,jm} = 1$ for all months in which it is 12 months or more since DCB policy implementation and, similarly, $D_{-12,jm} = 1$ for all months in which it is 12 months or more until implementation.[14] Store fixed effects control for time-invariant store level characteristics (i.e., store size, number of registers, types of departments offered). Month-of-sample fixed effects control for variation over time that effect all stores (i.e., holidays and seasons). The primary outcome variables I use for Y^B_{sjm} will be the number of product group B bags sold in store s and month-of-sample m (both in levels and in logs).

The β_l vector is the parameter of interest, as it traces out the differences in outcomes from before the DCB policies to after. I hypothesize that sales of trash bags deemed by customers to be substitutes for plastic carryout bags will increase. Thus, for any product group B that is a substitute for plastic carryout bags, I would expect the β_l coefficients in the post-policy period to be greater than zero.

The identifying assumption of the model is that, absent the DCB policies, outcomes at the treated stores would have remained similar to the stores yet to be treated. Underlying trends in the outcome variable correlated with DCB policy enactment are the most likely violation of this assumption. The pre-policy portion of the β_l vector provides a check against this possible violation. If DCB policies are unassociated with underlying trends, there should be no trend in the β_l vector in the pre-policy period. I discuss the pre-policy β_l estimates in Section 4.1. To preview these results, I find no evidence of differential trends during the pre-policy period.

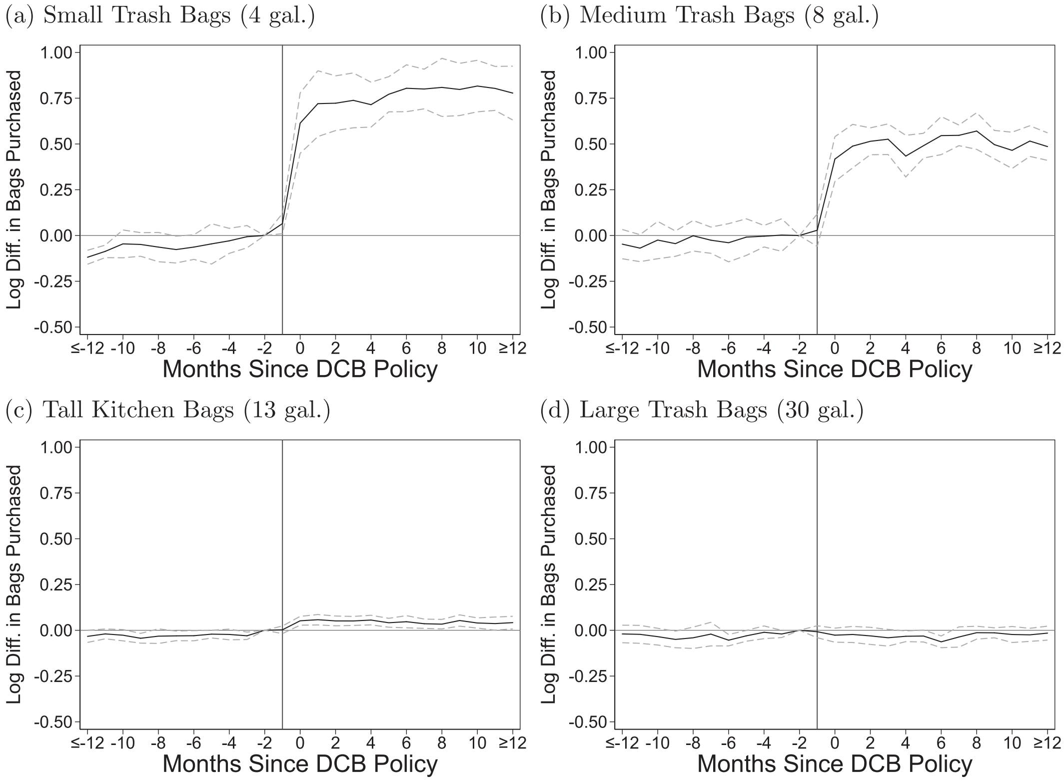
3.2. Observational data event studies

To examine the effects of DCB policies on the use of various carryout bags, I use the observational transaction-level data to estimate the following event study model:

$$Y^C_{tsjdm} = \sum_{l=-1}^{3} \beta_l D_{l,jm} + \beta_x X_{tsjdm} + \theta_{sj} + \delta_{dm} + \epsilon_{tsjdm} \tag{2}$$

where Y^C_{tsjdm} is the outcome variable for transaction t in store s on date d in month m with respect to carryout bag type C, $D_{l,jm}$ is the set of monthly event study dummies, X_{tsjdm} are control variables, θ_{sj} are store fixed effects, and δ_{dm} are date fixed effects. The control variables include indicators for the gender and race of the person paying, whether there was a checkout interruption, and whether a bagger was present. The primary outcome variable I use for Y^C_{tsjdm} is the number of carryout type C bags used per transaction.

[14] I bin at ±12 months because stores that implement policies later in the sample period mechanically have fewer post-policy months than stores with early implementation dates. While all 546 stores are in the sample eleven months prior to their policy period, only 318 stores are in the sample fifteen months post-policy, only 222 stores are in the sample 35 months post-period, and so on. Thus, binning the endpoints at 12 months provides the most consistent number of stores for each $D_{l,jm}$. I also examine whether the results are robust to binning at −24 and + 48 months.



Note: The figure panels display the $\hat{\beta}_l$ coefficient estimates from event study Equation 1. The dependent variable is logged number of product group B bags sold in store s, jurisdiction j, and month-of-sample m. Upper and lower 95% confidence intervals are depicted in gray, estimated using two-way error clustering at the policy jurisdiction and month-of-sample level.

Fig. 3. Effect of DCB policies on bag purchases (*Scanner Data*).

4. Results

4.1. Scanner data results

The figures in this section present the results from the estimation of event study Equation (1), where the $\widehat{\beta}_l$ point estimates and 95% confidence intervals are displayed graphically.[15] Unless specified otherwise, I cluster the standard errors two ways—by jurisdiction (19) and by month-of-sample (84)—to allow for spatial and temporal correlation in the data.[16]

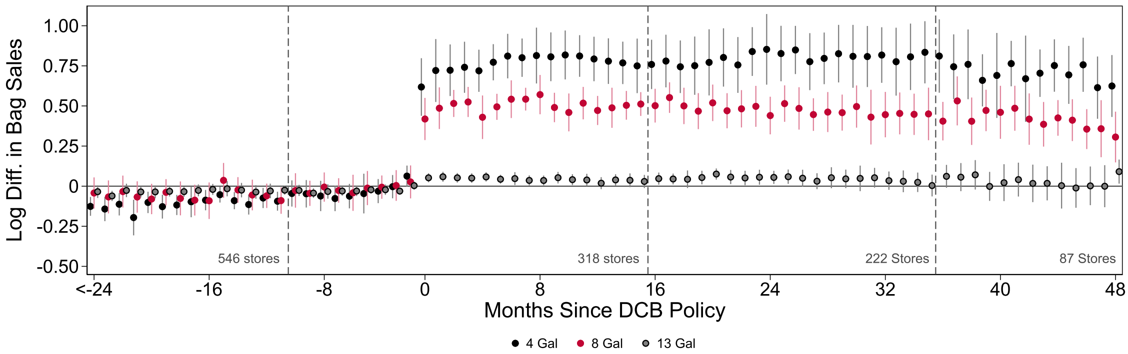
In Fig. 3, the scanner data are averaged to the store-by-month level for each product. The outcome variable, Y^B_{sjm}, is the logged number of product group B bags sold in store s and month-of-sample m, which means the $\widehat{\beta}_l$ point estimates measure the log difference in bag sales between treated and yet-to-be-treated stores l months from DCB policy implementation. The panels of Fig. 3 correspond to the following bag products: (a) small trash bags, (b) medium trash bags, (c) tall kitchen bags, and (d) large trash bags. Two months prior to implementation ($l = -2$) is the omitted category.

Among the four event studies presented in Fig. 3, panels (a) and (b) stand out. In panel (a), I find that the DCB policies lead to a large and significant increase in sales of small trash bags. The jump in sales begins immediately after policy implementation, with $\widehat{\beta}_0 = 0.627$ and $\widehat{\beta}_1 = 0.734$. These estimates mean that the average monthly sales of small trash bags at treated stores are 87% and 108% higher during the first and second months of a DCB policy.[17] The increase in sales remains stable over time, ending with $\widehat{\beta}_{12} = 0.789$. The $\widehat{\beta}_{12}$ coefficient indicates that for all months in which it has been a year or more since DCB policy

[15] I estimate all fixed-effect equations in STATA using the command `reghdfe` (Correia, 2014).

[16] One could be concerned that there are too few jurisdictions to cluster, however, standard errors are quite similar if I instead bootstrap jurisdictions with replacement.

[17] The percent change in the dependent variable can be found using $100 \times (e^{\widehat{\beta}} - 1)$, thus the coefficient $\widehat{\beta}_0 = 0.627$ translates to an 87% increase in sales and $\widehat{\beta}_1 = 0.734$ translates to a 108% increase in sales.



Note: The figure panels display the $\hat{\beta}_l$ coefficient estimates from event study Equation 1, with endpoints extended to 2 years prior to and 4 years after DCB policy implementation. The dependent variable is the logged number of product group B units sold in store s, jurisdiction j, and month-of-sample m. The $\hat{\beta}_l$ coefficients for: small trash bags (4 gal) are depicted in black, medium trash bags (8 gal) are depicted in red, and tall kitchen bags (13 gal) are depicted in gray. Upper and lower 95% confidence intervals are presented, estimated using two-way error clustering at the policy jurisdiction and month-of-sample level. Vertical dashed lines and corresponding text indicate the number of stores in the sample l months from policy implementation.

Fig. 4. Persistence analysis: Effect of DCB policies on trash bag purchases with extended endpoints.

implementation, sales of small trash bags at treated stores remain 120% higher than at the yet-to-be-treated stores. All of the post-policy $\widehat{\beta}_l$ coefficients are significantly greater than zero at the 1% significance level. Importantly, the pre-policy $\widehat{\beta}_l$ coefficients are close to zero and nearly parallel to the x-axis, which provides evidence in favor of the identifying assumption that differential trends in pre-policy small trash bag sales are not driving the results.

The results in panel (b) for medium trash bags follow a similar pattern as those in panel (a) for small trash bags. I find that average monthly sales of medium trash bags are 54% higher during the first month of a policy, 65% higher in the second month, and remain 64% higher 12 months or more after a policy. In panel (c), I also find a small increase in the sale of tall kitchen bags that corresponds to the implementation of DCB policies. Monthly sales of tall kitchen bags are 7% higher in the first and second month of a policy and 6% higher 12 months or more after a policy. Finally, in panel (d) I find no statistically significant change in large trash bag sales due to DCB policy implementation. To my knowledge, the only other estimate of changes in trash bags sales due to DCB policies comes from Ireland, where retailers self-reported a 77% increase in small trash bag sales and no change in larger trash bag sales (Nolan ITU, 2002).

Altogether, these results provide strong evidence that the elimination of plastic carryout bags due to DCB policies lead costumers to substitute towards purchasing more trash bags, and in particular, small and medium trash bags which are close in size and carrying capacity to plastic carryout bags. In other words, some customers are willing to pay for the trash bag services they gained from "free" plastic carryout bags. Furthermore, these results show that DCB policies have a persistent effect on trash bag sales, with increased sales extending 12 months and more after policy implementation. A potential concern is that a year is not enough time to draw conclusions about the permanence of the effects. In Fig. 4, I explore whether the effects of DCB policies on trash bag sales lessen over time if the event study model is binned at −24 and +48 months instead of ±12 months. I find the increases in bag sales persist even when the event study is binned 2 year before and 4 years after the policy change. However, the $\widehat{\beta}_l$ estimates grow noisier after D_{36}, when the number of stores in the sample experiencing that many months post-policy drops below 200. Thus the policy effects are persistent, at least over a three to four year horizon.

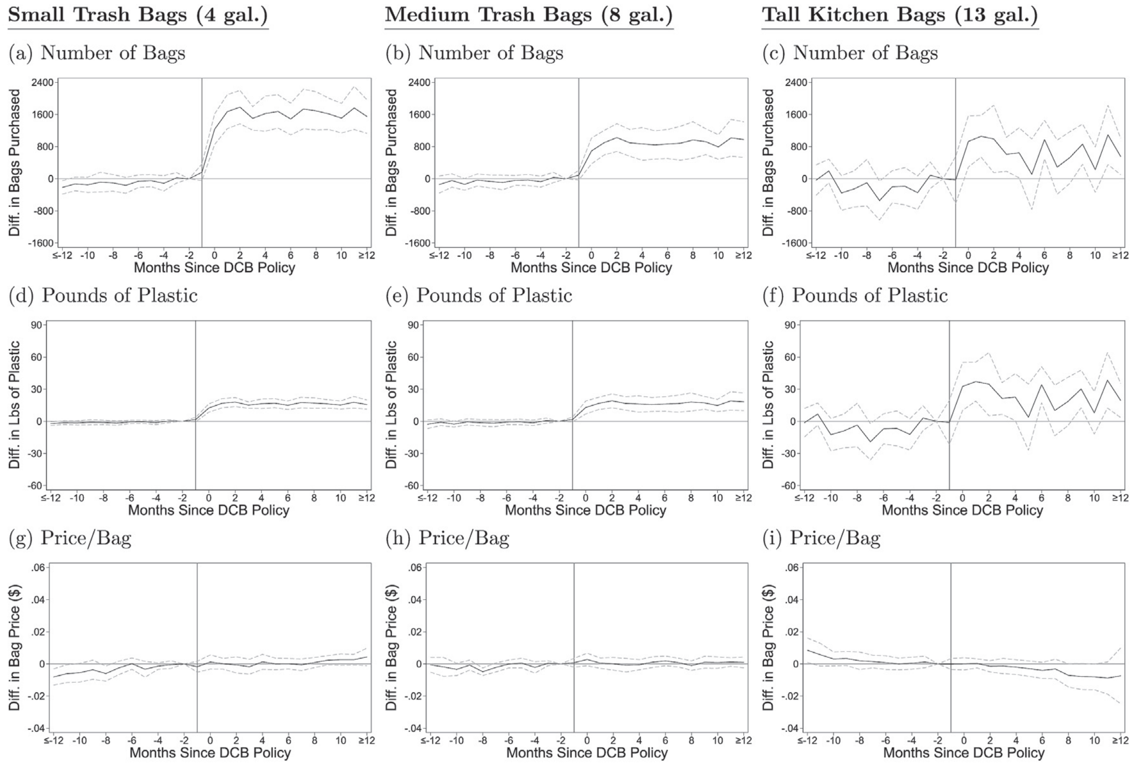
4.1.1. Additional measures of trash bag use

To understand the magnitude of the changes in trash bag sales, I estimate Equation (1) with the outcome variables in levels instead of logs. Fig. 5 presents the results of the event study model for small, medium, and tall kitchen trash bags. In panels (a), (b), and (c), I find that DCB policies cause a 1625 bag increase in small trash bag purchases per store-month, a 1046 bag increase in medium trash bag purchased per store-month, and a 654 bag increase in tall kitchen bags purchased per store-month.[18,19]

In panels (d), (e), and (f) of Fig. 5, I convert the bag types into their weight equivalents using the weights provided in Table 4. These panels show that DCB policies lead to 16, 20, and 23 additional pounds of plastic sold per store-month from increased purchases of small, medium, and tall kitchen trash bags respectively.[18] Thus even though the increase in the number of small trash bags is 2.5 times larger than the increase in the number of tall kitchen bags, because tall kitchen bags are 3.5 times heavier than small trash bags, the increase in plastic by weight is greater for tall kitchen bags. In section 5, I further discuss

[18] These numbers correspond to the $\widehat{\beta}_{12}$ estimates from Equation (1).

[19] Using a Tobit model instead of a linear model—to address potential concerns about months with zero bag sales—provides equivalent results.



Note: The figure panels display the $\hat{\beta}_l$ coefficient estimates from event study Equation 1. The dependent variables for store s in jurisdiction j and month-of-sample m are: panels (j) to (l)—the number of product group B bags sold; panels (m) to (o)—the pounds of product group B bags sold; and panels (p) to (r)—the price of product group B bags sold. Upper and lower 95% confidence intervals are depicted in gray, estimated using two-way error clustering at the policy jurisdiction and month-of-sample level.

Fig. 5. Effect of DCB policies on trash bag purchases (*Scanner Data*).

the environmental implications of these policy-induced changes in the consumption of plastic bags, with respect to carbon footprint, landfilling, and marine pollution.

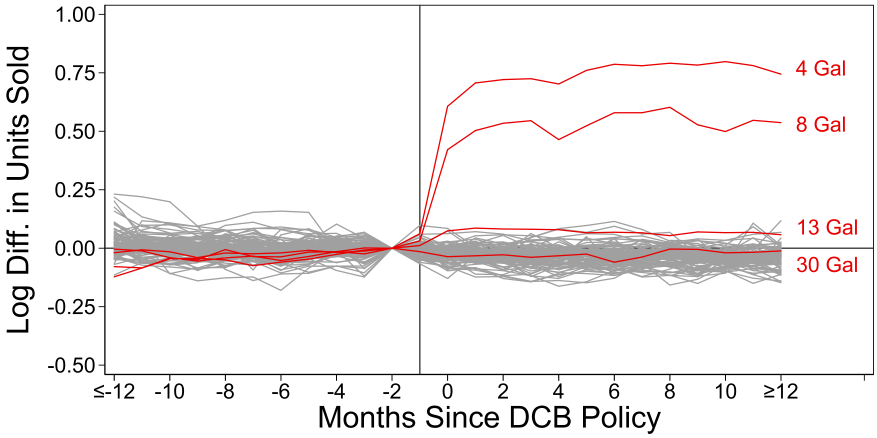
4.1.2. Testing alternative hypothesis

In order to rule out the alternative hypothesis that changes in bag prices are driving the changes in bag sales, I examine whether the price of bags change with DCB policy implementation in panels (g), (h), and (i) of Fig. 5. Reassuringly, I find no changes in bag price that are contemporaneous with policy implementation. Instead, I find the price of small trash bags trends slightly upward from the pre- to post-policy period while the price of tall kitchen bags trends downward. Even though a decrease in price might explain some of the persistent increase in tall kitchen bag sales, the same logic cannot be used for small and medium trash bags, which instead experience an increase or no change in price. Thus changes in prices do not appear to be driving changes in bag sales.

4.1.3. Placebo test

To test the validity of the above results, I estimate event study Equation (1) for each of the 114 product groups sold in my sample of stores, excluding trash bags. Product groups can be thought of as the categories shoppers might see on signs above a grocery aisle and include Breakfast Food, Cosmetics, Canned Fruit, Packaged Meats, Pasta, and Beer, to name a few.[20] Fig. 6 plots the $\widehat{\beta}_l$ coefficient from all 114 regressions (depicted in gray) alongside the $\widehat{\beta}_l$ coefficients from the four garbage bag regressions (depicted in red). The dependent variable in all regressions is logged so that the various product groups can be easily compared as log differences (i.e., Y^B_{sjm} is the logged number of product group B units sold in store s, jurisdiction j, and month-of-sample m). Fig. 6 reveals that the four bag groups have similar pre-policy $\widehat{\beta}_l$ estimates as the other product groups, which are all consistently close to zero. However, the post-policy $\widehat{\beta}_l$ estimates for the three smallest bag groups deviate from the other product groups and experience significant and persistent increases in sales. In fact, no other product group experiences increases in sales as large

[20] While Nielsen categorizes 2.6 million products into 125 product groups, only 114 of the product groups are sold in my sample of stores in all years of the sample.



Note: The figure panels display the $\hat{\beta}_l$ coefficient estimates from event study Equation 1, estimated 114 times for each product group sold in the sample of stores, excluding trash bags (depicted in gray) and 4 times for each trash bag group (depicted in red). The dependent variable is logged number of product group B units sold in store s, jurisdiction j, and month-of-sample m. Upper and lower 95% confidence intervals are depicted in gray, estimated using two-way error clustering at the policy jurisdiction and month-of-sample level.

Fig. 6. Robustness analysis: Effect of DCB policies on units purchased by product group.

as the 4 and 8 gallon trash bags and only a few product groups experience increases as large as the 13 gallon bags—and these increases are temporary. This placebo analysis provides strong evidence that the trash bag event study analyses above are not picking up spurious changes in sales.

4.2. Observational data results

This section uses the observational data collected in-store in order to examine how DCB policies affect the number and types of carryout bags use at checkout by customers. Fig. 7 presents the results from the estimation of event study Equation (2), where the $\widehat{\beta}_l$ point estimates and 95% confidence intervals are displayed graphically. I cluster the standard errors at the store-day level to account for the possibility that the errors are correlated within a given store and day, but not across stores and days.[21] In the top three panels of Fig. 7, outcome variable Y^C_{tsjdm} is the number of bags sold of carryout bag group C in transaction t, store s, jurisdiction j, day d, and month m. This means the $\widehat{\beta}_l$ point estimates measure the difference in bag usage between treated and control stores l months from the DCB policy implementation. The panels of Fig. 7 correspond to the following carryout bag groups: (a) plastic carryout bags, (b) paper carryout bags, and (c) reusable carryout bags.

As expected, I find that the DCB policies lead to a large and significant decrease in the use of plastic carryout bags. Customers use approximately 3.7 fewer plastic carryout bags per transaction when DCB policies go into effect ($\beta_0 = 3.685$). This reflects the fact that DCB policies prohibit the use of plastic carryout bags and that customers used 3.77 bags per transaction on average before DCB policies were implemented (Table 3). DCB policies also lead to significant increases in the usage of paper and reusable carryout bags. When policies are implemented, customers use 0.5 more paper bags ($\beta_0 = 0.473$) and 0.9 more reusable bags per transaction ($\beta_0 = 0.864$).[22]

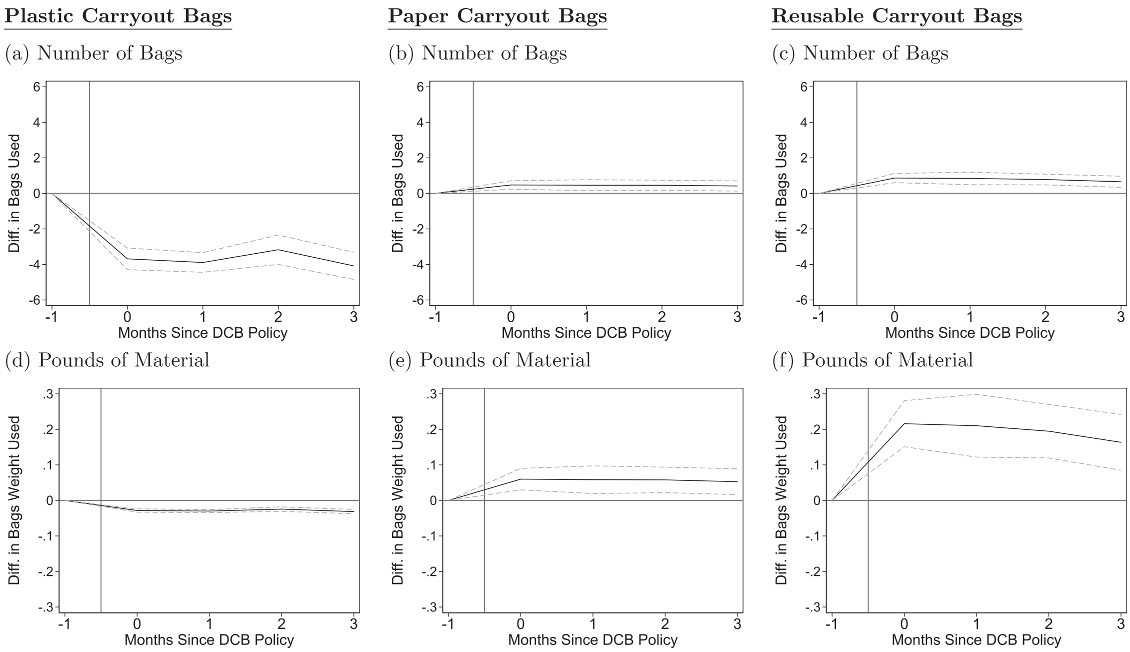
In panels (d), (e), and (f), I convert the bag types into their weight equivalents. DCB policies lead to 0.03 fewer pounds of plastic per transaction from the elimination of plastic carryout bags and 0.06 additional pounds of paper per transaction from the increased use of paper carryout bags. Thus, with respect to weight, the elimination of plastic is more than offset by the increased use of paper. I also find that the average transaction is using an additional 0.22 pounds of reusable bags per transaction. As to be discussed in section 5, how many times paper and reusable bags are reused, and how they are disposed of, will have major implications for the success of these policies.

5. Quantifying leakage

The previous section revealed that banning plastic carryout bags led to increased purchases of plastic garbage bags—with small, medium, and tall trash bag sales increasing by 120%, 64%, and 6% respectively. In this section, I calculate the leakage rate

[21] Given the low number of clusters, I also estimate Equation (2) using standard errors obtained via a cluster bootstrap procedure (Cameron and Miller, 2015).

[22] Using cluster-bootstrap standard errors at the store-day level, the event study results for plastic carryout bags and reusable carryout bags remain statistically significant at the 1% significance level, however, the event study results for paper carryout bags are no longer statistically significant.



Note: The figure panels display the $\hat{\beta}_l$ coefficient estimates from event study Equation 2. The dependent variables for transaction t in store s, jurisdiction j, day d, and month m are: panels (a) to (c)—the number of product group C bags used; and panels (d) to (f)—the pounds of product group C bags used. Upper and lower 90% confidence intervals are depicted in gray, estimated using standard errors clustered at the store-by-date level.

Fig. 7. Effect of DCB policies on carryout bag use (*Observational Data*).

by comparing the estimated increase in pounds of plastic trash bags to the estimated decrease in pounds of plastic carryout bags. This is a key contribution of the paper. To calculate the rate of leakage, it is not enough to show substitution towards trash bags (the numerator in the leakage rate); one needs a comparable denominator, which I obtain from the unique observational data.

To quantify the leakage rate, I first convert the scanner and observational estimates above to state-year equivalents—in order to calculate aggregate changes in the number of plastic bags, bag capacity, and pounds of plastic material used per year in California.[23] Table 5 presents these calculations. In columns (1) and (2), I estimate difference-in-differences versions of Equations (1) and (2), where the event dummies are collapsed to a single indicator, D_{jm}, equal to 1 if jurisdiction j has a DCB policy effective in month-of-sample m. Column (1) presents the $\widehat{\beta}_D$ estimates for small, medium, and tall kitchen trash bags and column (2) presents the $\widehat{\beta}_D$ estimates for plastic carryout bags. In column (3), I aggregate the estimates in columns (1) and (2) to the annual California level. To make this aggregation for trash bags, I use the estimate that California had 15,564 food and drug retail stores in 2015—10,766 grocery stores, 4507 pharmacy and drug store, and 291 warehouse clubs and supercenters.[24] To make this aggregation for plastic carryout bags, I use the estimate that Californian adults make 1.42 billion grocery transactions per year.[25] Finally, in columns (4) and (5), I calculate the changes in the weight and capacity of bags consumed per year in California using the bag capacity and weight information from Table 4.

Table 5 reveals that DCB policies lead to a 40.3 million pound reduction in plastic per year in California from decreased use of plastic carryout bags. However, this reduction is offset by an 11.5 million pound increase in plastic from additional purchases of trash bags—3.3 million, 3.6 million, and 4.6 million pounds from small, medium and tall kitchen trash bags respectively. Thus, DCB policies have a 28.5% leakage rate with respect to pounds of plastic. In other words, 28.5% of the plastic reduction of DCB

[23] I aggregate to the state level in part because California eventually passes a statewide DCB policy (and thus there is policy relevance for the entire state) and in part because the data I have for the number of food stores is at the state level.

[24] *Source*: U.S. Census Bureau, 2015 Statistics of U.S. Businesses. Online, *accessed 17 May 2018*.

[25] Hamrick et al. (2011) estimate how much time Americans spend on food and find that the average adult in the U.S. grocery shops once every 7.19 days, which is 50.74 times per year. According to the 2010 Census, there are 28 million adults in California. Thus Californian adults make roughly 1.42 billion trips to the grocery store annually.

Table 5
Effect of DCB policies on annual bag usage, weight, and capacity, in California.

	(1) Δ Bags/Store-Month[a]	(2) Δ Bags/Txn[a]	(3) Δ Bags/Year[b] (million)	(4) Δ Lbs/Year[c] (million)	(5) Δ Gal/Year[c] (million)
Trash Bags					
Small trash bag	1,727.554 (197.619)		323	3.3	1,291
Medium trash bag	1,032.274 (215.011)		193	3.6	1,542
Tall kitchen bag	699.095 (242.766)		131	4.6	1,697
Carryout Bags					
Plastic carryout bag		−3.689 (0.215)	−5238	−40.3	−20,952
Net Plastic Δ			−4591	−28.8	−16,422
Leakage Rate			12.4%	28.5%	21.6%

[a] *Note*: Changes in bag usage come from the estimation of difference-in-differences versions of equations (1) and (2). Standard errors, presented in parentheses, are estimated using two-way error clustering at the policy jurisdiction and month-of-sample level.
[b] *Note*: Changes in trash bag usage is calculated using the estimate that California had 10,766 grocery stores (naics = 44510), 4507 pharmacy and drug store (naics = 44611), and 291 warehouse clubs and supercenters (naics = 45291) in 2015, for a total of 15,564 stores (*source*: U.S. Census Bureau, 2015 Statistics of U.S. Businesses. Online, *accessed 17 May 2018*). Changes in carryout bag usage are calculated using the estimate that Californian adults make 1.42 billion grocery transactions per year. Hamrick et al. (2011) estimate how much time Americans spend on food and find that the average adult in the U.S. grocery shops once every 7.194 days, which is 50.74 times per year. According to the 2010 Census, there are 28 million adults in California. Thus Californian adults make roughly 1.42 billion trips to the grocery store annually.
[c] *Note*: Changes in the pounds of plastic material and gallons of bag capacity per year are calculated using the bag capacity and weight information from Table 4.

policies is lost due to consumption shifting towards unregulated bags.[26]

The results also provide a lower bound for the reuse of plastic carryout bags. The loss of 5.2 billion plastic carryout bags with a carrying capacity of 21.0 billion gallons is replaced by 647 million trash bags with a carrying capacity of 4.5 million gallons. If trash bags replace plastic carryout bags one-to-one in number, regardless of capacity, this suggests that 12.4% of plastic carryout bags were used as trash bags before the DCB policies went into effect. If instead, we equate volume capacity of bags, the results suggest 21.6% of plastic carryout bags were used as trash bags pre-policy. This is an important estimate in itself because life-cycle assessments have been shown to be sensitive to assumptions made about the weight and number of trash bags displaced by the secondary use of plastic carryout bags (Mattila et al., 2011). For instance, a UK Environmental Agency (2011) study calculated the global warming potential (measured in kilograms of CO2 equivalent) of various plastic, paper, and reusable carryout bags. They found that to have the same global warming potential as a traditional plastic carryout bag with zero secondary use, a paper carryout bag would need to be used 3 times, a non-woven polypropylene (PP) reusable bag would need to be used 11 times, and a cotton reusable bag would need to be used 131 times. If instead, 40% of plastic carryout bags were reused once as a trash bag, a paper carryout bag would need to be used 4 times to have the same global warming potential, a non-woven PP bag would need to be used 14 times, and a cotton bag would need to be used 173 times. Thus my results provide an important variable in calculating and interpreting life-cycle assessment results, which policymakers often reference.

The results in Table 5 reveal that DCB policies are shifting consumers towards fewer but heavier bags. This is especially true if we also consider the increase in paper carryout bag use. Replicating the calculations in columns 2–4 of Table 5 for paper carryout bags, DCB policies lead to the use of 652 million additional paper bags, weighing 82.6 million pounds (more than double the weight of the banned plastic bags). This result is concerning with respect to planet-warming emissions, given the carbon footprint of an object is generally proportional to its mass.[27,28]

Life-cycle assessments of carryout bags, such as UK Environmental Agency (2011) study, have consistently found that plastic carryout bags take significantly less energy and water to produce, require less energy to transport, and emit fewer greenhouse gases in their production than paper and other types of reusable bags (Freinkel, 2011).[29] However, while life-cycle assessments

[26] Another form of leakage is if shoppers decide to shop in jurisdictions that are unregulated in order to obtain plastic carryout bags. Taylor (2018) studies this type of border shopping behavior and finds that DCB policies lead to a 0.8% increase in sales at unregulated stores neighboring regulated jurisdictions. While this is an interesting form of leakage in and of itself, this type of leakage is not a major concern for the estimations in this paper because the biases cancel each other out. If some regulated customers are still getting "free" plastic grocery bags, these same customers would not need to purchase additional plastic garbage bags. Thus, the reduction of plastic grocery bags would be underestimated and the increase in plastic garbage bags also would be underestimated.

[27] *Source*: "Banning Plastic Bags is Great for the World, Right? Not So Fast." *Wired*. Jun. 10, 2016.

[28] Using a rough approximation to convert pounds of material into carbon dioxide equivalent per year in California, DCB policies would lead to a 68.0 million pounds decrease in CO_2 equivalent from plastic bags but a 127.2 million pounds increase in CO_2 equivalent from paper carryout bags (UKEA, 2011).

[29] The negative environmental impacts of paper bags include: paper bags are more energy and water intensive to manufacture than plastic bags; paper bag production generates 70% more air and 50 times more water pollutants than the production of plastic bags; it takes 98% less energy to recycle a pound of plastic than a pound of paper; and paper bags are 9 times heavier than plastic bags, requiring more space in transport and in landfills (*Source*: "Graphic: Paper or Plastic?" *The Washington Post*. Oct. 3, 2007).

do well measuring energy-related impacts, they have trouble with less easily quantified issues, such as litter and marine debris, the toxicity of materials, and impacts on wildlife (Freinkel, 2011). Jambeck et al. (2015) calculate that 1.7–4.6% of the plastic waste generated in coastal countries around the globe is mismanaged and enters the ocean. Plastic carryout bags are particularly problematic because they are lightweight and aerodynamic, which make it easy for them to blow out of waste streams (even when properly disposed of) and into the environment and waterways. The United Nations Environmental Programme (2014) estimates the environmental damage to marine ecosystems of plastic litter is $13 billion per year. This estimate includes financial losses incurred by fisheries and tourism as well as time spent cleaning up beaches. While plastic bags and films represent only 2.2% of the total waste stream (CA Senate Rules Committee, 2014), plastic carryout bags and other plastic bags are the eighth and sixth most common item found in coastal cleanups.[30] Once in waterways, plastic bags do not biodegrade, but instead break into smaller pieces, which can be consumed by fish, turtles, and whales that mistake them for food. A survey of experts, representing 19 fields of study, rank plastic bags and plastic utensils as the fourth severest threat to sea turtles, birds, and marine animals in terms of entanglement, ingestions, and contamination (Wilcox et al., 2016).

Plastic trash bags, on the other hand, are less likely to blow out of waste streams because they are weighed down by the trash they carry. With respect to my results in Table 5, this means a statewide DCB policy would lead to 40.3 million fewer pounds of plastic carryout bags that could end up in storm drains and oceans, and 11.5 million additional pounds of plastic trash bags that are more likely to remain in landfills. While a handful of studies have found evidence that DCB policies lead to less litter in waterways,[31] no study has examined whether DCB policies lead to changes in the amount of plastic entering landfills and how this affects the cost of landfilling.

In summary, when evaluating the environmental success of DCB policies, the benefits of reduced litter and marine debris need to be compared to the costs of greater greenhouse gas emissions and thicker plastics going into landfills. While the upstream relationship between plastic production and carbon footprint is well understood, the downstream relationship between plastic litter and marine ecosystems is less established. Moreover, it is challenging to quantify the emotional costs of litter. "Data-driven comparisons don't speak to our feelings about the two materials—our irrational sense of comfort with the feel of paper bags and our sense of discomfort with plastic's preternatural endurance. The presence of plastic where it doesn't belong—matter out of place—pisses people off" (Freinkel, 2011, p. 159). If carbon footprint was the only metric of environmental success, the results in this paper suggest DCB policies are having an adverse effect, especially if we consider the effect on paper carryout bag use. However, if the unmeasured benefits with respect to marine debris, toxicity, and wildlife are great enough, they could outweigh the greenhouse gas costs.

6. Heterogeneity analysis

Who are the subtractional customers—i.e., the customers that would have reused their plastic grocery bags as trash bags had they not been banned? To understand who is responding to DCB policies by purchasing trash bags, I estimate the difference-in-difference version of equation (1) interacted with several subgroups.[32] These subgroups are defined based on store and jurisdiction characteristics which are potentially correlated with reusing grocery bags as trash bags. First, I split the stores in half by the average number of items sold per month in the pre-policy period—a rough proxy for store size. Second, I split the stores in half by their average price per item sold in the pre-policy period, which proxies how expensive a store is on average.[33] Third, I split stores by the four characteristics shown in Fig. 2—i.e., by whether their jurisdiction is above or below the Californian (i) median income, (ii) share with Bachelor's degree, (iii) share white, non-Hispanic, and (iv) share voting for the Democratic candidate in the 2008 presidential election. Lastly, I split the sample by whether the store is in an urban jurisdiction, defined as having a population density greater than 1000 people per square mile.

Panel (a) of Fig. 8 presents heterogeneity results with the outcome variable being logged sales of trash bags (summing together sales of the small, medium, and tall bags by store and month). The result for the full sample of stores is juxtaposed with the results from the subsamples. Overall, I do not find large or statistically significant differences in policy effects by store or jurisdiction characteristics. An exception is when I split the sample by educational attainment. The effect of DCB policies on trash bag sales is 7 percentage points (ppt) larger in jurisdictions with a higher share of people with Bachelor's degrees. These results suggest grocery bag reuse as trash bags is present in all subsamples of stores—irrespective of a jurisdiction's political leaning, income level, and population density—but it appears to be positively correlated with higher education.

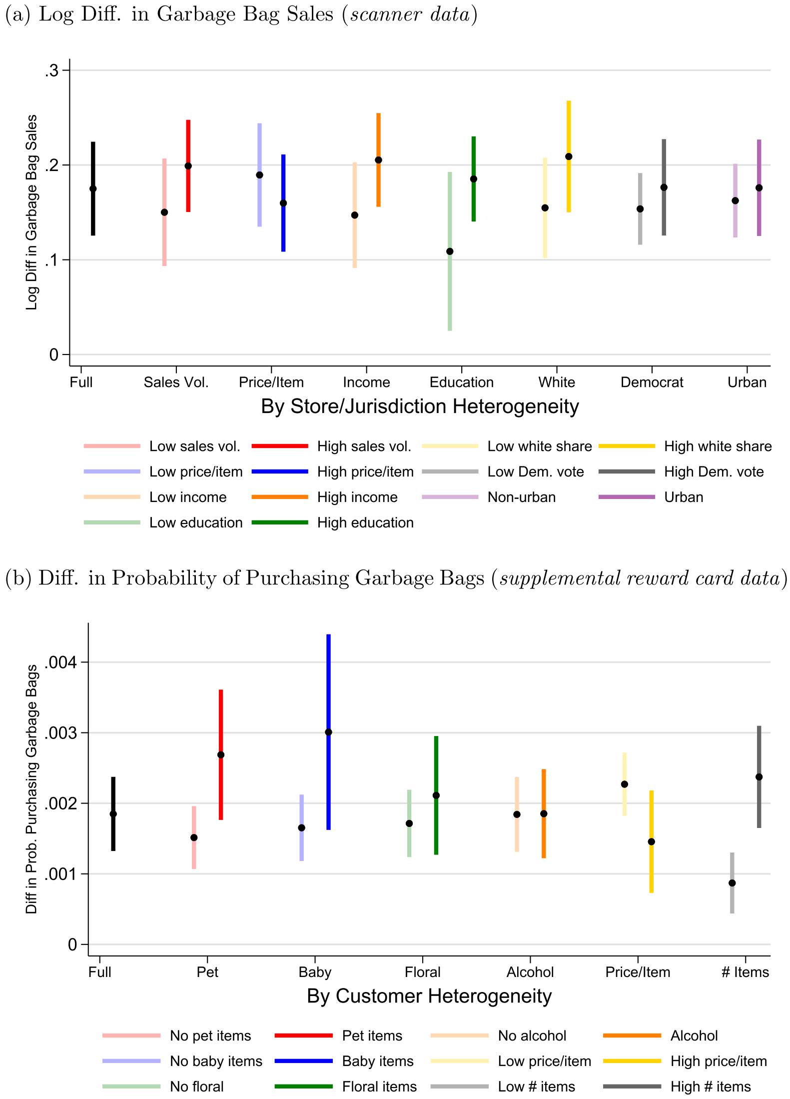
Given customers may vary greatly within the same store, these store and jurisdiction level subsamples are a blunt tool for looking at customer heterogeneity. To understand customer behavior at a finer level, I use additional data that tracks the purchases of reward card customers at 53 supermarkets in California. These data, as described in Taylor (2018), come from one retail chain and span January 2011 until May 2014 for select weekend hours. The purchases of customers using reward cards during these hours can be tracked over time using their de-identified card number. In total, there are over 1 million reward

[30] *Source*: "International Coastal Cleanup. Annual Report 2016." *Ocean Conservancy*.

[31] The City of San Jose performed creek and river litter surveys before and after the implementation of its 2012 DCB policy. These surveys indicated that plastic carryout bags comprised 8.2% of litter in 2011 and 3.7% of litter in 2012 (Romanow, 2012). Alameda County found the number of plastic bags observed in its storm drains decreased by 44% after its DCB policy went into effect (EOA, Inc., 2014).

[32] The difference-in-differences version of equation (1) collapses the event study indicators into a single indicator for whether a DCB policy has been implemented in jurisdiction j, store s, and month-of-sample m.

[33] The median number of items sold per month is 329,231. The median average price per item is $3.38.



Note: Panel (a) presents the difference-in-differences coefficients for the effect of DCB policies on logged garbage bag sales (in store s, jurisdiction j and month-of-sample m), for the full sample of stores and for subsamples of stores based on store or jurisdiction characteristics. Panel (b) presents the difference-in-differences coefficients for the effect of DCB policies on the probability that a customer i purchases garbage bags in store s, jurisdiction j and month-of-sample m, for the full sample of customers and by customer subsamples based on the items that customers purchase.

Fig. 8. Heterogeneity by store and customer characteristics.

card using customers in the data. I employ these data to analyze how the probability a customer purchases trash bags in a given month changes when DCB policies go into effect, and more importantly, how this probability varies for different types of customers.

I examine subsamples of customers based on the types of items they buy, and in particular, whether customers *ever* buy pet items, baby items, floral items, and alcohol. These items were chosen because they correspond to a supermarket aisle frequented only by subgroups of customers (i.e., less than 50% of customers purchase these items ever) and because I hypothesize they will be correlated with demand for grocery bags and/or trash bags. For instance, people who need to collect and dispose of fecal matter from pets and young children may have higher demand for inexpensive trash bags. I also look at subsamples of households by whether, on average, they buy more than the median number of items and by whether they spend more than the median per item. While reusing shopping bags as trash bags could be motivated by an individual's environmental concern, it also could be motivated by an individual's frugality and desire to save money (i.e., waste not, want not).

Panel (b) of Fig. 8 presents the customer-by-month level results, with the outcome variable being an indicator equal to one if customer *i* bought trash bags in jurisdiction *j*, store *s*, and month-of-sample *m*. The regression model now includes reward card fixed effects, in addition to store and month fixed effects, and standard errors are still clustered two-way by jurisdiction and month-of-sample. For the full sample of customers, DCB policies increase the probability a customer buys trash bags by 0.18 ppt. With only 1.1% of customers in the pre-policy period buying trash bags in a given month, this is a 16% increase in the probability of buying trash bags. Next, juxtaposing the result for the full sample of customers with the results from the subsamples, I find statistically significant differences between all subsamples, with the exception of the floral and alcohol subsamples. DCB policies have a 0.12 ppt larger effect on the probability of buying trash bags for customers that also buy pet items and a 0.14 ppt larger effect for those that buy baby items. Furthermore, the policy effect is 0.08 ppt lower for customers that spend more per item and 0.15 ppt higher for customers that buy more items per trip. Buying more items could be correlated with having a larger household or making fewer but larger supermarket trips.

In summary, the customer-level results suggest that, with respect to reusing grocery bags as trash bags, subtractional customers are more likely to be people with small children and pets, people who spend less per item (i.e., bargain shoppers), and people with larger purchases. The importance of these heterogeneity results is twofold. Knowing who the subtractional customers are allows policymakers (1) to extrapolate how large bag leakage could be if current DCB policies are implemented in states other than California and (2) to better target future DCB policies in order to reduce leakage. I discuss the policy implications of these heterogeneity results in the next section.

7. Conclusion

This article is the first to evaluate how regulating the use of plastic carryout bags affects the sale of unregulated disposable bags. Using quasi-random variation of local government policy adoption in California in an event study design, I find that the banning of plastic carryout bags leads to significant increases in the sale of trash bags, and in particular small and medium trash bags. When converted into pounds of plastic, 28.5% of the plastic reduction from DCB policies is lost due to consumption shifting towards unregulated plastic bags. The results also provide the first causally identified estimate of plastic carryout bag reuse, showing that between 12.4 and 21.6% of plastic carryout bags were used as trash bags before they were banned. Thus referring to disposable carryout bags as “single-use” is misconstrued.

In addition to the main results, heterogeneity analyses by store, jurisdiction, and customer characteristics provide important insights for whether the main results can be extrapolated to states other than California. On one hand, while California leans farther left politically than many other states and has a higher median income, I do not find that the Democratic candidate vote share or median income of a jurisdiction correlates with bag leakage. On the other hand, a jurisdiction’s education levels did positively correlate with the policy effects. While California has similar educational attainment levels as the U.S. average,[34] bag leakage may be higher (lower) if DCB policies are implemented in states with higher (lower) education levels than the U.S. average.

I also find larger policy effects for customers with small children and pets, for bargain shoppers, and for customers making larger purchases. For policymakers wishing to design DCB policies that minimize leakage, they should consider ways to target these subtractional customers. For instance, under the statewide Californian DCB policy, Supplemental Nutrition Assistance Program customers are exempted from having to pay for bags at checkout. Policymakers could consider similar exemptions for people with children and pets. In 2017, nearly 6 percent of U.S. households had a child under 5 years, 44% had a dog, and 35% had a cat.[35]

Alternatively, policymakers could incentivize the production and sale of inexpensive, thin grocery bags that are specifically designed and marketed to be used as trash bags after their use as carryout bags. These bags would need to be less than 9 cents per bag to be price competitive with current 4 gallon trash bags (see Table 2) and they would ideally be thin enough that their carbon footprint would not exceed traditional thin plastic grocery bags. In many ways, policies like this already exist. Instead of banning plastic grocery bags, some jurisdictions—such as Washington DC—have implemented 5-cent plastic bag fees. Bag fees allow customers to continue using plastic carryout bags as trash bags (for a small fee). However, bag fees have not required re-marketing disposable carryout bags as trash bags. Thus, these policies could be enhanced by establishing programs and materials to educate customers about the environmental benefits of the secondary uses of disposable products (e.g., reusing disposable products as much as possible is good for your wallet and good for the environment, because it displaces the purchase of additional disposable products).

Overall, my results suggest that DCB policies are shifting consumers towards fewer but heavier bags. The question remains: Do the benefits of reduced litter and marine debris outweigh the costs of greater greenhouse gas emissions from thicker plastic and paper bags? In order to answer this question and evaluate the environmental success of DCB policies, future research is needed on the costs and benefits of plastic marine debris reduction.

[34] In 2017, 32.0% of Californians and 30.3% of Americans over 25 have a Bachelor’s degree. (Source: United States Census Bureau, QuickFacts, www.census.gov/quickfacts/, *accessed Nov. 8, 2018*).

[35] Sources: United States Census Bureau, QuickFacts, www.census.gov/quickfacts/, *accessed Nov. 8, 2018*) and ASPCA, Pet Statistics, www.aspca.org, *accessed Nov. 9, 2018*.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jeem.2019.01.001.

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