Nudging Away from Plastic Bags with Charitable Donations

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ABSTRACT *To respond to the environmental problems posed by disposable plastic bags, several mechanisms exist, such as bag taxes and bans, but such policies are infeasible in several U.S. states and municipalities. This study uses a social quasi-experiment to examine the effect of a voluntary token-donation program, which reduces disposable plastic bag use by providing a small charitable donation incentive. We find that the token-donation program reduces the probability of disposable bag use by 11.4–12.9 percentage points, representing about 30%–34% decrease in bag use. Our results demonstrate effective mechanisms to reduce plastic bags exist without government-mandated policy.* (JEL Q53)

1. Introduction

Many countries excessively use single-use plastic bags (Rivers, Shenstone-Harris, and Young 2017). In the United States, disposable bag use was 103.5 billion in 2014, an 8.6% overall increase between 2009 and 2014 (U.S. International Trade Commission 2016). In the United Kingdom, seven major retailers consumed 1 billion single-use plastic bags from 2017 to 2018, 60% of the total bags used by all retailers (U.K. Government 2019). Grocery stores, convenience stores, and takeout restaurants are major users of single-use plastic bags (Smith 2004; Sharp, Høj, and Wheeler 2010; Wagner 2017). Consumers accustomed to the convenience of free single-use plastic bags has led to large quantities of bags being used (Sharp, Høj, and Wheeler 2010; Wagner 2017), but recycling rates are low in many countries (Smith 2004; Spokas 2008; Sharp, Høj, and Wheeler 2010). Since most plastic bags are not biodegradable, they create challenges for wildlife, landfills, landscapes, and stormwater management systems (Barnes et al. 2009).

Several mechanisms categorized by Rivers, Shenstone-Harris, and Young (2017) into four major policy alternatives exist to curtail the use of single-use plastic bags thus their negative effects: (1) prohibition or restriction, (2) market-based mechanisms, (3) consumer education, and (4) nudging. Plastic bag policies have rapidly expanded across the world, tripling in number since 2010, with the majority being bans (52%) and pricing mechanisms (32%) (Nielsen, Holmberg, and Stripple 2019). Although these policies reduce plastic bag use, challenges exist, such as resistance to the policies, difficulty measuring effects, and undesired side effects (Nielsen, Holmberg, and Stripple 2019). For instance, disposable bag regulations inadvertently affected unregulated plastic bag use, such as trash bags (Taylor 2019).

Multiple municipalities and states in the United States have implemented bans and market-based mechanisms with varying degrees of success; but in the United States, such policies may be unpopular, politically infeasible, or overturned (New York State 2018; Florida Senate 2019; Washington State Legislature 2019). Fourteen U.S. states have passed preemption legislation that prevents local government action of single-use plastic bag management such as bans, taxes, or improved

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recycling programs (National Conference of State Legislature 2019). In such circumstances, nudges or education may be more feasible for addressing the overuse of single-use plastic bags. Nudging involves gently encouraging alternative behaviors through reminders and cues but not through mandates (Thaler and Sunstein 2008). Examples of nudging include making healthy foods more prominent and visible relative to unhealthy foods in grocery stores or public display of warning signs of smoking hazards (Sunstein 2014). Several retailers have implemented donation programs to nudge against using single-use plastic bags and encourage customers to bring reusable bags by donating to charity on the customer's behalf. Although implementation is more feasible than other policies in the United States, as far as we know, no studies have considered a donation strategy to reduce plastic bag use.

Using a quasi-experiment, we contribute to the literature by testing the efficacy of a charitable donation program to nudge toward reduced plastic bag use in the context of university convenience stores. Shoppers who choose to forgo a bag will earn a token from the store, and they can subsequently use the token to signal the store to make a corresponding donation for them. We find that the token program reduces the probability of disposable bag use by 11.4–12.9 percentage points. This result demonstrates that effective nongovernment mechanisms to reduce plastic bags exist, warranting further study with expanded scope of application.

2. Literature Review

Effect on the Environment, Animals, and Human Health

Plastic is a major category of solid waste, responsible for 60%–80% of marine litter (Derraik 2002; Xanthos and Walker 2017). Plastic bags can travel significant distances even in low-speed winds, contributing to land and marine litter (Verghese, Jollands, and Allan 2006; Wagner 2017). Plastic debris threatens marine mammals, seabirds, turtles, fish, and crustaceans (Laist 1987; Hong et al. 2013), causing harm by ingestion, which blocks digestive tracts and displaces actual food consumption, or entanglement of floating or submerged debris (Moore 2019). Human consumption of microplastics has also been documented (Cox et al. 2019).

Plastic bag litter creates solid waste and high disposal costs for local government (Taylor and Villas-Boas 2016; Wagner 2017). Six major U.S. cities spent 3.2–7.9 cents per bag for plastic bag litter control (Burnett 2013; Taylor and Villas-Boas 2016). A cleanup of the Anacostia River in Washington, DC, cost an estimated $32.4 million, with plastic bags making up 47% of all litter (Anacostia Watershed Society 2008). In addition to being a threat to public health and wildlife (Clapp and Swanston 2009), plastic bags create sanitation and sewage issues, with plastic bag-clogged drains said to be partially responsible for several flooding events (*The Economist* 2009; Onyanga-Omara 2013).

Government Policies to Reduce Plastic Bag Use

Several types of policies exist to regulate plastic bag use, adopted either separately or in combination (Rivers, Shenstone-Harris, and Young 2017) and have been reviewed in a number of studies (Clapp and Swanston 2009; Li and Zhao 2017; Nielsen, Holmberg, and Stripple 2019).

Prohibition or Restrictions

Some municipalities have prohibited retailers from offering single-use bags at the point of sale, San Francisco becoming the first such city in the United States in 2007 (Wagner 2017). Taylor and Villas-Boas (2016) found that bag bans decreased disposable bag use. The percentage of customers using paper bags increased from less than 5% before the policy to over 40% afterward. Furthermore, these authors support that bag bans and fees have a similar effect on customers in terms of an increase in reusable bag use, with 46% and 47% of customers bringing their own reusable bags after introducing bans and fees, respectively. However, bans may be unpopular among consumers due to diminished freedom (Coulter 2010), although shoppers may be less resistant after implementation (Sharp, Høj, and

Wheeler 2010). Bans and fees may also cause stockpiling behavior reducing the efficacy of these policies (Dong and Klaiber 2019).

A similar type of policy regulates bag specification: the plastic bag should meet the specified standard for bag design, such as thickness, materials used, compostability, and pro-environmental messaging (Wagner 2017). For example, reusable plastic bags must be at least 2.25 mm thick in the United States (Romer and Tamminen 2014). However, such mandates can still contribute to pollution. For instance, some stores responded to a 2015 single-use plastic bag ban in Honolulu County, Hawaii, by distributing reusable bags for free (Soloman 2016).

Market-Based Mechanism

Many countries and municipalities have implemented single-use plastic bag taxes and fees between \$0.05 and \$0.10 since the late 2000s (Rivers, Shenstone-Harris, and Young 2017). Several studies show substantial effect, with plastic bag use decreasing by 60% in Washington, DC (District Department of the Environment 2013) and 90% in Ireland (Convery, McDonnell, and Ferreira 2007). Taxes and fees also significantly increase reusable bag use (Homonoff 2018; Poortinga, Whitmarsh, and Suffolk 2013; Rivers, Shenstone-Harris, and Young 2017). In contrast, Homonoff (2018) finds that offering a five-cent bonus for reusable bag use generated virtually no behavioral change, consistent with the theory of loss aversion where individuals prefer avoiding a loss rather than acquiring an equivalent gain. Similarly, communicating such fees as a monetary loss due to a tax may be more effective than a gain from avoiding a fee (Muralidharan and Sheehan 2016). However, market-based mechanisms may face challenges. First, local implementation of market-based mechanisms may be prohibited because of violation of national or state policies (Romer and Tamminen 2014; Wagner 2017). Furthermore, fees may induce short-run decreases in plastic bag use, but the effect may decay as consumers become accustomed to paying for bags (Dikgang, Leiman, and Visser 2012).

Consumer Education

Consumer education alerts the consumers by providing information on the negative effects of plastic bag use and ways to reduce plastic bag consumption and increase recycling through campaigns, visual prompts, and social messaging (Wagner 2017).[1] Monroe (2003) mentions educational programs for environmental literacy as a potential tool for changing environmental behavior. Wagner (2017) contends that although there is little or no explicit cost to consumers, education can be expensive to implement and unlikely to have a significant reduction on plastic bag consumption and recycling. Some success has been recorded only when consumer education is implemented in combination with other policy instruments, such as a bag tax (Convery, McDonnell, and Ferreira 2007).

Nudging

Thaler and Sunstein (2008, 6) defined nudging as "any aspect of the choice architecture that alters people's behavior in a predictable way without forbidding any options or significantly changing their economic incentives." The use of nudges has grown due to their relatively low cost and prospects in achieving public policy goals (Sunstein 2014), such as in health (Lai, List, and Samek 2020), education (Pugatch and Wilson 2018), and insurance (Handel 2013). Using verbal prompts on children's school lunch choices, Lai, List, and Samek (2020) found that 30% of students in the treatment group chose and consumed healthier white milk relative to sugar-sweetened chocolate milk. Pugatch and Wilson (2018) used information, framing, and incentives to nudge university students' study habits. Handel (2013) showed the positive effect of policies that nudge consumers toward more advantageous decisions on the insurance market by reducing inertia.

Nudging has also been shown to reduce plastic bag use, but primarily in the form of plastic bag taxes (Rivers, Shenstone-Harris,

[1] As pointed out by a reviewer, education may be considered a type of nudge. We maintain its separation because it is exclusively focused on intrinsic motivation, whereas nudges can be either rely on intrinsic or extrinsic motivators.

and Young 2017). Although Sunstein (2015) mentioned that nudging must maintain the freedom of choice, and therefore, taxes, subsidies, fines, or jail sentences may not be considered nudges, Rivers, Shenstone-Harris, and Young (2017) argue that "sufficiently small ($0.05 per bag)" bag taxes not collected by any government constitute a nudging policy rather than a classic market-based mechanism. In the field of medical ethics, Blumenthal-Barby and Burroughs (2012) categorized nudging into six types and referred to incentives used "to either reinforce a positive choice or to punish a negative choice" as "incentive nudges."

Recently, Chandra (2020) conducted a combination of lab and online experiments using different framing questions regarding plastic bags at checkout to nudge customers toward bringing their own bags and finds the nudges to be effective at reducing plastic bag use. Romano and Sotis (2021) exploit fan loyalty and rivalry to different football teams as a nudge to reduce the consumption of single-use carrier bags and find around 13% reduction in average bag use. The mechanism involved is when a customer buys a single-use carrier bag in the supermarket, they donate a small amount to an institution (related to the Juventus football team, which is despised by most people in that area) which is perceived negatively by customers (anticharity). Instead, when a customer does not purchase a bag, they transfer the same amount from the "anticharity" institution to the association that helps local children, which is likely to be perceived positively by customers (charity).

A related but emerging type of nudge to reduce plastic bag use is for retailers to make a donation on behalf of customers who forgo a plastic bag or use a reusable bag. Because the store pays for the donation, there is no explicit cost of forgoing a bag to the customer. Although the amount of donation per forgone bag (typically a few cents) may not be small to the actual cost of a bag, such an amount is likely small compared with the average transaction value made. This is consistent with Thaler and Sunstein (2008) that a nudge must be easy to implement and cheap for both sides of the policy. Several retail grocers have previously implemented this nudge in different ways:

- Lucky's Market's "Bags for Change" program:[2] Every time customers bring a reusable bag to the store, they receive a wooden dime for each one. They have the opportunity to donate that dime to their choice of a local nonprofit organization. At the end of the quarter, the store will double the amount raised.
- New Seasons Market's "Bag it Forward" program:[3] Customers can donate their five-cent reusable shopping bag refund to one of three nonprofits.
- New Leaf Community Market's "Bag it Forward" program:[4] Customers receive 10 cents for each reusable bag they used with the option to donate their dime to a local charity. The store will match every bag incentive forwarded to charity, so every reusable bag equals a 20-cent donation. The store has also implemented a similar donation program since 1993 known as "Envirotokens."[5] Under this program customers receive an Envirotoken worth 10 cents for each reusable bag they used and then can donate the Envirotokens to one of six local nonprofits selected by the community.

To our knowledge, no study has formally investigated the effectiveness of token/donation program nudges to reduce plastic bag use.

3. Methods

Data Collection and Experimental Design

To test the effectiveness of a token program at reducing single-use plastic bags, a quasi-experiment was implemented at two

[2] Lucky's Market, https://www.luckysmarket.com/community/programs/ (accessed on July 19, 2019; no longer available).

[3] New Seasons Market, https://www.newseasonsmarket.com/our-story/community/ (accessed on July 19, 2019).

[4] New Leaf Community Markets, http://www.newleafmarket.coop/about/donations/bag-it-forward (accessed on July 19, 2019; no longer available).

[5] New Leaf Community Markets, https://www.newleaf.com/different/community/ (accessed on August 26, 2021).

convenience stores: Wildcat Pantry at The 90 and Wildcat Pantry at Holmes Hall, at the University of Kentucky. Wildcat Pantry at The 90 was chosen to be treated with the token program intervention and the Wildcat Pantry at Holmes Hall as the control without the program. Examining on-campus convenience stores helps reduce the noise of the experiments brought by uncontrollable factors such as patron socioeconomic status. The university has several convenience stores, but these two were chosen because they are most similar in multiple respects. First, they have the largest volume of business and sales on campus, representing nearly all of the more than 30,000 plastic bags distributed per month. Second, these locations are both close to undergraduate student dorms, so they primarily cater to undergraduate students who presumably have similar overall purchasing behavior. Third, a greater portion of the sales of these two stores comes from traditional grocery items. Other convenience store locations cater to lunch crowds with more ready-to-eat foods, limited hours, and few items per transaction, and therefore low overall bag use. The two locations are approximately 0.8 miles from each other, and there is no direct vehicular path connecting the two. They are apart enough to have few overlapping customers. Social intervention studies may face experimental/information spillover or leakage (Strain, Shores, and Kerr 1976). To reduce such possibilities, the token program was not advertised and was only apparent inside of the intervention store location. The survey data described below support that spillover may not constitute a large concern.

Observation at these two locations occurred during a control period and an intervention period in which the token program was in place. The control period lasted from August 27 to September 5, 2017 (10 days). Admittedly, this control period is short for three reasons: (1) Wednesday, August 23, was the first day of the fall semester, in which traffic at the convenience stores reaches normal levels; (2) August 23–26 were used to finalize the data-collection process and train observers and survey enumerators; and (3) university dining services agreed to implement the token program for only one semester and wanted to launch it as early in the semester as possible. In the intervention period, the store where the token program was implemented at The 90 is hereafter referred to as store A. The control store at Holmes Hall is referred to as store B.

The token program worked as follows. Cashiers were instructed to inform the customers that if they are willing to forgo taking plastic bags in a transaction, they would receive a token worth \$0.05. They would then immediately donate toward one of three charities by dropping the token into a corresponding receptacle. The store would periodically tally the tokens and make corresponding donations to the charities. One token was provided per transaction such that forgoing multiple plastic bags did not yield multiple tokens. Signage for the token program appeared near the cash register. The token receptacles were positioned near the only entry/exit of the store, along with similar signage and a short description of the token program and the charities. The three charities were: Big Blue Pantry, Glean KY, and Sierra Club Kentucky Chapter. The charities were chosen by the director of the university dining services following relevant university guidelines on working with charities, and they represent the common categories of charities consumers see on a daily basis (environment and food). The types of charity may affect the overall customer participation in the token program as well as the relative donation received. A study on the effect of types of charity on participation, while useful, is beyond the scope of this analysis. The intervention occurred at store A at the request of dining services since it had the highest sales and bag use per month. The intervention period occurred for 72 days, starting on Wednesday, September 6, 2017 (two weeks after the start of the fall semester) through Friday, November 16, 2017.

Receipts of items purchased per transaction were unavailable. Moreover, because there was no tax/fee for the plastic bag, these receipts do not indicate the number of plastic bags a customer used, their decision to forgo one or multiple plastic bags, or whether they took a token. As a result, passive data collection was infeasible. Instead, data collection occurred via in-person observation, in which an observer collected as many transactions as possible during one-hour sessions.[6] Each one-hour observation session occurred simultaneously at both stores. Seventy-five sessions occurred during the experiment, with approximately 10 sessions per week, and one or two one-hour sessions occurring each day.[7] The observer recorded the cashier ID and the number of items purchased by a customer, the number of disposable plastic bags used, the number of reusable bags (if any), and the estimated size of each of the purchased items. Items smaller than a 12 oz. can of soda were considered small; items approximately equal to or larger than a two-liter bottle were considered large, and anything in between was medium. Observers were instructed that if they were undecided on the size of the item, assume the larger item size, meaning that if they were unsure if something is small or medium, code as a medium-sized item. Some items were considered nonbaggable, such as a 12-pack of soda, and were excluded from the count of total items. Instances of double bagging were also noted. Each observer participated in multiple training sessions to ensure that record-taking was consistent across observers. To reduce a Hawthorne effect, the observer stayed at least five feet away from the register and did not make eye or verbal contact with the shoppers. The position of the observers was slightly obstructed by a wall/pillar, and they recorded data on a laptop so as to be less conspicuous to customers.

As a supplement to the observational transaction and plastic bag use data, a survey enumerator was often present at both locations to collect survey responses from shoppers concurrent with observational data. Implementing this survey helps establish similarity or dissimilarity between the customers at the locations but cannot be linked back to individual customers, nor was such data collected from each customer during the one-hour session. Participants were selected at random to complete the survey after they had completed their purchase and were ready to leave the store. The frequency of selection was also a function of foot traffic. For example, if many customers were present, a lower proportion of customers were asked to participate to decrease unobservable correlation across customers. The survey was designed to take approximately 60–90 seconds to complete. Participants answered the survey on their phone via scanning a QR code, with the option to use an enumerator-provided device if necessary. Each respondent received a small snack in return for finishing the survey.

Statistical/Econometric Methods

We estimate the effect of the token program by comparing the use of plastic bags when the program is and is not implemented at the treatment location as well as between treatment (store A) and control (store B) location using a difference-in-difference approach. The effect of the token program was estimated as the coefficient of the interaction term between the intervention period and treatment location. The identification strategy is expressed in equation [1]:

$$Y_i = \beta_1 + \beta_2 Token_i + \beta_3 StoreA_i + \beta_4\ Token_i * StoreA_i + \boldsymbol{\theta X}_i + \varepsilon_i. \quad [1]$$

In this equation, Y_i is the outcome variable for transaction *i. Token* indicates the token program and takes a value of one for the intervention period (September 6–November 16), and zero for the control period. *StoreA* is a dummy variable indicating the treated store. X_i is a vector of control variables, and ε_i is the error term. All other symbols are associated parameters to be estimated. As the data show (next section), most transactions used one plastic bag and very few used more than two bags, so we created a binary dependent variable Y_i that takes the value one if the individual customer takes one or more disposable plastic bags

[6]Not all transactions were able to be logged in a one-hour session. During peak periods, a second, auxiliary register would operate, typically for 5–10 minutes. In these time periods, the observer would continue to record transactions from the first (and closer) register. Observers were trained to focus on the plastic bag outcome and the number of items purchased in situations of high volumes of purchases, so we have a high degree of consistency in these data-collection processes.

[7]The exact schedule of data collection is available on request.

Table 1
Descriptions of Variables

Variable	Mean	Std. Dev.	Description
Disposable bag	0.38	0.48	1 if customer used a plastic bag, 0 otherwise (dependent variable)
Token	0.85	0.36	1 if after implementation of token program, 0 otherwise
StoreA	0.70	0.46	1 if observation comes from the store A (treated convenience store), 0 otherwise
Total items	2.09	1.44	Total number of items purchased per transaction
Small items	1.29	1.19	Number of small items purchased per transaction (can of soda or smaller)
Medium items	0.63	0.97	Number of medium items purchased per transaction (any items in between small and large)
Large items	0.17	0.50	Number of large items purchased per transaction (2 liters of soda, half-gallon of milk, 6-packs of bottled water)
Evening	0.62	0.49	1 if purchase occurred in evening (after 5 p.m.), 0 otherwise
Weekday	0.93	0.26	1 if the purchase occurred Monday through Friday, 0 otherwise
Preceding customer	0.38	0.48	1 if the previous customer used a plastic bag, 0 otherwise
Female	0.49	0.52	Gender of the customer: 1 if female, 0 otherwise
Percentage of plastic bag use	0.44	0.13	Percentage of the customer using plastic bags for each day before intervention
Trend	4.5	2.36	Trend representing each day before the intervention of token program (since we had 8 control days, trend represented as 1, 2, …, 8)

during a transaction and zero otherwise. Because the dependent variable is binary, we use a logit model and a linear probability model (LPM) to study plastic bag use.

We incorporate several control variables, described in Table 1. We account for the number of items purchased with two specifications. The first uses the total number of items purchased. The second specification segments items based on their size into the number of small items, medium items, and large items. We control for timing with the *Evening* (i.e., if the purchase occurred after 5 p.m.) and *Weekday* (as opposed to weekends) variables. Because customers observe one another, we also control for this potential spillover, since the preceding customer's voluntary decision may inspire the next customer's choice. This is represented by *Preceding Customer*, which we expect to have a positive association with the dependent variable. Last, we record the gender of the customer. Beyond this characteristic, no other individual information from observational data was included in the model. However, we collected survey data (described below) to establish the similarity of store A and store B. Beyond the variables mentioned, we included fixed effects for our 14 observers to account for the variation in data due to personal factors, for example, determining the size of items. We also included fixed effects for 43 cashiers in stores during the experiment to address the variations, such as some cashiers who may inform customers of the token program in a more clear and motivational way than others do.

4. Results

In total, 5,630 transactions were recorded during the experiment, with 3,966 transactions from store A and 1,664 transactions from store B. Figure 1 shows the frequency of plastic bag use for stores A and B before and after the intervention of the token program, respectively.[8]

Parallel Trend Assumption

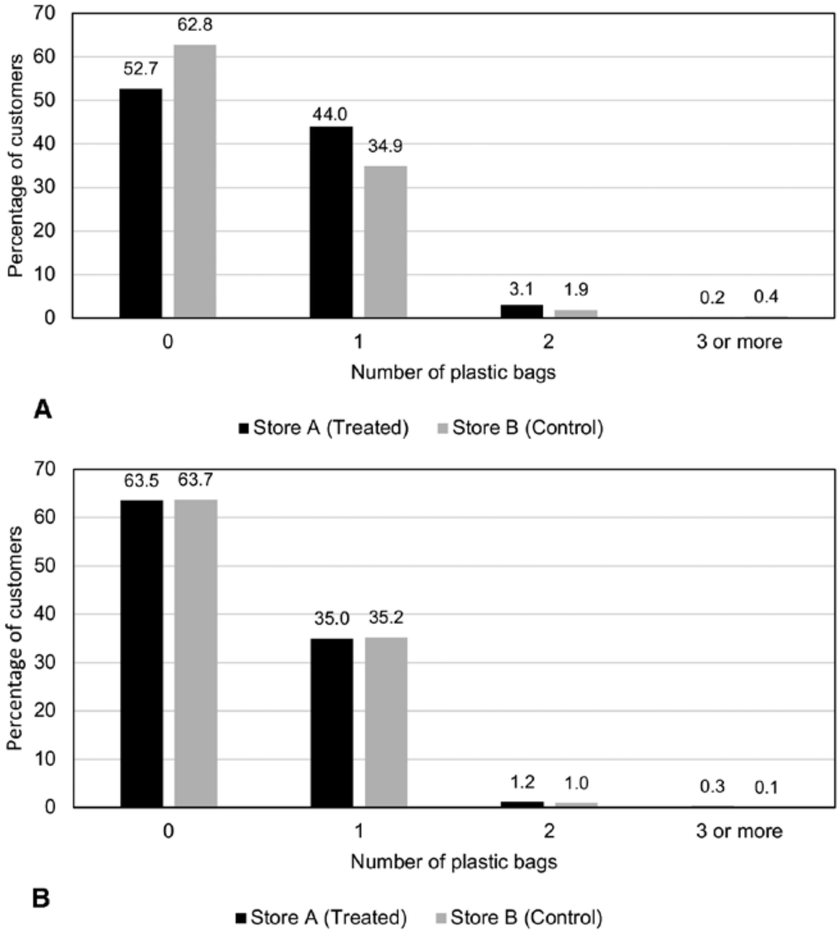
To examine parallel trends, we test whether the stores follow the same daily trend on the percentage of customers using plastic bags during an observation session before the intervention based on equation [2]:

$$\textit{Percentage plastic bag use}_{jt} = \alpha + \gamma \textit{Trend}_t + \beta \textit{Trend}_t {*} \textit{StoreA}_{jt} + \varepsilon_{jt}. \quad [2]$$

[8] The percentage of customers across categories sums to 100% for each store separately.

Figure 1

Plastic Bag Usage in Store A (Treated) and Store B (Control): Pre- and Postintervention of the Token Program
A: Plastic Bag Use for Store A (Treated) and Store B (Control) (Preintervention)
B: Plastic Bag Use for Store A (Treated) and Store B (Control) (Postintervention)



In this equation, j indicates an observation session and t indicates dates. $Trend_t$ equals 1, 2, …, 8, representing the eight days prior to the commencement of the intervention. The coefficient on *Trend*StoreA* differentiates the preintervention trend on the percentage of shoppers who used at least one plastic bag in the two stores, respectively. The results appear in Table 2. The coefficient on *Trend*StoreA* is not statistically significant, showing no difference in the trend between the two stores, and that plastic bag use was similar prior to the intervention, meeting the parallel trend assumption.

Comparison of Store A and Store B Using Survey Data

The brief survey collected basic demographic and student information, allowing the test of comparability between the shopper populations in the two stores. We compare gender, race, university status, living locations, and frequency of visiting store A and B. The results appear in Table 3 and show that customers at the two stores are not significantly different for any of these shopper characteristics, except for university status. Another issue is patrons from one store potentially visiting the

Table 2
Test on Parallel Trend Assumption

Dependent Variable	Coefficient	Std. Error	*p*-value
Trend	0.004	0.016	0.777
Trend*StoreA	0.015	0.013	0.262
Constant	0.388	0.071	0.000
R-squared	0.139		

Note: The dependent variable is the daily percentage of customers using at least one plastic bag. Results are based on a robust ordinary least squares estimation.

other, which may adulterate the effect of the token program. However, nearly 70% of respondents at store A never or rarely visit store B, and nearly 54% of respondents at store B never or rarely visit store A. This supports the notion that potential patron spillover may not be large.[9] We also divide and examine the data to compare shoppers during the control and intervention periods at the two stores, shown in Table 4. The analysis shows that store A is similar to store B before the intervention in terms of customers' gender, race, and living location. In addition, a majority (80% or more) of the students report frequenting the other location never, rarely, or sometimes, before or after the intervention.

There is some evidence of a change in the composition of customers in the two stores before and after the intervention. Specifically, the percentage of female patrons in store A and store B decreases 13 percentage points and 8 percentage points, respectively, after the intervention. This consistent change in both stores further supports the parallel trend assumption. Regarding race and living location, changes in store A before and after intervention and changes in store B before and after intervention follow closely between the stores. We recognize that some patrons' university status is different between the stores either before or after the treatments. However, these are not strong trends given other demographic characteristics. We tested the customers' university status before and after treatment for each store and did not find a significant difference

Table 3
Summary of Survey Data

Characteristic	Total (*n*=436)	Store A (*n*=282)	Store B (*n*=154)	*p*-value Testing Store A=B
Gender				0.719
Female	0.56	0.55	0.57	
Race				0.728
Black	0.19	0.18	0.2	
White	0.65	0.66	0.62	
University status				0.000
Freshman	0.49	0.41	0.63	
Sophomore	0.26	0.28	0.22	
Junior	0.15	0.20	0.07	
Senior	0.07	0.08	0.06	
Graduate	0.02	0.02	0.01	
Staff	0.01	0.01	0.01	
Living location				0.109
University dorms	0.82	0.80	0.86	
Off-campus <10 min. walk	0.11	0.12	0.09	
Off-campus further away	0.06	0.07	0.05	
Frequency of visiting store A				0.000
Never	0.14	0.05	0.29	
Rarely	0.18	0.15	0.25	
Sometimes	0.33	0.36	0.29	
Often	0.35	0.44	0.17	
Frequency of visiting store B				0.000
Never	0.33	0.48	0.06	
Rarely	0.20	0.22	0.15	
Sometimes	0.26	0.19	0.39	
Often	0.21	0.11	0.40	

(store A: $p = 0.123$; store B: $p = 0.490$). The stores also share a similar pattern in changes in visiting frequencies before and after intervention.

Difference-in-Difference Estimation Results

Model results of equation [1] using a logit specification appear in Table 5. Due to the nonlinearity of the models, marginal effects do not equal their corresponding coefficients

[9] Sample spillover may bias our estimation result. Ideally, if one can identify customers with their purchase and plastic bag usage information, a sensitivity analysis can be conducted to test for spillover effects. However, our data do not permit such an analysis.

Table 4
Comparison of Patrons to the Two Stores before and after Intervention

	Before Intervention				After Intervention			
Characteristic (*n*=436)	Total (*n*=148)	Store A (*n*=96)	Store B (*n*=52)	*p*-value Store A=B	Total (*n*=288)	Store A (*n*=186)	Store B (*n*=102)	*p*-value Store A=B
Gender				0.596				0.955
Female	0.49	0.47	0.52		0.60	0.60	0.60	
Race				0.915				0.728
Black	0.18	0.19	0.15		0.19	0.17	0.22	
White	0.62	0.62	0.65		0.66	0.69	0.60	
University status				0.044				0.001
Freshman	0.54	0.45	0.71		0.46	0.39	0.59	
Sophomore	0.24	0.30	0.13		0.27	0.27	0.27	
Junior	0.16	0.19	0.10		0.15	0.21	0.06	
Senior	0.04	0.03	0.02		0.09	0.10	0.07	
Graduate	0.01	0.02	0.00		0.02	0.02	0.01	
Staff	0.01	0.01	0.02		0.01	0.01	0.00	
Living location				0.514				0.123
University dorms	0.86	0.84	0.88		0.80	0.77	0.85	
Off-campus <10-min. walk	0.08	0.08	0.08		0.13	0.14	0.10	
Off-campus further away	0.05	0.06	0.04		0.07	0.08	0.05	
Frequency of visiting store A				<0.001				<0.001
Never	0.11	0.03	0.27		0.15	0.06	0.30	
Rarely	0.19	0.17	0.23		0.18	0.14	0.26	
Sometimes	0.34	0.35	0.31		0.33	0.36	0.28	
Often	0.36	0.45	0.19		0.34	0.44	0.16	
Frequency of visiting store B				<0.001				<0.001
Never	0.27	0.38	0.06		0.36	0.52	0.06	
Rarely	0.21	0.25	0.15		0.19	0.21	0.15	
Sometimes	0.34	0.24	0.52		0.22	0.17	0.32	
Often	0.18	0.13	0.27		0.23	0.10	0.47	

but can be calculated following Ai and Norton (2003) and Hu and Chen (2008). We see that the interaction term *Token*StoreA* is statistically significant and negative in each model, indicating that the token program does significantly reduce plastic bag use. Model I uses the total number of items purchased and model II splits the total number of items purchased into small, medium, and large items. Models III and IV repeat model I and II, respectively, except that models III and IV consider week fixed effects. Models III' and IV' also repeat models I and II, respectively, but instead of week fixed effects, they group weeks into phases, which will be explained next. Represented by the marginal effect (at the mean) of *Token*StoreA* and depending on model specification, the probability of using a plastic bag is reduced by 11.4 percentage points (model I) to 12.9 percentage points (model IV) after the introduction of the token program.

Most recently Chandra (2020) and Romano and Sotis (2021) examine methods to reduce single-use carrier bags. While these two studies have dissimilar context than ours in several aspects (e.g., Romano and Sotis 2021 occurs in supermarket, considers biodegradable bags, and does not use a dummy variable for bag use; Chandra 2020 uses a combination of lab and online experimental settings), both show promising effects of nudging on bag use reduction.

Several other studies (Taylor and Villas-Boas 2016) examine bans, and Homonoff (2018) examines taxes and bonuses using dummy variable specifications for bag use,

Table 5
Results Using Logit Model

	Model I		Model II		Model III		Model III’	
	Coefficient	Marginal Effect	Coefficient	Marginal Effect	Coefficient	Marginal Effect	Coefficient	Marginal Effect
Token	0.044	0.006	0.021	0.003	0.248	0.035	0.273	0.039
	(0.212)	(0.031)	(0.235)	(0.030)	(0.295)	(0.042)	(0.229)	(0.032)
StoreA	1.031***	0.148***	1.243***	0.160***	1.001***	0.143***	1.021***	0.147***
	(0.335)	(0.048)	(0.376)	(0.048)	(0.340)	(0.049)	(0.334)	(0.048)
Token*StoreA	–0.747***	–0.114***	–0.915***	–0.128***	–0.788***	–0.115***	–0.795***	–0.115***
	(0.258)	(0.041)	(0.279)	(0.042)	(0.260)	(0.043)	(0.259)	(0.058)
Total items	1.516***	0.218***			1.521***	0.218***	1.517***	0.218***
	(0.052)	(0.004)			(0.053)	(0.004)	(0.053)	(0.004)
Small items			1.310***	0.169***				
			(0.055)	(0.005)				
Medium items			2.054***	0.265***				
			(0.076)	(0.006)				
Large items			2.969***	0.383***				
			(0.146)	(0.015)				
Evening	0.281***	0.040***	0.275**	0.036**	0.325***	0.047***	0.280***	0.040***
	(0.106)	(0.015)	(0.113)	(0.015)	(0.111)	(0.016)	(0.108)	(0.015)
Weekday	–0.359*	–0.052*	–0.178	–0.023	–0.415**	–0.059**	–0.346*	–0.050*
	(0.184)	(0.026)	(0.192)	(0.025)	(0.189)	(0.027)	(0.185)	(0.026)
Preceding customer	0.184**	0.026**	0.165**	0.021**	0.166**	0.024**	0.174**	0.025**
	(0.073)	(0.011)	(0.077)	(0.010)	(0.074)	(0.011)	(0.073)	(0.011)
Female	0.174***	0.025***	0.127*	0.016*	0.176***	0.025***	0.172***	0.025***
	(0.066)	(0.009)	(0.070)	(0.009)	(0.066)	(0.009)	(0.066)	(0.009)
Constant	–4.960***		–5.316***		–5.023***		–4.986	
	(0.402)		(0.445)		(0.421)		(0.406)	
Middle							–0.393***	–0.056***
							(0.128)	(0.018)
End							–0.257**	–0.037**
							(0.128)	(0.018)
Token*Middle								
Token*End								
Observer FE	Yes		Yes		Yes		Yes	
Cashier FE	Yes		Yes		Yes		Yes	
Week FE	No		No		Yes		No	
Pseudo R-squared	0.329		0.388		0.331		0.330	

(table continued on following page)

Table 5

Results Using Logit Model *(continued)*

	Model III''		Model IV		Model IV'		Model IV''	
	Coefficient	Marginal Effect	Coefficient	Marginal Effect	Coefficient	Marginal Effect	Coefficient	Marginal Effect
Token	0.273	0.039	0.231	0.030	0.236	0.030	0.236	0.030
	(0.229)	(0.033)	(0.335)	(0.043)	(0.252)	(0.032)	(0.252)	(0.032)
StoreA	1.021***	0.147***	1.223***	0.157***	1.233***	0.159***	1.233***	0.159***
	(0.334)	(0.048)	(0.378)	(0.049)	(0.375)	(0.048)	(0.375)	(0.048)
Token*StoreA	–0.795***	–0.115***	–0.963***	–0.129***	–0.960***	–0.128***	–0.960***	–0.128***
	(0.259)	(0.040)	(0.281)	(0.045)	(0.280)	(0.042)	(0.280)	(0.042)
Total items	1.517***	0.218***						
	(0.053)	(0.004)						
Small items			1.313***	0.169***	1.310***	0.169***	1.310***	0.169***
			(0.056)	(0.005)	(0.055)	(0.005)	(0.055)	(0.005)
Medium items			2.059***	0.265***	2.056***	0.265***	2.056***	0.265***
			(0.076)	(0.006)	(0.076)	(0.006)	(0.076)	(0.006)
Large items			2.966***	0.381***	2.966***	0.382***	2.966***	0.382***
			(0.147)	(0.015)	(0.146)	(0.015)	(2.966)	(0.015)
Evening	0.280***	0.040***	0.316***	0.041***	0.269**	0.035**	0.269**	0.035**
	(0.108)	(0.015)	(0.119)	(0.015)	(0.114)	(0.015)	(0.114)	(0.015)
Weekday	–0.346*	–0.050*	–0.225	–0.029	–0.171	–0.022	–0.171	–0.022
	(0.185)	(0.026)	(0.197)	(0.025)	(0.193)	(0.025)	(0.193)	(0.025)
Preceding customer	0.174**	0.025**	0.150*	0.019*	0.158**	0.020**	0.158**	0.020**
	(0.073)	(0.011)	(0.077)	(0.010)	(0.077)	(0.010)	(0.077)	(0.010)
Female	0.172***	0.025***	0.128*	0.016*	0.125*	0.016*	0.125*	0.016*
	(0.066)	(0.009)	(0.069)	(0.009)	(0.070)	(0.009)	(0.070)	(0.009)
Constant	–4.986***		–5.376***		–5.324***		–5.324***	
	(0.406)		(0.458)		(0.447)		(0.447)	
Middle					–0.389***	–0.050***		
					(0.138)	(0.018)		
End					–0.222	–0.029		
					(0.137)	(0.018)		
Token*Middle	–0.393***	–0.056***					–0.389***	–0.050***
	(0.128)	(0.018)					(0.138)	(0.018)
Token*End	–0.257**	–0.037**					–0.222	–0.029
	(0.128)	(0.018)					(0.137)	(0.018)
Observer FE	Yes		Yes		Yes		Yes	
Cashier FE	Yes		Yes		Yes		Yes	
Week FE	No		Yes		No		No	
Pseudo R-squared	0.330		0.391		0.389		0.390	

Note: n = 5,513. Standard errors appear in parentheses. Model I uses the total number of items purchased, and model II splits the total number of items purchased into small, medium, and large items. Models III and IV repeat models I and II, respectively, except that models III and IV consider week fixed effects. Models III' and IV' repeat model III and IV, respectively, except that models III' and IV' consider groups of weeks instead of individual week fixed effects. Models III'' and IV'' repeat models III and IV, respectively, except that models III'' and IV'' consider interaction between token and groups of weeks instead of individual week fixed effects.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

allowing comparison to our outcomes. Taylor (2019) finds that the ban leads to a decrease in plastic bag consumption by 81.57 percentage points and 89.05 percentage points in national chain stores and discount chains, respectively. Homonoff (2018)'s study on five-cent tax finds a 51.41% reduction in preintervention average plastic bag use of 81.7%; our study on five-cent token finds a 30–33.95% decrease in preintervention average plastic bag use of 38%. He (2012) finds a 49% decrease in plastic bag consumption due to mandatory fees. In contrast, bonuses have been shown to have virtually no change in plastic use behavior (Homonoff 2018). However, our study shows that a donation strategy is effective, making it a more feasible bag reduction strategy in U.S. states with preemption legislation (National Conference of State Legislature 2019) or resistance to plastic bag policies (Nielsen, Holmberg, and Stripple 2019).

As expected, there is a significant and positive relationship between the total number of items purchased and the likelihood of plastic bag use in all models. The models show a significant and positive relationship between the number of all size items and the likelihood of plastic bag use. Postestimation tests show that coefficients of large versus medium items ($p < 0.001$), large versus small items ($p < 0.001$), and medium versus small items ($p < 0.001$) are statistically different from each other. This means that an increase in the number of large items is more likely to increase the probability of plastic bag use than for the same number increase of small or medium items. One potential explanation anecdotally observed is that small items can be placed inside a backpack or a greater number of small items fit inside a single plastic bag compared to medium or large items.[10]

Plastic bag use is significantly higher in the evening, matching prior findings (Homonoff 2018). Weekday use is significant and negative in models I, III, and III', indicating less bag use compared with weekends. Preceding customer is significant and positive, showing that the preceding customer's decision to forgo a plastic bag decreases the likelihood of plastic bag use by the subsequent customer.[11] Similar to Taylor and Villas-Boas (2016), we find that female customers are more likely to use plastic bags than are male customers.[12] We also control for differences among observers using fixed effects in all models, with most significantly affecting plastic bag use, which may be explained by the observer's reminder to the cashier to advertise the token program. As well, cashier fixed effects show that some of cashiers significantly affect plastic bag use, indicating differences across cashiers to mention the token-donation program.

Some studies have examined behavior maintenance over time (Kwasnicka et al. 2016; Nemati and Penn 2020), testing the efficacy of the experimental intervention on behavior as the intervention progresses. We test if the amount of reduction changes over time by including dummies for 10 different weeks during the intervention, shown in models III and IV.[13] Using the first week of intervention as the reference week, all week dummies are negative except the second, third, and ninth week in model III and the third and ninth week in model IV but are significant only for the fourth and sixth week in both models, showing that the reduction in plastic bag use is not consistent across the weeks. This may be explained by the relatively short intervention and examination period of the experiment. In addition, we reestimate our models by dividing the total number of weeks after the intervention into three phases; early intervention phase (*Beginning*) constituted by

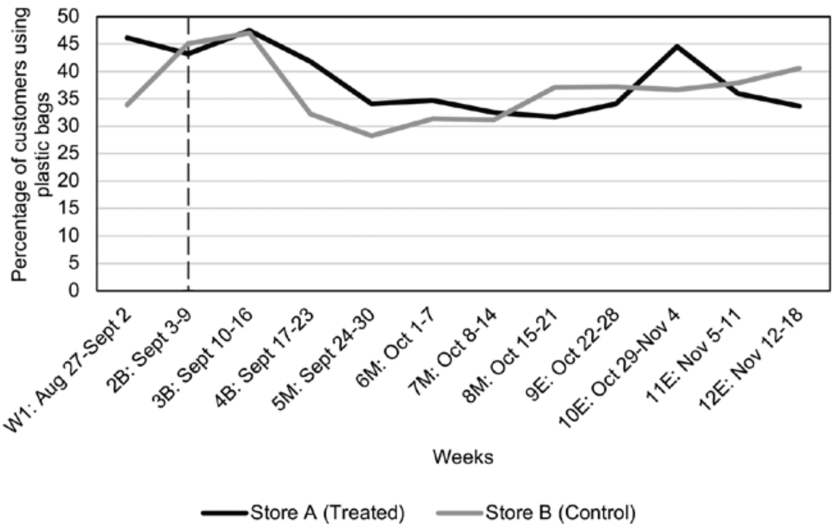
[10] A separate model that uses the total number of items and two indicator variables for medium and large items demonstrates a consistent finding that more large items increase the probability of bag use.

[11] Admittedly, only the sequence of transactions was recorded rather than the actual time of purchase. This means that the preceding customer's bag use decision may or may not be seen by the next customer. Consequently, we consider the coefficient to be a "lower bound" estimate of the effect of preceding customer.

[12] Given the outcome that women are more likely to use plastic bags, we include a female*treatment interaction to test whether women are more affected by the token program, but we find no such evidence.

[13] We also estimate a model including weekly trend of plastic bag use and square of weekly trend of plastic bag use to test whether the effect is nonlinear, but we find no such evidence.

Figure 2
Effect of a Token Program on Plastic Bag Use



the first three weeks of the intervention, mid-intervention phase (*Middle*) containing the fourth to seventh week of the intervention, and late intervention phase (*End*) including the last four weeks of the intervention. The results appear in models III' and IV' in Table 5. Using *Beginning* as the reference period, plastic bag use was further reduced in the *Middle* and *End* periods and the effects are significantly different in both models except that *End* is insignificant (but close) in model IV'. While consistent with findings from models III and IV using individual week fixed effects, these models do suggest somewhat a decay in the efficacy of the token program during the *End* period.

Furthermore, to understand the policy effects over time, we estimate the models by interacting the treatment variable with groups of weeks as *Token*Middle* and *Token*End*; results appear in models III'' and IV'' in Table 5. The interaction results in model III'' and IV'' are consistent with model III' and IV', respectively, showing that compared to the *Beginning* phase, plastic bag use was further reduced significantly in the *Middle* phase and somewhat in the *End* phase (the interaction with *End* is close but insignificant in model IV). We present the effect of the token program over time in Figure 2.[14] Altogether we had 12 weeks of experiment and the token program was implemented in the middle of the second week on September 6. Figure 2 also shows a decrease in the percentage of customers using at least one plastic bag after intervention but less pronounced in the late intervention phase.

Auxiliary model results using LPM appear in Appendix Table A1. Overall, the results from the LPM models are consistent with the logit model, leading to similar outcomes of reduced probability of bag use (8.9–9.9 percentage points) and significant explanatory variables. As another robustness check, we include fixed effects for the time of purchase by assigning dummy variables to represent the time of the observation session, shown in Appendix Tables A2 and A3. The results and magnitude are consistent with our main findings. Compared to the reference group, 11 a.m.–12 p.m., 7 p.m.–8 p.m. has a significant positive effect on plastic bag use, but 12 p.m.–1 p.m. has a significant negative

[14] Dashed vertical line shows the start of the token program (in the middle of the second week on 6 September). The preintervention period is August 27–September 5. The numbers 1–12 indicate the weeks of the experiment, and the letters B, M, and E denote the beginning, middle, and end phases of the intervention, respectively.

effect. The remaining observation times are not significant.

5. Conclusion and Discussion

This study tests the efficacy of a behavioral nudge through a token-drop donation program to reduce plastic bag use. Using quasi-experiment data collected among convenience store patrons at a large public university, we estimate that the token program significantly reduces the probability of disposable plastic bag use by 11.4–12.9 percentage points, amounting to a 30%–34% reduction in bag use, a substantial change given that less than two-fifths of customers used plastic bags during a transaction. Given the large quantities of disposable plastic bags used in convenience stores, our study suggests a nonnegligible contribution of such a program to reduce total plastic bag use.

Our findings show that a donation program may be a feasible alternative to reduce plastic bag use. This alternative may be useful among U.S. states with preemption laws, given that a state would allow stores to voluntarily adopt the donation program. Stores may be reluctant to implement self-imposed bag control strategies such as bans, fees, or bonuses due to the response and acceptance of consumers and other stakeholders (Convery et al. 2007). For example, consumers may protest even trivial fees as a financial burden or feel guilty/shameful if they forget to bring a reusable bag. Conversely, less antagonistic policies such as bonuses may be less effective due to loss aversion (Homonoff 2018). A donation program may be more palatable to consumers and reduces the number of bags used. For stores, part of the charitable donations would replace the expense of bags, but the former is presumably tax-deductible and creates more positive publicity than do fees. Consumer characteristics may be important leading stores to decide whether to adopt, with the previously mentioned store programs and other known programs, such as Trader Joes featuring customers with above average income and education.

The trade-offs of the voluntary programs, including donations, demonstrate the need for more formal benefit-cost analysis to estimate whether stores accrue positive net benefits and potential for scalability. Initial setup, overhead, and variable costs may vary with each strategy and store type. For example, bag use per customer per transaction in large grocery stores exceeds that of convenience stores. On the other hand, benefit (such as public image) may also vary across store types. More broadly, such analysis should also consider societal benefits and compare against mandatory regulations such as bans and taxes.

Opportunities exist to improve our work. First, the analysis has little individual-specific information on customers (except gender) to explain behavior. Second, there is potential correlation across observations because customers could observe another customer checking out at the register and listen to the cashier's prompt to forgo a plastic bag to make a donation. Anecdotally, it seemed that once a student had refrained from taking a bag, others had a higher chance to do the same. The results obtained from a preceding customer's bag use are evidence of this. A study addressing this issue can observe transactions occurring every several other customers. However, this approach increases the number of days needed to collect sufficient data, thus researchers should be careful dealing with the challenges of treatment/information leakage. Third, our experiment occurred in the restricted context of a university convenience store with predominantly student patrons. Future work should be conducted in traditional grocery and retail settings, where customers are more representative of the general public and regularly use multiple bags. One can then potentially match customer profiles with their purchases and plastic bag use. Such a strategy will enhance the external validity of our analysis framework by using real-world shoppers and the explanatory power of customer characteristics on plastic bag use. Acknowledging that our experiment was not completely random, and we had a relatively short preintervention period, we recommend future studies with a random experiment design containing a relatively longer preintervention period. Moreover, despite our effort to reduce overlapping customers, the possibility exists for patron spillover, which may lead to a biased estimate of the true effect of the donation program.

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