Bag "Leakage": The Effect of Disposable Carryout Bag Regulations on Unregulated Bags

PRELIMINARY – COMMENTS WELCOME

Rebecca Taylor*

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Abstract

Governments often regulate the consumption of products with negative externalities. Leakage occurs when partial regulation results in increased consumption of these products in unregulated parts of the economy, undermining the benefits from the regulations. This article quantifies leakage from an increasingly popular environmental policy—the regulation of disposable carryout bags (DCB). In California, DCB policies prohibit retail food stores from providing customers with thin plastic carryout bags at checkout and require stores to charge a minimum fee for paper carryout bags. However, all remaining types of disposable bags are unregulated (e.g., garbage bags, food storage bags, paper lunch sacks). Using quasi-random variation in local government policy adoption in California from 2008-2015, I employ an event study design to quantify the effect of bag regulations on the consumption of plastic and paper carryout bags, as well as the consumption of other disposable bags. The results show that a 44 million pound reduction of plastic from the elimination of plastic carryout bags is offset by an additional 16 million pounds of plastic from increased purchases of garbage bags (i.e., sales of small, medium, and tall garbage bags increase by 67%, 50%, and 5%, respectively). Additionally, DCB policies lead to a 61 million pound increase in paper carryout bags used annually. Altogether, I show that DCB policies are shifting consumers towards fewer but heavier bags. I conclude by discussing the environmental implications of policy-induced changes in the composition of plastic and paper bags, with respect to carbon footprint, landfilling, and marine pollution.

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1 Introduction

Governments often regulate the consumption of products with negative externalities (e.g., alcohol, tobacco, sugar, and gasoline). However, regulations are not always complete, applying to only a subset of products contributing negative externalities. Leakage occurs when partial regulation results in increased consumption of these products in unregulated parts of the economy. If unregulated consumption is easily substituted for regulated consumption, 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 an increasingly popular environmental policy—the regulation of disposable carryout bags (DCB). Many DCB policies prohibit retail food stores from providing customers with thin plastic carryout bags at checkout and require stores to charge a minimum fee for paper carryout bags. However, all remaining types of disposable bags are left unregulated (e.g., garbage bags, storage bags, and lunch sacks). Given DCBs can be reused as garbage bags, storage bags, and lunch sacks, this article asks the empirical question: Do bans and fees on carryout bags cause consumers to increase their purchases of other unregulated bags?

To answer this question, I bring together two data sources: (i) weekly retail scanner data with store-by-product level price and quantity information, and (ii) transaction level data collected in-store at checkout. Using quasi-random variation in local government DCB policy adoption in California from 2008-2015, I employ an event study design to quantify the effect of DCB policies on the consumption of plastic and paper carryout bags, as well as the consumption of nine other types of disposable bags.

My main results show that a 44 million pound reduction of plastic per year from the elimination of plastic carryout bags is offset by an additional 16 million pounds of plastic from increased purchases of trash bags. In particular, sales of small, medium, and tall trash bags increase by 67%, 50%, and 5%, respectively. This plastic bag "leakage" is an unintended consequence of DCB policies that offsets the benefits of reduced plastic carryout bag use. Additionally, I estimate that DCB policies lead to an additional 61 million pounds of paper annually from increased paper carryout bag use, which is driven by the fact that paper carryout bags are substantially heavier than plastic carryout bags.

These policy-induced changes in plastic and paper bag use have implications for greenhouse gas emissions, marine debris, and landfilling. I conclude this article by comparing the benefits of reduced litter and marine debris from thin plastic carryout bags to the costs of greater emissions from the production of thicker bags, and to the costs of thicker bags taking up more space in landfills. While the upstream relationship between plastic production and carbon footprint is well established, the downstream relationship between plastic litter and marine ecosystems is harder to quantify, making it challenging to evaluate the environmental success of DCB policies. However, it is clear from the results of this article that not examining the leakage effects overstates the regulation's welfare gains.

This article 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),[1] 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. Aguilar et al. (2016) study a countrywide sugary drink tax in Mexico and document a decrease in the consumption of sugar due to the tax. However, they also find an increase in the consumption of fat, sodium, and cholesterol, and no change in overall calories consumed, indicating substitution towards non-taxed goods. Similar to these studies, I find that DCB policies are circumvented by consumers substituting towards unregulated disposable bags.

This article also provides a key variable for the field of life-cycle assessments—studies that estimate a product's cradle-to-grave environmental impact. Life-cycle assessments of plastic and paper 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 bags (Mattila et al., 2011). My results provide an estimate for the reuse of plastic carryout bags—suggesting that at least 15.8% of plastic carryout bags were used as trash bags before the DCB policies went into effect. This estimate can be used as a benchmark for calculating

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

and interpreting life-cycle assessment results going forward.

The remainder of the article is organized as follows. Section 2 catalogs the data. Section 3 describes the event study empirical design. Section 4 presents the main results. Section 5 discusses the environmental implications of changes in the composition of plastic and paper bags, with respect to carbon footprint, landfilling, and marine pollution. Section 6 concludes.

2 Data

2.1 Retail Scanner Data

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 information generated by point-of-sale systems for participating retail chains across the United States.[2] I use a subset of retail scanner data from participating stores in California between January 2008 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) and mass merchandising stores (e.g., supercenters and big-box stores) because these stores formats regularly sell non-food grocery items, such as food wrapping materials and 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 all of the following criteria: (1) the jurisdiction is located in California, (2) the jurisdiction implemented a DCB policy between January 2008 and December 2015, and (3) the jurisdiction is either an entire county or can be uniquely identified based on its 3-digit zip code. The third criteria is due to a limitation of the Nielsen scanner data—the exact location of each store is not provided—making it difficult 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 the 5 counties and 2 cities uniquely identified by their 3-digit zip code that implemented DCB policies during my sample period. This gives me a total of 201 stores. Table 1 presents characteristics of

[2] 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.

the seven jurisdictions in my sample, organized by order of DCB policy implementation. In addition to the jurisdiction name, implementation date, and store-sample count, Table 1 also reports the 2015 estimated population and median household income for each jurisdiction.

I aggregate the raw microdata to the store-by-month-by-product-group level. With respect to bags, there are 9 product groups: (1) Small Trash Bags, (2) Medium Trash Bags, (3) Tall Kitchen Bags, (4) Large Trash Bags, (5) Sandwich Bags, (6) Freezer Bags, (7) Food Storage Bags, (8) Oven Bags, and (9) Paper Lunch Sacks. Table 2 presents the summary statistics for the quantity and price variables by product group from 2008 to 2011, 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 greatly in their quantities sold and in their prices. On average, stores in my sample sell 58,892 sandwich bags, 2,319 small trash bags, and 345 oven bags per month. The average box of 26 large trash bags costs $6.58 and the average box of 106 sandwich bags costs $2.72.

2.2 In-store 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 treated and control stores during the months before and after a DCB policy change in the 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.[3] 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, the length of the transaction in minutes, and basic

[3]Each visit lasted 1 to 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.

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. The average transaction at a store without a DCB policy used 3.73 plastic bags, 0.04 paper bags, and 0.15 reusable bags, while the average transaction at a store with a DCB policy used 0.00 plastic bags, 0.50 paper bags, and 1.01 reusable bags.

2.3 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 nine categories of 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 and storage bags, sandwich bags are the lightest and carry the least volume (0.0038 lb; 0.2 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:

$$(1) \qquad Y^{B}_{sjm} = \sum_{l=-8}^{8} \beta_l D_{l,jm} + \theta_{sj} + \delta_m + \epsilon_{sjm}$$

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 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 $D_{8,jm} = 1$ for all months in which it is 8 months or more since DCB policy implementation and, similarly, $D_{-8,jm} = 1$ for all months in which it is 8 months or more until implementation. The month prior to implementation ($l = -1$) is the omitted category. 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.

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 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. Part of the appeal of event study designs is that 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.

3.2 In-store Data Event Studies

To examine the effects of DCB policies on the use of various carryout bags, I use the in-store, 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 variables I use for Y^C_{tsjdm} will be the number of carryout type C bags used per transaction.

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 $\hat{\beta}_l$ point estimates and 95% confidence intervals are displayed graphically.[4] Unless specified otherwise, I cluster the standard errors at the store level to account for the possibility that the errors are correlated within a given store, but not across stores.[5]

In Figure 1, the scanner data are averaged to the store-by-month level for each product, for a total of 17,906 observations. 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 $\hat{\beta}_l$ point estimates measure the percent difference in bag sales between treated and yet-to-be-treated stores l months from DCB policy implementation. The panels of Figure 1 correspond to the following bag products: (a) small trash bags, (b) medium trash bags, (c) tall kitchen bags,

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

[5] Ideally, standard errors would be clustered at the jurisdiction level, since that is the level of treatment. However, with only 7 jurisdictions this would lead to biased standard errors. Clustering the standard errors at the jurisdiction-by-month-of-sample level instead of at the store level does not change the significance of the results.

(d) large trash bags, (e) sandwich bags, (f) freezer bags, (g) food storage bags, (h) oven bags, and (i) paper lunch sacks.

Among the nine event studies presented in Figure 1, 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 $\hat{\beta}_0 = 0.534$ and $\hat{\beta}_1 = 0.681$. These estimates mean that the average monthly sales of small garbage bags at treated stores are 53.4% and 68.1% higher during the first and second months of a DCB policy. The increase in sales remains stable over time, ending with $\hat{\beta}_8 = 0.666$. The $\hat{\beta}_8$ coefficient indicates that for all months in which it has been 8 or more months since DCB policy implementation, sales of small garbage bags at treated stores remain 66.6% higher than at the yet-to-be-treated stores. All of the post-policy $\hat{\beta}_l$ coefficients are significantly greater than zero at the 1% significance level. Importantly, the the pre-policy $\hat{\beta}_l$ coefficients are close to zero and nearly parallel to the x-axis, which provides evidence in favor of the identifying assumption that small garbage bag sales were not trending before the DCB policies went into effect.

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 29.7% higher during the first month of a policy, 44.6% higher in the second month, and remain 49.9% higher 8 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 3.6% higher in the first month of a policy, 4.8% higher in the second month, and 5.4% higher 8 months or more after a policy. 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).

The remaining six bag product groups in Figure 1 do not experience significant or persistent increases in sales that are contemporaneous with policy implementation. All together, 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. These results also indicate that some customers are willing to pay for the trash bag services they gained from "free" plastic carryout bags.

To understand the magnitude of the changes in the sales of trash bags, I estimate Equation 1 with the outcome variables in levels instead of logs. Figure 2 presents the results of the event study model for small, medium, and tall kitchen trash bags. In panels (j), (k), and (l), I find that DCB policies cause a 2,547 bag increase in small garbage bag purchases per store-month, a 1,719 bag increase in medium garbage bag purchased per store-month, and a 1,020 bag increase in tall kitchen bags purchased per store-month.[6]

In panels (m), (n), and (o) of Figure 2, I convert the bag types into their weight equivalents. These panels show that DCB policies lead to 26, 32, and 36 additional pounds of plastic sold per store-month from increased purchases of small, medium, and tall kitchen trash bags respectively. 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 the environmental implications of these policy-induced changes in the consumption of plastic bags, with respect to carbon footprint, landfilling, and marine pollution.

In order to rule out the alternative hypothesis that changes in bag prices are driving the changes in bag demand, I examine whether the price of bags change with DCB policy implementation in panels (p), (q), and (r) of Figure 2. I find no changes in bag price that are contemporaneous with policy implementation. However, four months after the policy implementation, the price of small trash bags at treated stores begins to increase. In panel (p), $\hat{\beta}_8 = 0.006$, which approximately is a 4% increase in the price per small garbage bag. This is consistent with suppliers of trash bags responding to the exogenous change in small trash bag demand by increasing their prices.

4.2 In-store Data Results

The figures in this section present the results from the estimation of event study Equation 2, where the $\hat{\beta}_l$ point estimates and 90% confidence intervals are displayed graphically. I cluster

[6] In Figure 2, for small, medium, and tall kitchen bags respectively, $\hat{\beta}_8 = 2547.237$, 1718.857, and 1020.362.

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.

In the top three panels of Figure 3, 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 $\hat{\beta}_l$ point estimates measure the difference in bag usage between treated and control stores l months from the DCB policy implementation. The panels of Figure 3 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 use of plastic carryout bags. Customers use approximately 4 fewer plastic carryout per transaction bags when DCB policies go into effect. This reflects the fact that DCB policies prohibit the use of plastic carryout bags and that customers used 3.73 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 0.3 more paper bags and 0.6 more reusable bags per transaction.[7]

In panels (d), (e), and (f), I convert the bag types into their weight equivalents. DCB policies lead to 0.031 fewer pounds of plastic per transaction from the elimination of plastic carryout bags and 0.043 additional pounds of paper per transaction from the increased use of paper carryout bags.[8] 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 0.148 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, will have major implications for the success of these policies.

5 Quantifying Leakage

The event study results above show that DCB policies lead to decreased use of plastic carryout bags, increased use of paper and reusable carryout bags, and increased purchases of

[7] $\hat{\beta}_3 = -4.032$ in Figure 3(a), $\hat{\beta}_3 = 0.337$ in Figure 3(b), and $\hat{\beta}_3 = 0.591$ in Figure 3(c).

[8] $\hat{\beta}_3 = -0.031$ in Figure 3(d), $\hat{\beta}_3 = 0.043$ in Figure 3(e), and $\hat{\beta}_3 = 0.148$ in Figure 3(f)

garbage bags. To evaluate the environmental impacts of these changes, I convert the number of bags used into pounds and calculate the annual change in pounds of material used per year in California. Table 5 presents these calculations. Columns (1) and (2) present the changes in bag usage from the estimation of event study Equations 1 and 2, as shown in Figures 2 and 3. For the trash bag products, the $\hat{\beta}_8$ estimates are used (column 1) and for the carryout bags, the $\hat{\beta}_3$ estimates are used (column 2). 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 14,286 food stores in 2014—10,891 supermarkets, other grocery stores and specialty food stores and 3,395 general merchandise stores.[9] To make this aggregation for carryout bag, I use the estimate that Californian adults make 1.42 billion grocery transactions per year.[10] Finally, in column (4) I calculate the changes in the pounds of material consumed per year in California using the bag material and weight information from Table 4.

Table 5 reveals that DCB policies lead to a 44.1 million pound reduction in plastic per year in California from decreased use of plastic carryout bags. However, this reduction is offset by a 16.0 million pound increase in plastic from additional purchases of trash bags—4.4 million, 5.5 million, and 6.1 million pounds from small, medium and tall kitchen trash bags respectively. Thus, DCB policies have a 36% leakage rate with respect to pounds of plastic. In other words, 36% of the plastic reduction benefits of DCB policies are lost due to consumption shifting towards unregulated bags. Furthermore, DCB polices lead to a 60.7 million pound increase in paper per year in California from increased use of paper carryout bags. Therefore, on net DCB policies lead to 32.6 million additional pounds of disposable bags.

How do the changes in bag usage presented in Table 5 compare to average annual bag usage in California? According to CalRecycle, Californians dispose of 766.3 million lbs of plastic trash bags, 314.8 million lbs of plastic grocery and other merchandise bags, and 141.3

[9] *Source*: U.S. Census Bureau, 2014 County Business Patterns. Online, *accessed Apr. 25, 2017.*

[10] 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.

million lbs of paper bags each year.[11] Comparing these averages to column (5) of Table 5, DCB policies lead to a 2% increase in the use of trash bags, a 14% decrease in the use of plastic grocery bags and other merchandise bags, and a 43% increase in the use of paper bags.

The results in Table 5 reveal that DCB policies are shifting consumers towards fewer but heavier bags. While 4,339 million fewer bags are estimated to be used per year in California, the weight of bags used is 32.6 million pounds greater. This result is concerning with respect to planet-warming emissions, given the carbon footprint of an object is generally proportional to its mass.[12] 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, a paper carryout bag would need to be used 3 times, a low-density polyethylene (LDPE) reusable bag (the same material as trash bags) would need to be used 4 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.

My results also provide a lower bound for the reuse of plastic carryout bags—suggesting that at least 15.8% of plastic carryout bags were used as trash bags before the DCB policies went into effect. 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, the UK Environmental Agency (2011) study also estimated the global warming potential of various bags if 40% of plastic carryout bags were reused once as a trash bin liner. With this assumption, a paper carryout bag would need to be used 4 times to have the same global warming potential, a LDPE bag would need to be used 5 times, 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.

[11] *Source*: "2014 Disposal-Facility-Based Characterization of Solid Waste in California." *CalRecycle*. Online, *accessed Apr. 25, 2017.*

[12] *Source*: "Banning Plastic Bags is Great for the World, Right? Not So Fast." *Wired*. Jun. 10, 2016. Online, *accessed Apr. 25, 2017.*

Life-cycle assessments of carryout bags, such as UK Environmental Agency (2011) study, have constantly 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).[13] However, while life-cycle assessments 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) 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.[14] 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 44 million fewer pounds of plastic carryout

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[13] 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 transportation trucks and landfills (*Source*: "Graphic: Paper or Plastic?" *The Washington Post*. Oct. 3, 2007. Online, *accessed Apr. 25, 2017*.

[14] *Source*: "International Coastal Cleanup. Annual Report 2016." *Ocean Conservancy*. Online, *accessed Apr. 25, 2017*.

bags that could end up in storm drains and oceans, and 16 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 liter in waterways,[15] 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, in evaluating the environmental success of DCB policies, the benefits of reduced litter and marine debris needs 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 Table 5 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.

6 Conclusion

This article is the first to evaluate how regulating the use plastic and paper carryout bags affects the sale of unregulated disposable bags. Using quasi-random variation in 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 trash bags. When converted into pounds of plastic, 36% of the plastic reduction from DCB policies is lost due to consumption shifting towards unregulated plastic bags. More-

[15]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 (City of San Jose Transportation & Environment Committee, 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)

over, the increase in pounds of paper used from paper carryout bags more than offsets the decrease in pounds of plastic, which has negative implications with respect to the carbon footprint of DCB policies.

Overall, my result 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 and thicker plastics going into landfills? In order 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.

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Table 1: **Jurisdiction and Store-Sample Characteristics**

Jurisdiction	Implementation Month	# Stores in Sample	Pop. (2015)	Med. HH Inc. (2015)
City of San Jose	January 2012	40	1,026,908	$84,647
San Luis Obispo County	October 2012	17	281,401	$60,691
Alameda County	January 2013	68	1,638,215	$75,619
Mendocino County	January 2013	5	87,649	$42,980
San Mateo County	April 2013	41	765,135	$93,623
City of Richmond	January 2014	5	109,708	$55,102
Sonoma County	September 2014	25	502,146	$64,240

Note: Jurisdictions were chosen based on meeting all of the following criteria: (1) Jurisdiction is located in California, (2) Jurisdiction implemented a DCB policy by December 31, 2015, and (3) Jurisdiction is either an entire county or can be uniquely identified based on its 3-digit zip code. *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). Online, *accessed Apr. 25, 2017.*

Table 2: **Scanner Data Store-by-Month Summary Statistics; Pre-policy (2008-2011)**

Variable	Mean	Std. Dev	Min	Max	Obs.
Small Trash Bags (4 gal.)					
Boxes sold per month	52.25	53.51	0.00	439.00	9,136
Bags sold per month	2,318.99	3,514.17	0.00	34,740.00	9,136
Bags per box	35.79	13.59	22.00	112.50	9,012
Price per box	2.89	0.67	1.36	5.49	9,012
Price per bag	0.09	0.02	0.03	0.19	9,012
Medium Trash Bags (8 gal.)					
Boxes sold per month	33.73	31.08	0.00	338.00	9,136
Bags sold per month	1,218.39	2,033.91	0.00	23,850.00	9,136
Bags per box	27.80	16.09	20.00	100.00	8,733
Price per box	3.13	0.86	1.69	5.75	8,733
Price per bag	0.13	0.03	0.03	0.22	8,733
Tall Kitchen Bags (13 gal.)					
Boxes sold per month	412.98	347.56	23.00	3,304.00	9,136
Bags sold per month	21,209.03	21,734.06	1,419.00	190,217.00	9,136
Bags per box	49.77	6.98	31.64	77.57	9,136
Price per box	6.80	0.85	3.88	9.35	9,136
Price per bag	0.16	0.02	0.09	0.25	9,136
Large Trash Bags (30 gal.)					
Boxes sold per month	137.47	85.93	4.00	869.00	9,136
Bags sold per month	3,484.93	2,631.15	140.00	27,556.00	9,136
Bags per box	26.25	4.20	11.67	40.85	9,136
Price per box	6.58	0.90	3.92	9.48	9,136
Price per bag	0.30	0.03	0.16	0.53	9,136
Sandwich Bags					
Boxes sold per month	546.84	512.17	6.00	6,252.00	9,136
Bags sold per month	58,891.85	60,442.03	720.00	743,510.00	9,136
Bags per box	106.01	11.85	66.00	155.63	9,136
Price per box	2.72	0.26	1.59	3.63	9,136
Price per bag	0.04	0.07	0.02	1.22	9,136
Freezer Bags					
Boxes sold per month	324.32	222.32	20.00	2,219.00	9,136
Bags sold per month	8,450.76	7,050.96	461.00	78,028.00	9,136
Bags per box	23.34	3.82	14.67	42.00	9,136
Price per box	3.24	0.54	1.59	6.11	9,136
Price per bag	0.16	0.03	0.08	0.30	9,136

Variable	Mean	Std. Dev	Min	Max	Obs.
Food Storage Bags					
Boxes sold per month	570.28	416.84	40.00	3,928.00	9,136
Bags sold per month	18,999.07	15,815.79	865.00	184,290.00	9,136
Bags per box	30.09	2.34	16.50	45.27	9,136
Price per box	3.23	0.42	1.33	5.61	9,136
Price per bag	0.23	0.20	0.06	2.13	9,136
Oven Bags					
Boxes sold per month	86.06	131.20	0.00	2,968.00	9,136
Bags sold per month	344.58	423.19	0.00	9,385.00	9,136
Bags per box	5.56	1.13	1.00	10.00	9,069
Price per box	3.24	0.59	0.39	5.49	9,069
Price per bag	0.95	0.37	0.14	3.89	9,069
Paper Sacks					
Boxes sold per month	56.27	54.86	0.00	604.00	9,136
Bags sold per month	4,837.58	4,003.18	0.00	35,650.00	9,136
Bags per box	89.01	17.58	31.67	100.00	9,118
Price per box	2.12	0.32	1.21	3.63	9,118
Price per bag	0.03	0.01	0.01	0.16	9,118

Source: Author's calculations from retail scanner data.

Table 3: **In-Store Data Summary Statistics**

Variable	Mean	Std. Dev	Min	Max	Obs.
Without DCB Policies					
Plastic bags per txn.	3.73	3.71	0.00	30.00	2,017
Paper bags per txn.	0.04	0.39	0.00	8.00	2,017
Reusable bags per txn.	0.15	0.63	0.00	7.00	2,017
With DCB Policies					
Plastic bags per txn.	0.00	0.00	0.00	0.00	2,407
Paper bags per txn.	0.50	1.19	0.00	14.00	2,407
Reusable bags per txn.	1.01	1.42	0.00	10.00	2,407

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

Table 4: **Bag Product Group Characteristics**

Bag Product Group	**Material**	**Weight (lb/bag)**	**Volume Capacity (gal/bag)**
Trash & Storage Bags			
Small trash bag	LDPE; 18in×17in× 0.5mil	0.0101	4
Medium trash bag	LDPE; $20\frac{1}{2}$in×20in×0.69mil	0.0187	8
Tall kitchen bag	LDPE; 24in×$28\frac{3}{8}$in×0.78mil	0.0351	13
Large trash bag	LDPE; 30in×33in×0.85mil	0.0555	30
Sandwich bag	LDPE; $6\frac{1}{2}$in×$5\frac{7}{8}$in×1.50mil	0.0038	0.2
Freezer bag	LDPE; $10\frac{1}{2}$in×$10\frac{3}{4}$in×3.00mil	0.0224	1
Food storage bag	LDPE; 13in×15in×1.75mil	0.0225	2
Oven bag	Nylon; 22in×20in×1.18mil	0.0428	8
Paper sack[1]	Kraft Paper	0.0220	1
Carryout Bags			
Plastic carryout bag[2]	HDPE	0.0077	4
Paper carryout bag[3]	Kraft Paper; Flat Handles	0.1267	5
Reusable carryout bag	Woven PP[4]	0.3086	6
–	Non-woven PP[5]	0.2372–0.2736	5–6
–	Cotton[5]	0.1735–0.5051	5–9
–	Heavy duty LDPE[5]	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. Online, *accessed Apr. 25, 2017*). HDPE has a density of 0.0347 lb/in^3 (Plastics International. Online, *accessed Apr. 25, 2017*). Nylon has a density of 0.0412 lb/in^3 (AZO Materials. Online, *accessed Apr. 25, 2017*). mil = a thousandth of an inch. Unless otherwise indicated, bag weights are calculated by author using material densities and standard bag dimensions.

[1] *Source*: Uline. "Paper Grocery Bags – 6 × $3\frac{5}{8}$ × 11", #6, Kraft" Online, *accessed Apr. 25, 2017.*

[2] *Source*: CalRecycle. "Diversion Study Guide, Appendix I; Conversion Factors: Glass, Plastic, Paper, and Cardboard." Online, *accessed Apr. 25, 2017.*

[3] *Source*: Uline. "Paper Grocery Bags – 12 × 7 × 14", 17 Barrel, Flat Handle, Kraft" Online, *accessed Apr. 25, 2017.*

[4] *Source*: ReuseThisBag.com. "Woven Polypropylene Grocery Bag." Online, *accessed Apr. 25, 2017.*

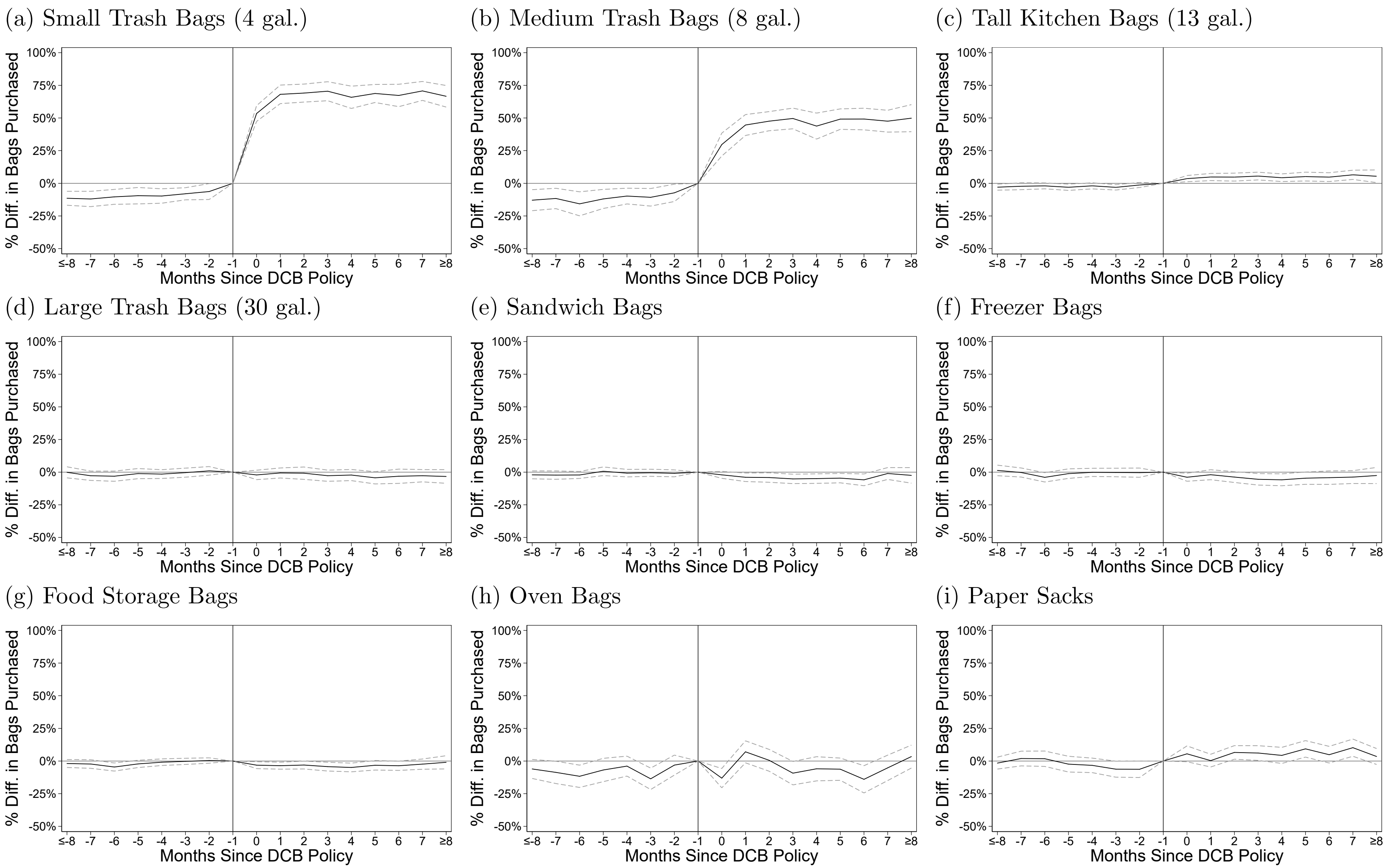
[5] *Source*: Environment Agency. "Life Cycle Assessment of Supermarket Carrier Bags: A Review of the Bags Available in 2006." Online, *accessed Apr. 25, 2017.*

Table 5: **Effect of DCB Policies on Annual Bag Usage and Weight in California**

	(1) **Δ Bags/ Store-Month**[1]	(2) **Δ Bags/ Txn**[1]	(3) **Δ Bags/ Year**[2]	(4) **Δ Lbs/ Year**[3]
Trash Bags				
Small trash bag	2,547		437 million	4.4 million
Medium trash bag	1,719		295 million	5.5 million
Tall kitchen bag	1,020		175 million	6.1 million
Carryout Bags				
Plastic carryout bag		-4.032	-5,725 million	-44.1 million
Paper carryout bag		0.337	479 million	60.7 million
Net Plastic Δ			-4,818 million	-28.1 million
Net Plastic + Paper Δ			-4,339 million	32.6 million

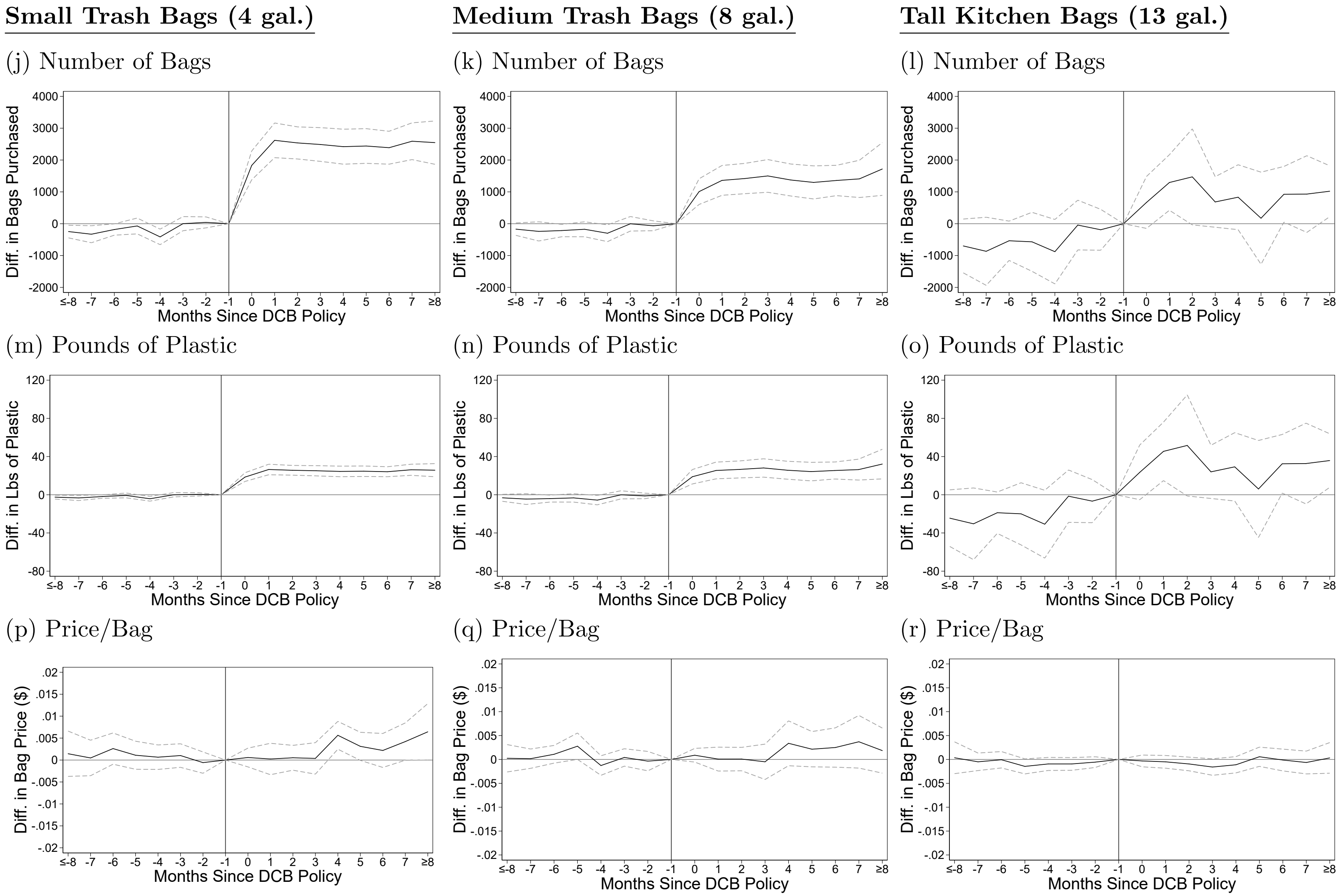
[1] *Note*: Changes in bag usage come from the estimation of event study equations 1 and 2, as show in figures 2 and 3. For the trash bag products, I present the $\hat{\beta}_8$ estimates and for the carryout bag products, I present the $\hat{\beta}_3$ estimates.
[2] *Note*: Changes in trash bag usage is calculated using the estimate that California had 10,891 supermarkets, other grocery stores and specialty food stores and 3,395 general merchandise stores in 2014, for a total of 14,286 food stores (*source*: U.S. Census Bureau, 2014 County Business Patterns. Online, *accessed Apr. 25, 2017*). Changes in carryout bag usage is 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.
[3] *Note*: Changes in the pounds of material per year are calculated using the bag material and weight information from Table 4.

Figure 1: **Effect of DCB Policies on Bag Purchases (*Scanner Data*)**



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 standard errors clustered at the store level.

Figure 2: **Effect of DCB Policies on Trash Bag Purchases (*Scanner Data*)**



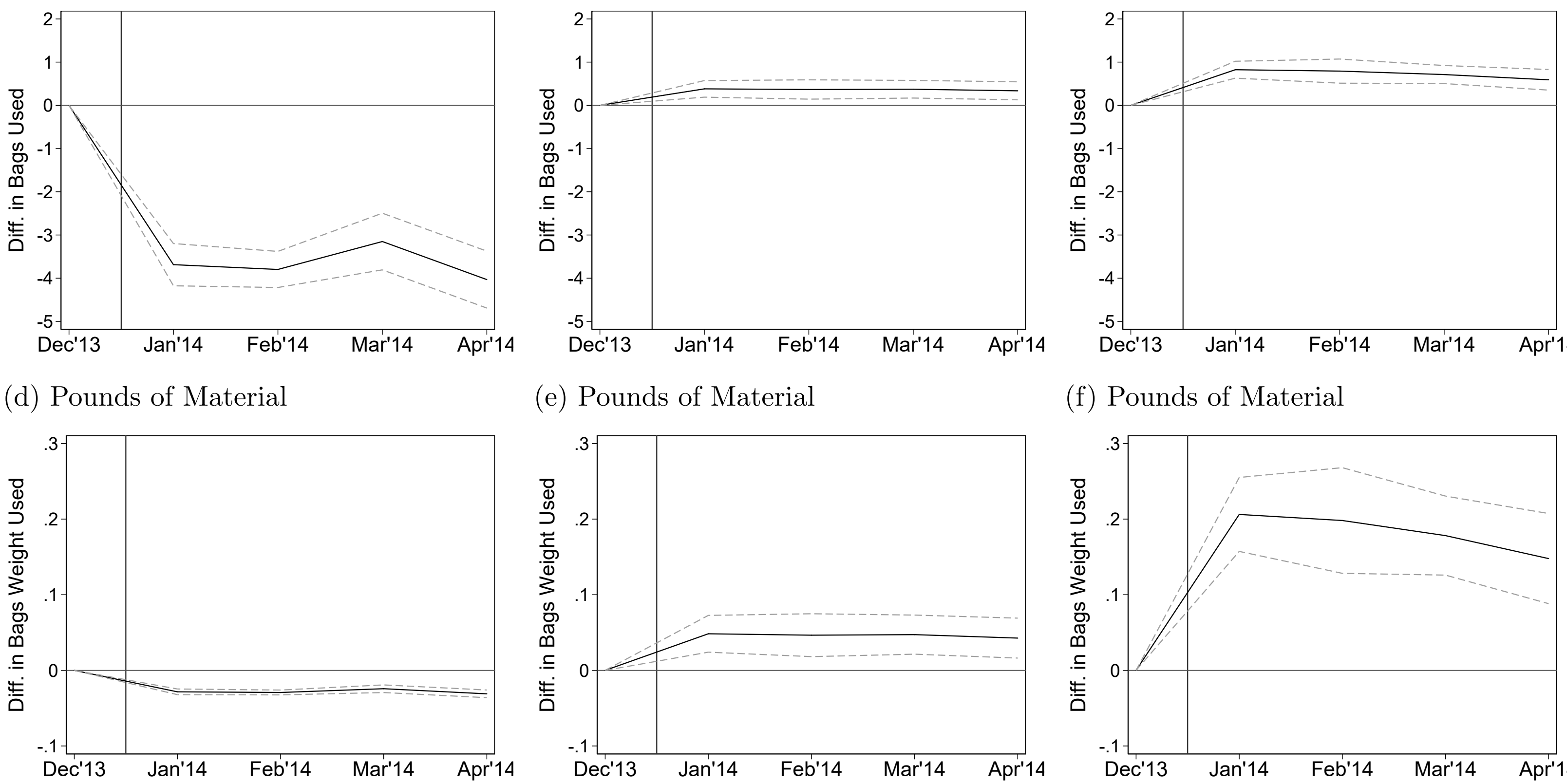
Note: The figure panels display the $\hat{\beta}_l$ coefficient estimates from event study Equation 1. The dependent variables for store s in jurisdiction j and month-of-sample m are: panels (j) to (l)—the number of product group B bags sold; panels (m) to (o)—the pounds of product group B bags sold; 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 standard errors clustered at the store level.

Figure 3: **Effect of DCB Policies on Carryout Bag Use (*In-store Data*)**

Plastic Carryout Bags | **Paper Carryout Bags** | **Reusable Carryout Bags**

(a) Number of Bags | (b) Number of Bags | (c) Number of Bags

(d) Pounds of Material | (e) Pounds of Material | (f) Pounds of Material



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.