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Reducing Recycling Contamination Using an Information Nudge

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REDUCING RECYCLING CONTAMINATION USING AN INFORMATION NUDGE

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Abstract

Recycling contamination is a central challenge to recycling programs but is infrequently studied due to the difficulty of measuring contents and the inconvenience of sorting through recycling bags by hand. We conducted two simultaneous experiments to address both the issue of recycling contamination and the infrequency of its study at Louisiana State University in Fall 2021. We implemented two signage treatments, the first explicitly instructing passersby not to recycle a short list of common recycling contaminants, including Styrofoam, food wrappers, plastic bags, and face masks, and the second generally encouraging recycling but excluding specific instructions on what to recycle. To improve data collection, trail cameras were utilized in this research area, which is a novel approach. After concluding that trail cameras were a useful approach in measuring recycling contents, we analyzed the results of the nudge experiment by both camera data results and hand count bag data results. Results of the nudge experiment showed that signage with explicit instructions reduced contamination rates.

Chapter 1. Introduction

Waste management is a global challenge that affects the environment, human health, and the economy. The problem stems from the sheer amount of waste that is generated. The United States alone generated an average of 276.4 million tons of municipal solid waste (MSW) per year from 2016 to 2018, with a combined recycling and composting average of only 93.9 million tons (34%) of this waste (EPA, 2020).

One major challenge to recycling programs is contamination, which occurs when non-recyclable items are placed in recycling bins. Separation of recyclables from waste occurs at materials recovery facilities (MRFs). Excessive contamination in a load of recyclables regularly forces MRFs to landfill the entire load of items rather than cost-prohibitive task of sorting items (Henslovitz, 2021). Finding solutions to recycling behavior and contamination are needed to reduce this problem.

Some studies examine behavior change mechanisms to improve recycling behavior, such as signage, bin location, and bin design (De Young, 1990). Recycling contamination behavior is infrequently studied though, with only 15 publications identified. One reason so few studies exist is the difficulty of data collection.

The first approach to measuring contamination is by weighing the bag (Ahmed, et al., Andrews, 2013, Brothers, et al., 1994, Miller, 2016). While convenient, this approach has potential measurement error; bag weight may only loosely correlate to contamination, so potentially a poor measure to understand recycling behavior.

The second approach to measuring contamination is by hand counting and recording all items per bag. Its major drawback is that it requires a relatively large number of labor hours, inconvenient scheduling constraints, and the discomfort of sorting through recycling bags by

hand. This may explain why only four recycling behavior studies measured recycling by hand counts (Allan, et al., 2011, O'Connor, 2010, Rosenthal and Linder, 2021, Zelenika, et al., 2018).

Third, recycling behavior can be measured using self-reports via surveys (Catlin, et al., 2020, Leeabai, et al., 2021, Rosenthal, 2018). The major disadvantage of this technique again stems from measurement error common in surveys such as recall bias (inaccuracy due to over-reporting good behavior) and social desirability bias (inaccuracy due to over-reporting ‘good behavior’) (Deming, 1994).

Lastly, other approaches such as visual observations of user choices and ranking of contamination levels through observation of bin contents are sometimes used (Anarat, 2016, De Young, et al., 1995, Leigh and Gorham, 2018, Werner, et al., 1998).

These various approaches limit research either due to the resource intensity (hand counts) or measurement error (weight or surveys) barriers, diminishing our understanding of recycling behavior. One potential solution is the use of cameras to improve efficiency in waste management. A few facilities have already implemented the use of cameras to monitor both trash and recycling bins and while promising in terms of measurement, this technology does not address the human behavior underlying the contamination.

The purpose of our first study is to test the accuracy of trail cameras installed inside of recycling bins to measure contents. We conduct both a lab and field test of trail cameras to explore their potential usefulness to monitor items tossed into the recycling bins. To verify the accuracy of the camera data, we compared it to a manual inspection and hand count of all discarded items each day.

There are two main approaches to help reduce contamination. First, MRFs can install more sophisticated equipment or employ more labor hours to sort loads. This increases labor and equipment costs, which can be prohibitive for some recycling facilities.

The second approach is to reduce contamination before waste arrives at the recycling center by modifying end-user behavior. For example, recycling bins commonly feature information signage, often providing a list of acceptable items. Signage can be considered a type of nudge, which is “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” (Thaler and Sunstein, 2008). Green nudges are a type of intervention that are designed to encourage pro-environmental behavior while maintaining the freedom of choice for individuals. They typically involve subtle changes in the physical or social environment that make sustainable behavior more visible, appealing, and convenient. Green nudges are often low-cost, and can be implemented on a small scale, making them a promising tool for policymakers and businesses to promote sustainability (Carlsson, et al., 2021).

Several studies have demonstrated the effectiveness of green nudges in promoting recycling behavior, though these studies mainly focus on recycling rate, and we find no studies that used these types of nudges to make a change to the contamination levels found in recycling bins.

The purpose of our second study is to assess the impact of signage on recycling contamination rates. We test two types of signage, a “Quality” treatment on what to specifically not put into the recycling bins, and a “Quantity” treatment that encourages general recycling. We measure the effect of the signage both using the bag data, which perfectly captures contents versus the effect measured by the camera data, which is less accurate, but much less resource

intensive. The results of the analysis will help us to understand how to reduce contamination levels and how to maintain sustainable recycling practices, leading to possible reductions in pollution and climate change.

Chapter 2. Testing the Accuracy of Trail Cameras to Monitor Recycling Behavior

2.1. Abstract

Examining recycling contents is infrequently studied in part due to the difficulty of measuring contents, necessitating a large number of labor hours and inconveniences of sorting through recycling bags by hand. To address this issue, we employed a proof-of-concept experiment on recycling contamination using trail cameras to collect bag data on the individual item level compared to conventional hand counting. We initially pre-tested seven camera models for accuracy of item identification. Based on these results, we selected one camera to conduct three trials in a lab setting to further assess camera accuracy. Lab experiment results show that the trail camera tested had on average 82% accuracy of capturing items being thrown away in recycling bins. We then conduct a field experiment, testing the accuracy of six cameras in recycling bins across a university campus. Collectively, 1343 items were thrown into the recycling bins. Of these, 68.5% of the items were successfully photographed and identified by the trail camera. 93.3% of items caught on camera matched the items found in the hand count of the bags. This difference in percentages could be attributed to items smaller than a credit card, which had the largest difference in composition of items between the bag dataset and camera dataset. We conclude that the use of trail cameras in research using recycling bins is an effective method.

Key words: recycling; contamination; trail camera; university

2.2. Introduction

Municipal solid waste (MSW) in the United States has increased drastically from 88.1 million tons in 1960 to 292.4 million tons in 2018 (EPA, 2020). Recycling also increased from 5.6 million tons (6.3% of 1960 MSW) to 69.1 million tons recycled (24% of 2018 MSW) over the same time frame (EPA, 2020). A key disadvantage of recycling programs today is contamination of recycling bins with non-recyclable items, such as Styrofoam and food waste, which further reduces the recycling rate. Contamination is a major barrier to increasing the percentage of recyclable material that is actually recycled. Finding solutions to recycling behavior and contamination are needed to reduce this problem.

A major challenge in effective recycling programs is compliance in correct recycling according to bin instruction. The goal is to increase recycling rates without increasing contamination (Atkinson, et al., 2022). Often times when recycling rates increase, the problem of over-inclusive recycling arises, sometimes referred to as ‘wishcycling’. ‘Wishcycling’ occurs when people try to do the ‘right’ thing by recycling items that they are not sure are 100% recyclable, resulting in higher contamination rates (MacKay, et al., 2016).

Some studies examine behavior change mechanisms to improve recycling behavior, such as signage, bin location, and bin design (De Young, 1990). Recycling contamination behavior is infrequently studied though, with only 15 publications identified. One reason so few studies exist is the difficulty of data collection.

The first approach to measuring contamination is by weighing the bag (Ahmed, et al., Andrews, 2013, Brothers, et al., 1994, Miller, 2016). While convenient, this approach has potential measurement error; bag weight may only loosely correlate to contamination, so potentially a poor measure to understand recycling behavior. For example, a bag with five full

water bottles versus another bag with five empty water bottles both have the same amount of recyclable material, but measuring by weight, the recycling rate will appear higher in the bag of full water bottles. Andrews (2013) separated recyclable and non-recyclable material from three recycling bins over the course of 30 days and then weighed recyclable vs non-recyclable materials. They replaced each recycling bin's bag liner each weekday. Pulled bags were labeled with bin number and location and transported to the sorting area, where they were sorted through by hand and then weighed. Liquids were also emptied from bottles and containers to measure the amount of food/liquid residue contamination.

The second approach to measuring contamination is by hand counting and recording all items per bag. Its major drawback is that it requires a relatively large number of labor hours, inconvenient scheduling constraints, and the discomfort of sorting through recycling bags by hand. This may explain why only four recycling behavior studies measured recycling by hand counts (Allan, et al., 2011, O'Connor, 2010, Rosenthal and Linder, 2021, Zelenika, et al., 2018). Allan et al. (2011) described several difficulties in sorting through and calculating recycling and contamination rates. First, some items are difficult to categorize since they potentially belong in multiple categories (e.g., a plastic lid for a paper coffee cup could be categorized as either plastic or paper). Second, items contaminated with food or other materials make it difficult to make a determination. Finally, some items lack a recycling symbol, making placement of the item in the correct bin and subsequent categorization of the item by researchers more difficult. Rosenthal and Linder (2021) ran an experiment on contamination levels by making participants believe that they were participating in a yogurt taste test study. Each participant entered a room by themselves, tasted the yogurt in a plastic cup and then were told to dispose of it once they were done, but were exposed to several types of disposal situations. For example, some participants

had co-located recycling bins and trash bins, while some did not, some recycling bins had declarative information, some procedural information, and some with combinations of both types of information. At the end of every session, the researchers collected the used yogurt cup from the disposal site and scored it on a scale of 1 to 5 on level of contamination by visual inspection of the cup. Although this gives a much clearer view of contamination and the ability to judge contamination levels, it is much more time consuming to have to wait for participants to complete the study, and then take time after every session to take the cup out of the bin, inspect, and rank it. Although the amount of time that the entire study took was not directly reported, they did state that they had 409 participants and each session took up to 30 minutes. By approximation, this would add up to 12,270 minutes (204.5 hours or 8.5 days assuming a 24-hour day). It also exposes researchers to touching food waste. In addition, this is just the recycling of a single type of item, which is not reflective of the other challenges associates with identifying other types of items. Furthermore, a lab setting may not reflect actual disposal behavior.

Third, recycling behavior can be measured using self-reports via surveys (Catlin, et al., 2020, Leeabai, et al., 2021, Rosenthal, 2018). The major disadvantage of this technique again stems from measurement error common in surveys such as recall bias (inaccuracy due to over-reporting good behavior) and social desirability bias (inaccuracy due to over-reporting ‘good behavior’) (Deming, 1994).

Lastly, other approaches such as visual observations of user choices and ranking of contamination levels through observation of bin contents are sometimes used (Anarat, 2016, De Young, et al., 1995, Leigh and Gorham, 2018, Werner, et al., 1998). These various approaches

limit research either due to the resource intensity (hand counts) or measurement error (weight, surveys, or visual observation) barriers, diminishing our understanding of recycling behavior.

One potential solution is the use of cameras to improve efficiency in waste management. A few facilities have already implemented the use of cameras to monitor both trash and recycling bins. For instance, Compology places cameras inside dumpsters to take pictures several times a day. Using machine learning techniques, it can detect fullness of the dumpster, reducing time and efforts spent on waste collection, reducing unnecessary and expensive pickups. While promising in terms of measurement, this technology does not address the human behavior underlying the contamination. Additionally, majority of items places in dumpsters are contained in trash bags, unable to sort through individual items to determine contamination levels.

The purpose of this study is to test the accuracy of trail cameras installed inside of recycling bins to measure contents. We conduct both a lab and field test of trail cameras to explore their potential usefulness to monitor items tossed into the recycling bins. To verify the accuracy of the camera data, we compared it to a manual inspection and hand count of all discarded items each day.

2.3. Lab Test Methods

Given the disadvantages of hand counting items, we first test the usefulness of trail cameras to capture and measure bag contents via a lab test. Prior to the lab test though, we initially consulted a researcher with trail camera expertise for guidance on finding an affordable and easy-to-use camera. They stressed the importance of trail camera quality and accuracy varying greatly between different camera brands and models as well as the context of their use (e.g., capturing close-up images of insects versus more distant images of mammals).

Based on this feedback, before starting the lab test, we first began a pre-experimental test, comparing seven trail cameras in terms of their accuracy to identify items placed inside the recycling bin as well as several camera settings. Appendix A gives the protocol for testing and comparing each camera as well as the results. These cameras were based on recommendations and availability of the aforementioned expert. We completed a preliminary trial for each camera and added subsequent tests based on the accuracy of the preliminary trials.

For the camera settings, five of the cameras featured two photo capture modes, time lapse and motion capture. Timelapse takes a photo at a set time interval (e.g., every 1, 2, 5, 10 minutes, etc.). Motion capture takes a photo any time motion is detected. We assess the pre-trial data of the cameras based on the accuracy of the photos, which is the percent of items placed in the bag correctly identified in the photos. These data demonstrate that for cameras with both modes, timelapse provided substantially higher accuracy than motion capture photos (Table A3). Consequently, we dismissed motion capture from further consideration, so all subsequent discussion of accuracy is with respect to time lapse photos. Among the five timelapse trail cameras, accuracy varied from 73-93% of items captured. We selected the Muddy Outdoors trail camera (MUD-MTC24VK V2; referred to as 'camera' hereafter), which successfully identified over 90% of items.

We then proceeded to test and measure accuracy of the camera in additional lab trials. The benefit of a lab trial is that the actual items placed into the bin are already known by the researcher, eliminating the chance of misidentification. Appendix B contains the complete protocol, including necessary materials, experimental setup, and procedures. In the lab trial, we used the Rubbermaid FG396873BLUE Recycling Receptable (hereafter 'recycling bin'), the same container present on the university campus for the field experiment (explained below) and

common to many campuses. The camera was attached to the top inside lid of the recycling bin. The camera was set to timelapse mode and set to take a photo every two minutes for 60 minutes. Importantly, based on initial testing, we used blue recycling bags and ensured that the bags were widely spread out in the bins to give the camera a clear view.

The lab experiment consisted of three trials, placing 50 items into the recycling bin during each trial (150 total items). These include recyclable items (e.g., cardboard, glass, cans, plastic bottles) and contaminants (e.g., Styrofoam, candy wrappers, food contamination). For the items to be thrown into the bin, we intentionally left some food and beverage containers half-full in order to test whether the residue appeared on the camera since food and liquid residue are common forms of contamination (Andrews, 2013). Mixing food and liquid residues with recyclable materials is problematic because they can attract insects and rodents, creating health and safety risks for workers who handle the materials. Additionally, liquids can cause paper and cardboard to become soggy and reduce the quality of the fibers, making them less desirable for recycling (personal communication, Andres Harris). Small amount of liquids, such as less than ¼ of a water bottle being filled were not considered to be contamination. Additionally, food residue, such as a small amount of sauce left inside of a plastic container was not considered to be contamination. Any amount of large food particles, however, were considered to make an item a contaminated item. For example, a half-eaten hamburger left inside of a to-go box, a half-full bottle of Coca-Cola, or a soup container with 1/3 of the soup left inside. These items reflect a composition typically found in recycling bins around the university campus. One contradiction to a realistic situation of common recycling practices is that all liquid and food residue was sealed inside of containers to maintain the integrity of items between each trial. For example, if liquid residue was in a to-go cup and the lid came off after it was thrown into the bin, it would

contaminate other items, specifically paper items. Then in the subsequent trials, an item that was originally not considered to be contaminated would now be considered contamination.

Each trial occurred indoors, in which two people placed items into the recycling bin, recording a description of the item(s) and timing. A combination of one, two, or three items were thrown into the bin every two minutes until all 50 items were in the bin. This mimics the reality that one or multiple people may consecutively place several items into the bin. Each trial lasted approximately 80 minutes, varying due to different combinations of the number of items dropped at a time. All items collected for the use of the lab trial were contained in a single bag and drawn at random without replacement within each trial. After each individual trial was conducted, the items thrown into the bin in that trial were replaced in the bag containing the rest of the items, mixed up, and used to redraw from in the subsequent trial. This was done so that if we maintained an equal probability of drawing each item type per trial. After each trial finished, all photos were posted to a shared folder. A third person with no knowledge of the items discarded in the bins served as a reviewer, examining each trial's photos, recording the time of the photo and their best guess of the item(s) observed. This person had no knowledge of what items were contamination or not and had no training on the topic. They were only responsible for giving their best guess as to what each item was and giving an as detailed as possible description of what they saw in the photos. No breaks were taken during the observation of items in each individual trial. We found it easier to identify new items that fell into the bin if you clicked through photos one after the other and observed the changes between each photo. After this was done, we compared the reviewer's observations to the original datasheet which contained the correct items and the order in which they were thrown into the bin.

We measure accuracy of the camera with a dummy variable called *Bag Match*. If the item recorded by the reviewer matched the item that we threw into the bag in the original datasheet, then *Bag Match* equals 1 (correct identification), otherwise it coded as 0 (incorrect identification or if the object was not identified at all). To examine whether accuracy varies with item characteristics or conditions, we conduct a logit regression with *Bag Match* as the dependent variable. We also use dummy variables to control for the type of item, such as *Bottle*, *Can*, *Paper*, and *Other* items. Other included items such as plastic items, candy wrappers, cardboard boxes, glass, or Styrofoam. We code for items smaller than a credit card (*SmallCC*) because, according to the MRF used by the university, their process is unable to separate out recyclables and non-recyclables at such a small size. In our experiment, we measured SmallCC size by dimension. Therefore, although a mint container is larger in volume than a credit card, dimensionally it is the same size or smaller, and therefore coded as 1 for the SmallCC variable. Additional examples include a balled-up piece of paper or a crushed can flattened vertically. All such small items are automatically landfilled. Table 2.3.1 lists and describes each of the variables considered along with several variables specific to the field test, explained further below.

Table 2.3.1. Variable Descriptions

Variable	Description
Bag Match	1 if camera identification matches the item found in the bag data
Contamination	1 if any kind of contamination
Paper	1 if paper
Bottle	1 if bottle
Can	1 if can
SmallCC	1 if smaller than credit card
	Else 0 (other types of items)
Field Experiment Variables	
Event	1 if event on that day, ex. Midterms, fall break, sporting events
Camera Match	1 if matches the item in the photo taken by the camera.

(Table cont'd.)

Variable	Description
Field Experiment Variables	
Orange	1 if orange bag
Blue	1 if blue bag
	Else 0 (black bag)
Bin1	1 if bin1
Bin2	1 if bin2
Bin3	1 if bin3
Bin4	1 if bin4
Bin5	1 if bin5
	Else 0 (bin6)

2.4. Lab Test Results

The number and types of items and outcomes of the lab trials for camera accuracy per trial appear in Table 2.4.1.

Table 2.4.1. Camera Accuracy (%BagMatch) per trial per item type for lab experiment

	Combined			Trial 1			Trial 2			Trial 3		
	Count	%BagMatch	%BagMatch excl. SmallCC	Count	%BagMatch	%BagMatch excl. SmallCC	Count	%BagMatch	%BagMatch excl. SmallCC	Count	%BagMatch	%BagMatch excl. SmallCC
Overall	150	82.0	83.8	50	92.0	93.3	50	74.0	67.6	50	80.0	88.6
Paper	15	78.6	50.0	2	100.0	100.0	7	71.4	100.0	5	80.0	100.0
Bottles	44	75.0	75.0	16	81.3	81.3	16	62.5	62.5	12	83.3	83.3
Cans	29	93.1	93.1	13	100.0	100.0	6	100.0	100.0	10	80.0	80.0
Other	62	82.5	90.0	19	94.7	100.0	21	76.2	69.2	22	78.3	100.0
SmallCC	33	75.8		5	80.0		13	92.3		15	60.0	
Contam	72	83.3	89.7	20	95.0	100.0	25	80.0	66.7	27	77.8	100.0

%Match calculated as the percent of items that were a match between what the photo reviewer identified on camera and what was thrown into the bag.

The collective accuracy (as determined by whether an item is correctly identified, i.e., *Bag Match*=1) was 82%. Individually, accuracy was 92%, 74%, and 80% in the first, second, and third trial, respectively. Trials 2 and 3 may have had lower match results because they had more *SmallCC* items than trial 1. Problematically, during trials 2 and 3 the bag also shifted into the view of the camera, causing decreased photo accuracy.

Accuracy tends to vary with certain types of items. *Cans* had the highest accuracy, with a 93% correct identification. The second highest accuracy occurred with the identification of *Other* types of items and items considered to be contamination, both at about 83%, and third highest accuracy occurred with *Paper* items with 79%. The lowest accuracies occurred with the identification of *Bottles* and *SmallCC* items, with accuracy of about 75% and 76%, respectively.

One possibility that identification of bottles was low may be that several of the bottles were water bottles, and even though several were different brands, it may have been harder to identify whether a bottle thrown into the bag was a new bottle or a bottle that had already been identified. Identifying *SmallCC* may be less critical since all such items are automatically landfilled, therefore differentiating them for recycling purpose is less important. Table 2.4.1 also assesses camera accuracy excluding these items. Overall accuracy of trials 1 and 3 were increased once these items were removed, as well as the accuracy of the combination of each trial. Trial 2, however, showed decreased overall accuracy removing *SmallCC* items.

Table 2.4.2 shows the logit model results with Bag Match as the dependent variable.

Table 2.4.2. Logit Regression results based on lab trial (N=150), dependent variable = Bag Match

	I	II
Constant	0.133	1.386***
	(1.035)	(0.354)
Paper	0.461	
	(0.820)	
Bottle	0.965	
	(1.092)	
Can	2.469**	
	(1.268)	
SmallCC	-1.148*	
	(0.694)	
Contam	2.026*	
	(1.156)	
Trial1		1.056*
		(0.630)
Trial2		-0.340
		(0.478)
Log-likelihood	-66.395	-67.611
Pseudo R^2	0.0610	0.0438
N	150	150

Omitted reference group is *Other* items that are larger than a credit card and not contamination (Model I) and Trial3(Model II)
*, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.
Standard errors shown in parentheses.

Model I regresses item type on the bag match variable. Recall that the Constant reflects the omitted reference categories, *Other* items that are larger than a credit card and not considered contamination. The coefficients of both can and contamination are positive and significant, indicating that these types of items increase the probability of correct identification on camera. The coefficient of SmallCC is negative and significant, meaning that items smaller than a credit card decrease the probability of correct identification. No other item types had significant effects on identifiability. We conduct several Wald tests based on Model I to further explore differences in accuracy across types of items, with p-values reported in Table 2.4.3.

Table 2.4.3. P-value of post-estimation tests of match based on Table 3

	Paper	Bottle	Can	SmallCC
Bottle	0.628			
Can	0.101	0.064		
SmallCC	0.185	0.121	0.016	
Contam	0.162	0.094	0.623	0.047

To test accuracy across trials, Model II includes dummies for trials 1 and 2 (relative to trial 3). Results show that the constant is positive and significant, meaning that trial3 increased the probability of an item match. Trial2 had no significant effect on the bag match variable, but trial1 was also positive and significant, meaning that trial1 items increased the probability of an item match.

We have several conclusions based on this evidence. We conclude that the trail camera is useful for the purposes of our experiment, but accuracy may differ based on item type. Bottles filled with liquid reflect light off of the camera and create a glare in the image. In our experience, we believe the accuracy of trials 2 and 3 were adulterated by bag placement. The bag must be spread out across the bottom of the bin, open enough for the camera to always have a clear view of the bottom of the bag. When items are dropped in, they sometimes move the bag, putting it in the way of the view of the camera. For this reason, it is best to tape the sides of the bag to the inside of the bin to keep it from moving. Based on the success of lab trail, we proceed to field test the camera.

2.5. Field Test Methods

We conducted a field experiment to further test the accuracy of the trail camera to monitor items placed in the recycling bin. Six cameras were installed in the same way as the lab experiment on six recycling bins at different locations, shown in Figure 2.5.1 during the fall 2021

semester. We received permission and cooperated with the university's office of sustainability and facility services to conduct the test.

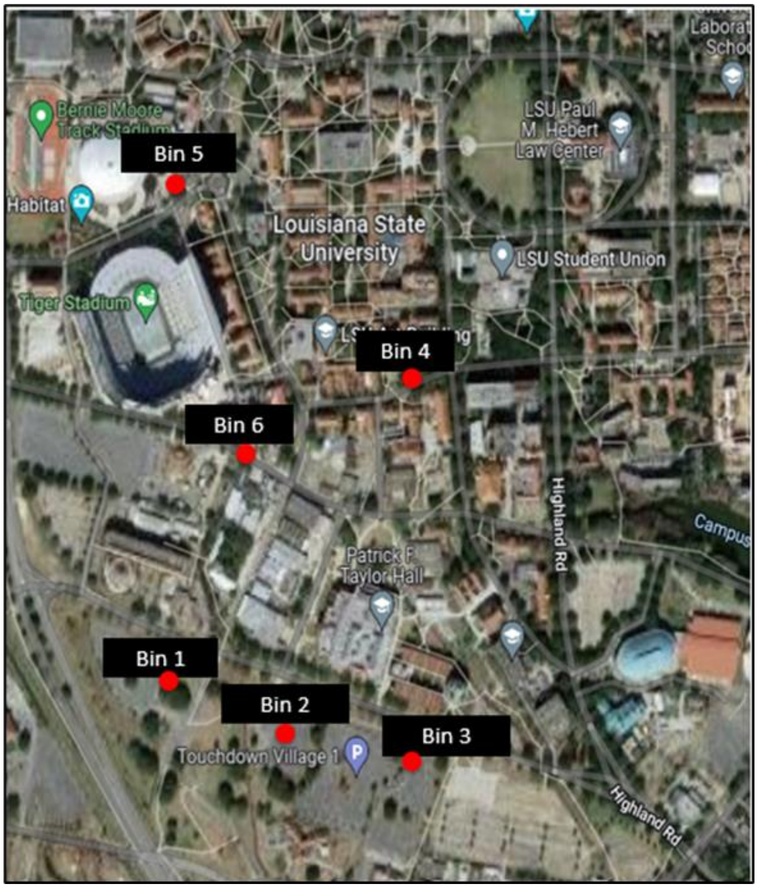


Figure 2.5.1. Bin locations for field experiment

The university's office of sustainability helped us to identify and use these six among its hundreds of recycling bins for several reasons. First, the bins are relatively similar in terms of being located near high-traffic buildings, having a large volume of pedestrian traffic that pass by each day. The buildings have high traffic throughout the day, with common study places for students both during and after school hours and a dining establishment, which may contribute to food waste contamination in the bins. Second, all locations are in the campus interior, meaning that from 7am to 4:30pm, vehicle traffic is limited to university vehicles only, meaning that students represent the majority of pedestrian traffic. Third, the bins are relatively spread far apart

such that more types of people and items are likely being measured. Three bins on the south side of campus are approximately 180 meters apart, and the other three bins on the north side of campus are approximately 640 meters apart. Distances are reported as Euclidian distances, or “as the crow flies”.

We conducted preliminary observation prior to the field trials. We initially observed and collected data from several recycling bins prior to the field experiment to determine how frequently people discarded items into the bins. These tests revealed that bin use occurred about every 10-15 minutes, lower (every 15-20 minutes) during inactive periods, such as during class times, and higher (every 5 minutes) during busier periods such as lunch time and transition times between classes. Consequently, we set trail cameras to take timelapse photos every 10 minutes from 7am to 7pm each day. This time interval limits the number of photos generated, while still providing accurate representation of bin use and user behavior. We also observed that trail cameras were out of sight from users unless the person crouched down to explicitly look directly inside the bin, meaning that the likelihood of a Hawthorne effect from knowingly being observed was minimal.

Our process for field test data collection was as follows. Bag collection by the research team occurred at approximately 5pm every day for all six bins, generating a dataset of photos for a roughly 10-hour period, roughly 60 photos per bin per day. As mentioned previously, cameras were set to take photos until 7pm so that if we did not reach the bin immediately at 5pm to change the bag, the cameras would continue to take photos of discarded items to generate a data set as large as possible. During bag collection, we replaced each trail camera’s SD card and verified the camera was set to begin taking photos at 7am the next day. Photos from the that day’s SD card were uploaded to cloud storage along with relevant information such as date and

bin number. Three student workers participated in the data collection process. Prior to the start of the quasi-experiment, each worker received field training and written instructions on proper bag collection and replacement as well as camera and card settings. Bag and photo data collection for the experiment occurred for 27 days mid-October to mid-November 2021. This excludes weekends because the experiment occurred during football season, events with extremely high foot traffic of non-university students tailgating throughout campus and high volumes of trash, such that recycling bins are often used in lieu of full trash bins. With approximately 60 photos per bin per day over a 27-day period, about 9,720 photos throughout the entire experiment.

In order to have a benchmark for comparison (like in the lab experiment) to compare the photos against, the contents of each bag were hand inspected by these student workers. To document the items in the camera photos, other individuals who did not participate in the bag sorting, inspected each photo for the appearance of new items. We assess the accuracy of the camera data by benchmarking it against the hand counted bag data of items. The bag data has virtually zero measurement error in terms of the contents because each bag is sorted through by hand, enabling perfect identification of each item. The inherent disadvantage is a much greater labor requirement and inconvenience, whereas the camera can potentially avoid these constraints.

Like the lab experiment, we did a side-by-side comparison of the items recorded in the camera dataset and bag dataset per bin per day. We used the Bag Match variable in the camera data set, equal to 1 if the item recorded in the camera data set matched the item found in the hand count and recorded in the bag data set. Unlike the lab experiment, we also had a Camera Match variable in the bag data set. This variable was equal to 1 if the item that we found in the hand count and recorded in the bag data set matched the item recorded from the photos in the camera

data set. Therefore, there was a discrepancy between Bag Match and Camera Match. For example, if the first item in the bag data set for bin 1 day 1 read 'Lacroix can', we went through each item photographed in bin 1 on day 1 recorded in the camera data set and searched for a Lacroix can. If the item was found in the camera dataset, it was marked as a match in both data sets (Bag Match = 1 & Camera Match = 1). However, if we found an item in the bag data set that was not recorded in the camera data set, the Camera Match variable in the bag data set would be equal to 0. Similarly, if we had an item recorded in the camera data set that was not found in the bag data set, the Bag Match variable for that item in the camera data set would be equal to 0. As another example, suppose ten items were recorded in the bag data set for bin 1 on day 1, but only five items recorded in the camera data set, then Camera Match in the bag dataset would be 50%, because we found five extra items in the bag data set that were not recorded on camera. All five of the items recorded in the camera data set, however, may have also been items found in the bag data set, making the Bag Match percent for the camera dataset in bin 1 on day 1 to be 100%.

To identify which types of items are more clearly observed on camera, we code for all the same characteristics per item, including type of item (e.g., *Paper*, *Bottle*, *Can*, *Other*, and *SmallCC*), as well as several other control variables unique to the field experiment, all described in Table 2.3.1.

The indicator *Event* controls for time periods of special events such as basketball games or fall break.[1] Event times started an hour before each event and ended an hour after each event in the camera data spreadsheet. We used the event variable to give reason to certain observations. For example, during sporting events we may see an increase in the number of materials thrown into the bins, or a different composition of materials thrown into the bins due to the difference in

[1] Event cannot be recovered in the bag data because recovering the timing of each item is not possible.

the demographic of users present on campus during those times. Conversely, however, during events such as fall break, when there is much less foot traffic on campus, we may see much less items being thrown into the bins, or we may have more days where the bin is empty.

Further, bag color varied in the field test. *Orange* and *Blue* indicate the color of the bag (relative to black) to control for whether this affects item identification accuracy on the camera photos.

To be transparent, there were two days at two bins that had data issues. On October 18th, for bin 3, no photos were taken by the camera, indicating an error in the set-up process. On November 11th, in bin 4, the SD card corrupted and we were not able to obtain photos. Data for these bags were still obtainable in the bag dataset.

2.6. Field Test Results

Summary statistics of items captured in the bag and camera data given in Table 2.6.1, along with compositions of items in the bag data versus the camera data.

Table 2.6.1. Item composition for bag and camera data from field trial

	Bag Data	Camera Match	Camera Data	Bag Match	% Difference in item composition
Total Items	1343	920 (68.5%)	1030	961 (93.3%)	23.0%
Paper	189 (14.0%)[1]	49 (25.9%)	117 (11.4%)	79 (67.5%)	37.6%
Bottles	424 (31.6%)	364 (85.9%)	383 (37.0%)	373 (97.4%)	9.7%
Cans	222 (16.5%)	188 (84.7%)	188 (9.3%)	184 (97.9%)	15.3%
Other	422 (31.4%)	287 (68.0%)	342 (33.0%)	325 (95.0%)	18.5%

(Table cont'd.)

	Bag Data	Camera Match	Camera Data	Bag Match	% Difference in item composition
SmallCC	170 (12.7%)	48 (28.2%)	58 (6.0%)	39 (67.2%)	65.9%
Contamination	499(37.0%)	246 (49.3%)	313(30.0%)	285 (91.1%)	37.5%
%contam that is SmallCC	34.1%		18.5%		

[1] Whole number refers to the total amount of each type of item. Percent in parentheses refers to the percent of each type of item out of the total number of items.
% difference calculated by (bag data ⋕ -camera data ⋕)/(bag data ⋕) for example: for total items, 23.0% of items in the bag were not recorded on the camera.

Overall, the hand count data of the bags revealed 1343 items with 920 (69%) matching the items in the photos. The camera photographed 1030 items, with 961 (93%) of these items matching the items found in the bag dataset. The match rate among all types of items was lower in the camera dataset than the bag dataset. In the bag dataset, the variable camera match represents the match rate. The highest match rates in the bag dataset occurred with bottles and cans at about 86% and 85%. The next highest match rate was 68% with other types of items, followed by 49% for contaminated items, 28% for *SmallCC* items, and the lowest at 26% for paper items. In the camera dataset, the match rate is recorded by the bag match variable. Cans and bottles had the highest match rates in the camera dataset, with match rates of 98% and 97%. The next highest match rate occurred with other types of items at about 95%, followed by items considered to be contamination at 91%, paper items at 68%, and lastly SmallCC items at 67%.

Bottles and cans had the lowest discrepancies in composition between the two datasets, with only a 9.7% difference in composition between the bag and camera dataset for bottles, and a 15.3% difference in cans. The largest difference in composition of items that we found were between paper items (37.6%) and *SmallCC* items (65.9%). In the bag dataset, the ranking of items from largest composition to smallest composition was bottles, other, cans, paper, then

SmallCC. We see the same trend in the camera dataset even with less items than the bag dataset. Additionally, we measure the percent of contamination composed of SmallCC items, which is 34% in the bag data set and 19% in the camera data set.

Some of this discrepancy could also be due to differing quality of photos throughout the experiment, which made it harder to identify certain items. For example, Figure 2.6.1 shows an image taken in bin 1 at 7:00am on October 14th, 2021. The black object to the right could be multiple things, but it is unclear what exactly is in this photo. Additionally, it is hard to tell whether the object to the left is a crushed piece of paper or a paper bag.

Figure 2.6.1. Example photo 1.

In Figure 2.6.2, however, you can clearly see each of the objects, even in enough detail to read their labels.

Figure 2.6.2. Example photo 2.

Results of camera accuracy shown in Table 2.6.2.

Table 2.6.2. Logit model results for matches item in bag or camera data

	MODEL I	MODEL II	MODEL III	MODEL IV	MODEL V	Model VI
Dependent Variable:	Bag Match	Bag Match	Bag Match	Camera Match	Camera Match	Camera Match
Constant	2.813***	2.824***	2.881***	0.676***	1.121***	1.070***
	(0.313)	(0.434)	(0.419)	(0.130)	(0.171)	(0.196)
Event	-0.125					
	(0.264)					
Paper		-1.828***			-1.372***	
		(0.444)			(0.199)	
Bottle		0.824			0.683***	
		(0.534)			(0.220)	
Can		1.005			0.595**	
		(0.666)			(0.251)	
SmallCC		-1.705***			-1.057***	
		(0.536)			(0.204)	
Contam		0.485			-0.566***	
		(0.551)			(0.184)	
Orange	-0.521			0.087		
	(0.390)			(0.182)		
Blue	-0.034			0.l40		
	(0.360)			(0.151)		
Bin1			-0.775*			-0.660***
			(0.447)			(0.213)
Bin2			0.498			0.053
			(0.722)			(0.296)
Bin3			1.006			-0.179
			(0.657)			(0.238)
Bin4			-0.269			0.156
			(0.557)			(0.281)
Bin5			0.757			0.776**
			(0.830)			(0.367)
Log-likelihood	-254.172	-201.222	-243.428	-836.277	-692.266	-814.236
Pseudo R^2	0.0066	0.2135	0.0486	0.0005	0.1726	0.0269
N	1031	1031	1031	1343	1343	1343

Standard errors are reported in parentheses.
***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.1 level, respectively.

Models I-IV are run using the camera dataset with the dependent variable Bag Match. Model I shows the effect of bag color and event days on item match. None of the coefficients of event, orange, or blue are significant, indicating that event days and orange and blue bags did not affect the probability of correct identification of items. The constant is positive and significant indicating that non-event days using black bags significantly increase the probability of correct identification of items.

Model II reports the results of the effect of item type on the Bag Match variable. The constant reflects the omitted categories, representing other types of items that are larger than a credit card and not considered to be contamination. The constant is positive and significant, meaning that these types of items increase the probability of correct identification. The only other significant variables are paper and SmallCC items, both of which have negative and significant coefficients, meaning that paper items and SmallCC items decrease the probability of correct identification on camera. Bottles, cans, and contaminated items were not found to have significant effects on the probability of correct identification.

Model III was run to test the different effects of bin locations on the match variable. The constant, which reflects bin6 is positive and significant, indicating that items in bin6 increased the probability of correct identification. The coefficient of bin1 is negative and significant, which tells us that items in this bin decreased the probability of correct identification. No other bins had a significant effect on identifiability.

Models IV-VI are run on the bag dataset with the dependent variable Camera Match. Model IV shows the results of the effect of bag color on item identification. We do not include the dependent variable event in this model, because as stated before, there is not account of time periods in the bag dataset. Similar to Model I, the coefficients of orange and blue are not

significant, indicating that these bag colors do not affect the probability of correct item identification. The constant in positive and significant, indicating that black bags increase the probability of correct identification.

Model V was also used to test the effect of item type on identification, using the Camera Match variable as the dependent variable. Like Model II, the constant is positive and significant, indicating that other types of items that are larger than a credit card and not considered contamination increase the probability of correct identification. Likewise, the coefficients of paper and SmallCC show the same results as Model II, being negative and significant, indicating that these types of items decrease the probability of correct identification on camera. Unlike Model II, all other variables in this model are significant. The coefficients of both bottles and cans are positive and significant, meaning that items that are bottles or cans increase the probability of correct identification. The coefficient of contamination is negative and significant, indicating that contaminated items decrease the probability of correct identification on the camera.

Model VI was also run to test the different effects of bin locations on the Camera Match variable. Like Model III, the constant of this model is positive and significant, indicating that bin6 increased probability of correct identification, and the coefficient of bin1 is negative and significant, indicating that items in this bin decreased the probability of correct identification. In this model, the coefficient of bin5 is also positive and significant, indicating that items in this bin also increased the probability of correct identification, but no other variables are found to have significant effects.

We conduct post-estimation test of the Camera Match and Bag Match variables for Models II and V to further prove our results, shown in Table 2.6.3.

Table 2.6.3. P-value of post-estimation tests of match for camera data and bag data based on Table 2.6.2

	Paper	Bottle	Can	SmallCC
Bottle	0.000/0.000			
Can	0.000/0.000	0.763/0.705		
SmallCC	0.885/0.301	0.004/0.000	0.005/0.000	
Contam	0.000/0.002	0.467/0.000	0.393/0.000	0.031/0.072

2.7. Discussion and Conclusions

Conducting experiments involving recycling contamination involves a tradeoff of either measuring accurately with tedious hand counts, or more convenience of weighing bags, but greater measurement error, which may explain the small number of studies. Our study evaluates the effectiveness of using trail cameras to monitor recycling contents and to identify any limitations or challenges associated with this approach.

Initial testing of cameras in general revealed several issues with motion detection and identification of objects being thrown into the bin. Timelapse showed improved accuracy across all cameras, but translucent items such as clear plastics were still harder to identify due to their transparency and the potential for glare. Additionally, the placement of the bag inside the bin proved to be an issue, as it often moved and blocked the view of the camera. To address this, it was found to be most effective to tape the sides of the bag to the inside of the bin.

Our selected trail camera showed an average accuracy of 82% in the lab experiment. Model results show that items smaller than a credit card are less likely to be photographed and accurately identified in the camera. In our case, this is okay because the materials recovery facility (MRF) landfills all such small items. We see similar results in our field test, where it was found that items smaller than a credit card decreased the probability of identification on camera. Bottles and cans, however, increased the probability of identification in the results of the bag data (although showed no significant effects in the lab experiment or in the camera data set),

which we believe to be the more accurate results, because they reflect the entirety of the contents thrown into the bins. Also, in contradiction to the lab experiment outcomes, where contamination is shown to increase probability of correct identification, the contamination variable was shown to have no effect on identification in the camera data set but decreases the probability of correct identification in the bag data set. One reason for discrepancy between the lab experiment results and the field experiment results may be due to the issue of cross contamination of items in the field experiment. As discussed in the lab experiment methods, food and liquid residue were enclosed in containers to prevent cross contamination of items. In the field experiment, however, we could not prevent this from occurring, and when items such as half-full to-go cups were thrown into the bins, they sometimes opened and spilled onto other items. This is mainly an issue for paper items, as when paper becomes wet/soggy and starts to fall apart it is no longer recyclable and now considered to be contamination. This also explains the difference in composition of contamination between the bag and camera data sets in the field experiment. The camera captures photos every ten minutes, whereas bag data is collected at the end of the day by sifting through the entire bag. If the camera captures a photo in the first ten minutes of the observation period that shows only five paper items, they would not be considered contamination when being observed in the photos. There is no way for us, however, to note in the photos that in a ten-minute period later in the day somebody may have thrown a cup into the bin with liquid that could have spilled onto the paper. Therefore, at the end of the day when sifting through the bag data, the paper would be considered contamination, where it was not considered to be contamination in the camera data set. Additionally, the average daily temperature in the field portion of our experiment was about 72 degrees, which could have resulted in the melting of

certain objects like frozen foods, candies, or chocolates that could have cross contaminated other items in the bin.

There were several challenges in the field trials. First, whereas the lab trials occurred indoors (highly controlled conditions), the field trials occurred outdoors, such that the wind/weather, shifting the position of the bag, or variable sunlight/lighting may affect the accuracy of the cameras. In future experiments, bags may be custom designed to enable best camera recording, such a heavier-on-the-bottom bags or self-adhesive bags. Also, the field experiment used different bag colors and had missing data on certain days. We found that black bags were best for item identification. Additionally, some photos were captured in color and others in black and white. Overall, we believe that the use of trail cameras is a useful approach to measure recycling bin contents, although it cannot explain human behavior underlying contamination.

We have several thoughts about the use of trail cameras for future work. First, daily visitation is not necessarily a requirement of a successful experiment. We believe the data quality would be the same even if SD cards and bags were replaced less frequently, dramatically cutting down on the number of labor hours needed. Second, it is even more efficient to use internet-connected trail cameras which use a subscription to cellular service to wirelessly transmit photos, eliminating physical SD cards. As well, advancements in camera technology may improve motion capture technology to help to capture images of items more quickly and detect the motion of smaller items in the vicinity of the camera. With improvement, trail cameras may be able to measure items placed in waste bins, which have much greater variety in the types of items, though this would need to be tested further.

Chapter 3. Reducing Recycling Contamination Using an Information Nudge

3.1. Abstract

A central challenge to waste and recycling management is recycling contamination, the incorrect placement of discarded items. Addressing contamination involves behavior modification interventions, such as signage. Studies on the efficacy of these methods are infrequent due to the large labor hour requirements, inconvenient scheduling constraints, and the discomfort of sorting through recycling bags by hand. The purpose of this study is to quantify and assess the impact of signage on recycling contamination rates. We conducted a field experiment in Fall 2021 at Louisiana State University to test the effect of two types of signs. We used two different approaches in the signage treatments. The first treatment explicitly instructs passersby to not recycle a short list of common recycling contaminants, including Styrofoam, food wrappers, plastic bags, and face masks. The second treatment provides general encouragement to promote recycling, excluding specific instructions on what to recycle. To improve data collection, we utilize trail cameras, a novel approach in this research area. Results show that signage with explicit instructions reduces contamination rates.

Key Words: Recycling, contamination, nudge; information

3.2. Introduction

Waste management is a global challenge that affects the environment, human health, and the economy. The problem stems from the sheer amount of waste that is generated. The United States alone generated an average of 276.4 million tons of municipal solid waste (MSW) per year from 2016 to 2018, with a combined recycling and composting average of only 93.9 million tons (34%) of this waste (EPA, 2020). With the majority of MSW going to landfills, waste contributes to pollution and climate change. For example, leachates, formed when rain water filters through landfills, contributes to soil and water pollution (EPA, 2023). As well, landfills contribute to air pollution as the third-largest source of human-related methane emissions, about 15% of methane emissions in the United States in 2020 (EPA, 2023). Finding ways to reduce the total amount of waste produced and improve the recycling stream to reduce landfilling are both important. This study contributes to the latter.

Recycling helps reduce landfilling. However, one major challenge to recycling programs is contamination, which occurs when non-recyclable items are placed in recycling bins. The percentage of non-recyclable items (either by number or by weight) is often referred to as contamination rate. Separation of recyclables from waste occurs at materials recovery facilities (MRFs). Excessive contamination in a load of recyclables regularly forces MRFs to landfill the entire load of items rather than cost-prohibitive task of sorting items (Henslovitz, 2021). The company Waste Management reported landfilling 25% of all its recycling due to contamination in 2018 (Albeck-Ripka, 2018). Similarly, Republic Services landfilled 23% of its recyclable loads from contamination (Andres Harris, personal communication).

Furthermore, one report showed that contamination rates have been gradually increasing from 2007 to 2019 (Townsend and Anshassi, 2020). Contamination not only decreases the amount of recovered recyclable material thus increasing landfilling, but also increases processing

costs, consequently decreasing revenue and profitability which further disincentivizes firms to engage in sorting contaminated materials. A survey of 15 MRFs in 10 states conducted by the Northeast Recycling Council revealed that the value of an average ton of recyclables during the second quarter of 2019 was $45.83, but excluding the negative impact of contamination this value rose to $51.65 (Paben, 2019).

There are two main approaches to help reduce contamination. First, MRFs can install more sophisticated equipment or employ more labor hours to sort loads. This increases labor and equipment costs, which can be prohibitive for some recycling facilities.

The second approach is to reduce contamination before waste arrives at the recycling center by modifying end-user behavior, which is the main contribution of our study. For example, recycling bins commonly feature information signage, often providing a list of acceptable items. Signage can be considered a type of nudge, which is “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” (Thaler and Sunstein, 2008). Green nudges are a type of intervention that are designed to encourage pro-environmental behavior while maintaining the freedom of choice for individuals. They typically involve subtle changes in the physical or social environment that make sustainable behavior more visible, appealing, and convenient. Green nudges are often low-cost, and can be implemented on a small scale, making them a promising tool for policymakers and businesses to promote sustainability (Carlsson, et al., 2021).

Several studies have demonstrated the effectiveness of green nudges in promoting recycling behavior. For instance, one study found that adding a recycling bin to a workplace kitchen, along with a sign that emphasized the importance of recycling, significantly increased

recycling rates (Abrahamse, et al., 2005). Another study increased recycling rate and decreased total MSW production simultaneously by implementing a clear bag policy, where recycling bins were required to use clear trash bags so that users could see the contents of the bag (Akbulut-Yuksel and Boulatoff, 2021). While green nudges can promote pro-environmental behavior, recycling studies mainly focus on recycling rate, and we find no studies that used these types of nudges to make a change to the contamination levels found in recycling bins.

The limited number of studies examining recycling contamination is in part due to the difficulty in collecting and measuring such behavior. Typically, measuring contamination is done by recording all items per bag, requiring numerous labor hours, inconvenient scheduling constraints, and discomfort of sorting through bags by hand. To overcome this, we use a new approach using trail cameras installed inside recycling bins to measure contents previously tested in a proof-of-concept by Rivette and Penn (2023). They show that trail cameras are reasonably accurate in terms of identifying and measuring recycling bag contents, reducing effort and discomfort necessary to study contamination. As far as we know, we are the first to use this approach to examine the effect of nudges on recycling contamination.

The purpose of this study is to assess the impact of signage on recycling contamination rates. We test two types of signage, a "Quality" treatment on what to specifically not put into the recycling bins, and a "Quantity" treatment that encourages general recycling. We measure the effect of the signage both using the bag data (in which we manually sorted through items), which perfectly captures contents versus the effect measured by the camera data (obtained through photos), which is less accurate, but much less resource intensive. The results of the analysis will help us to understand how to reduce contamination levels while maintaining sustainable recycling practices, leading to possible reductions in pollution and climate change.

3.3. Literature Review

To make recycling more cost-effective, it is important to understand the factors that influence recycling behavior in order to develop effective strategies to not only promote recycling, but also encourage people to recycle correctly. Many studies exist in this area and have shown several factors are important: 1. Attitudes and beliefs: Studies have shown that positive attitudes and beliefs towards recycling are strong predictors of recycling behavior (Gamba and Oskamp, 1994, Schultz and Oskamp, 1996). 2. Convenience: Convenience is also an important factor in recycling behavior. People are more likely to recycle if recycling is convenient (Ando and Gosselin, 2005, DiGiacomo, et al., 2018, Gardner and Stern, 1996). 3. Social norms: Social norms also play an important role in recycling behavior. Several studies have shown that people are more likely to recycle if they believe that recycling is socially acceptable (Abbott, et al., 2013, Schultz and Oskamp, 1996, Schultz, et al., 1995, Thogersen, 1995, Thomas and Sharp, 2013, Viscusi, et al., 2011). For example, a study by Thogersen (1995) found that people were more likely to recycle if they believed that their neighbors were also recycling. 4. Education and awareness: Education and awareness campaigns have been found to be effective in promoting recycling behavior (Ryan and Dunlap, 1989, Sidique, et al., 2010, Wang, et al., 2020). 5. Incentives: Incentives can also be effective in promoting recycling behavior(Gardner and Stern, 1996, Suttibak and Nitivattananon, 2008, Vicente and Reis, 2008). Overall, these studies suggest that attitudes and beliefs, convenience, social norms, education and awareness, and incentives are important factors in promoting recycling behavior. By understanding these factors, policymakers and environmental advocates can develop effective strategies to promote recycling behavior and encourage sustainable behavior.

Much of the literature on recycling behavior can be considered a nudge because it impacts human behavior without directly affecting or motivating individuals. Nudges have been

found useful in a multitude of settings, such as increased organ donation (Johnson and Goldstein, 2003), retirement savings (Beshears, et al., 2021), and healthy eating (Montagni, 2020). Extensive evidence (Carlsson, et al., 2021) demonstrates the success of several types of nudges such as default, social norms, and reminders in multiple environmental/conservation settings such as reduced utility use (Abrahamse, et al., 2005), food waste (Barker, et al., 2021), and plastic bag use (Penn, et al., 2021).

Recycling behavior experiments have largely focused on augmenting recycling rates (Phulwani, et al., 2020). Studies have considered the number of bins, bin proximity, visual prompts, bin design, and some combinations of these, each with varying effects on recycling rates. Regarding informational prompts and signage, one study showed that pro-environmental labeling increased recycling rate as well as contamination rate in recycling bins (Catlin, et al., 2020).

Comparatively few studies examine contamination rates. Three studies showed that the presence of multi-bins decrease contamination, bins that accepts multiple types of recyclable material (Allan, et al., 2011, Andrews, 2013). One study found that closer proximity of recycling multi-bins to trash bins decreases contamination (Andrews, 2013). Trash bins adjacent to recycling bins makes correct placement of waste and recyclables more convenient for users, therefore decreasing contamination in the recycling bins.

Regarding informational prompts and signage, our review found that studies commonly tested three types of signage, declarative information, procedural information signage and pro-environmental signage. All three are types of information nudges. Declarative information states why a behavior is important for resolving a problem. A common example of a declarative statement is “Don’t recycle food waste.” Several studies found that declarative information

decreases contamination; (Lohse and Healy, 2012, Rhodes, et al., 2014, Verdonk, et al., 2017). A procedural statement, on the other hand, instructs individuals on how to perform a behavior. It might state “If an item is contaminated with food waste, rinse the food waste off of the container before recycling it.” Among the four studies that test procedural information on contamination, all four found a decrease (Buelow, et al., 2009, Durdan, 1985, Rosenthal and Linder, 2021), but in some cases only among those with no prior knowledge of proper recycling (Rosenthal, 2018). Implementing both declarative and procedural information increased recycling rates and decreased contamination simultaneously (Rosenthal and Linder, 2021). Others (Catlin, et al., 2020, Durdan, 1985, Verdonk, et al., 2017) found that pro-environmental receptacle signage, which relates the effects of recycling to the condition of the environment, to increase both the recycling and contamination rate. This type of signage may state, “Save the Earth, please recycle”. The increase in contamination occurs due to ‘wishcycling’. This is a common issue in recycling programs, as individuals may not know whether an item is recyclable or not and may place it in the recycling bin as a "wish" that it can be recycled.

3.4. Experimental Design/ Data Collection Methods

To test the effectiveness of signage change at reducing recycling contamination, a quasi-experiment was implemented using six recycling bins at a large public university. The use of six recycling bins in the study was a deliberate choice made to control for other potential factors that could affect recycling contamination rates. By only using six bins, we were able to limit the number of potential sources of variation and better isolate the effects of the signage changes on recycling contamination. Additionally, using a smaller number of bins allowed for the study to be conducted within a specific time frame, budget and manage the data collection efficiently. Six bins were considered to be a suitable sample size for the study as it allowed for the collection of

enough data to detect meaningful changes in contamination rates while minimizing the resources required for data collection.

We implement two information signage treatments and a control, using two bins for each. The first information treatment, Quantity, implores individuals to place more of their discarded items into the recycling bin, as shown in Figure 3.4.1.

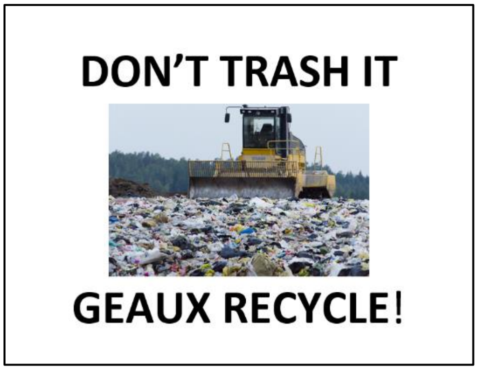


Figure 3.4.1. Quantity Treatment

The Quantity sign aligns with previous pro-environmental labeling studies, which show that such language can increase recycling rates but may unfortunately also increase recycling contamination rates (Catlin, et al., 2020, Durdan, 1985, Verdonk, et al., 2017). The second information treatment, Quality, specifically instructs individuals to not recycle a specific list of four common contaminants as shown in Figure 3.4.2.

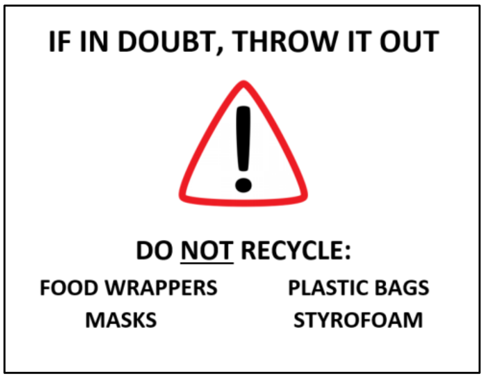


Figure 3.4.2. Quality Treatment

These items are food wrappers, plastic bags, face masks, and styrofoam and were listed based on preliminary inspection and discussion of common forms of contamination on campus. This signage is based off the finding in our literature review pertaining to declarative information interventions to decreases contamination rates (Lohse and Healy, 2012, Rhodes, et al., 2014, Verdonk, et al., 2017).

H_0: Equal contamination rate across treatments

H_A: Unequal contamination rate across treatments

The null hypothesis is that the Quantity and Quality treatments will have no effect on contamination rate. The alternative hypothesis is that the contamination rate across treatments is unequal for Quantity and/or Quality. This hypothesis assumes that any observed differences between the treatment and control groups are due solely to the effect of the treatment itself.

Quasi-experiment social intervention studies like ours may face experimental/information spillover or leakage (Strain, et al., 1976). A quasi-experiment is a research design that shares similarities with a true experiment but lacks the complete control over the independent variable that a true experiment would have (Cook and Campbell, 1979). In a quasi-experiment, researchers manipulate an independent variable but do not randomly assign participants to conditions. Instead, they use pre-existing groups or conditions to compare outcomes. In the context of social intervention studies, quasi-experiments are commonly used to evaluate the effectiveness of social interventions that cannot be assigned randomly to individuals or groups due to ethical or practical reasons.

Experimental or information spillover, also known as leakage, refers to situations where information or treatment intended for one group of participants unintentionally spreads to another group. This can happen, for example, when participants in the treatment group

communicate with participants in the control group, or when participants in the control group learn about the treatment through other channels (Strain, et al., 1976). Experimental or information spillover can have a potential effect on your study because it can compromise the validity of your results. If the treatment leaks to the control group, for example, any differences observed between the treatment and control groups may not be due to the treatment itself, but rather to the contamination of the control group with the treatment. This can lead to an estimation of the treatment effect, which can have negative consequences for policy and practice. To reduce such possibilities, the experiment was not advertised and only apparent at the bin locations in terms of new signage on four of the bins. Conducting the study on a university campus takes advantage of the student and staff traffic higher than in some other public spaces such as a park. This allows us to collect larger amounts of data under a given time thus reducing the likelihood of information spillover and leakage.

Observation at these six locations occurred during both a pre-treatment (without signage) and post-treatment period in which the signage intervention took place. Bag and photo data collection for the experiment occurred for 27 days, from October 14, 2021, to November 19, 2021, excluding Saturdays and Sundays. We excluded weekends because the experiment occurred during football season, events with extremely high foot traffic of non-university students tailgating throughout campus and high volumes of trash, such that recycling bins will be used in lieu of full trash bins. The pre-treatment period occurred from October 14, 2021, to November 3, 2021. The post-treatment period began on November 4, signage interventions were placed on each of the bins.

The location of the six bins used in the quasi-experiment appears in Figure 3.4.3.

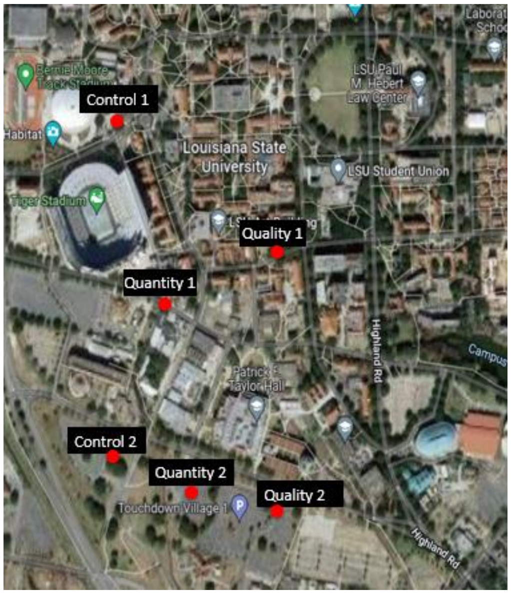


Figure 3.4.3. Bin locations
Taken from Google Maps

We received permission and cooperated with the university's office of sustainability and facility services to conduct the experiment. The office of sustainability helped us to identify six similar bin locations that were far enough apart to reduce information spillovers. The university has hundreds of outdoor recycling bins across campus, but these six were chosen as they are most similar in multiple respects. First, they have a large volume of people including students, teachers, and other campus visitors and staff that pass by the bins each day. Second, these locations are all close to university buildings where students attend class each day. Third, all locations are located along the campus transit system route, which caters only to students, and they are blocked off from outside campus traffic. Other bin locations are located near dining halls, convenience stores, or other locations that have food service nearby, which would increase the rate of recycling contamination due to excessive food waste.

The locations selected for bin 1 (Control1), bin 2 (Quantity1), and bin 3 (Quality1) were each about 200 yards apart (Euclidian distance/ 'as the crow flies') located adjacent to a parking lot across from the business and engineering buildings. These buildings have high pedestrian-

traffic throughout the day, with common study places for students both during and after school hours and a dining establishment, which may contribute to food waste contamination in the bins. Even though 200 yards apart, it is still possible that individuals could walk past and learn from a treatment bin, influencing their choice in front of a control bin, creating bias. Bin 4 (Control2) was located between the life science building and student union, which contains several restaurants. Bin 6 (Quality2) was located near a stadium parking lot. A disadvantage it holds is the possibility of a higher concentration of athletes and the possibility of more athletic events due to its proximity to the university stadium as well as the athletic training center. Bin 5 (Quantity2) was on the opposite side of the stadium between the parking lot and the mid-campus area. This location also shared the advantage of higher traffic due to its adjacency to a parking lot.

This approach has several issues. First, specific majors or demographics of students may congregate around certain buildings. For example, bins 1-3 are adjacent to the business school. The different demographics being centered around different treatment bins is a disadvantage to each bin because of the difference in the typical beliefs/outlooks on recycling that each type of group holds. Second, students may pass by several of the experimental bins. This could lead to potential bias if they catch on to the experiment and know that they are being observed, which could influence their recycling behavioral decisions at other bin locations.

To capture the recycling contents, trail cameras were attached to the inside lid of each bin facing down and out of sight from users. To determine an appropriate interval for the camera to take a photo, we set up trail cameras in several recycling bins during a pre-experimental trial period to measure how frequently people discarded items. The cameras took photos every 5 minutes, and these photos were reviewed each day. This revealed that bin use occurred about every 10-15 minutes. Bin use was lower (every 15-20 minutes) during inactive periods, such as

during class times, and higher (every 5-10 minutes) during busier periods such as lunch time and transition times between classes. Consequently, trail cameras were set to take every 10 minutes. This time interval limits the number of photos/data generated, while still providing accurate representation of bin use and user behavior. Although the camera was set to continue taking photos from 7am until 7pm, bag collection occurred at 5pm every day, generating a dataset of photos for a roughly 10-hour period.

Several steps occurred each day to manage the bags of recyclables and photo data. During bag collection the SD cards of that day's photos were removed, labeled, then replaced with a new SD card, and the camera reset to begin taking photos at 7am the next day. At the end of each day, we uploaded the photos to cloud storage along with relevant information such as date and bin number. Three student workers participated in the data collection process. Prior to the start of the quasi-experiment, each worker received field training and written instructions on proper bag collection and replacement as well as camera and SD card settings.

With approximately 60 photos per bin per day over a 27-day period, there were about 9,720 photos throughout the entire experiment. Photos were inspected to detect new items per 10-minute interval, entered into a spreadsheet with the date, bin number, time that the item appeared on camera, and a detailed description of the item. Notably, there were two days in which errors occurred in the experiment. On October 18th, for the Quality1 bin, no photos were taken by the camera, indicating an error in the set-up process. On November 11th, for the Control2 bin, the SD card corrupted and we were not able to obtain photos. There were nine days in the camera dataset in which photos showed that no items had been tossed into the bin on that day. There were 10 days in the bag dataset that the bag was found to be empty. These factors

may contribute to the differences in levels of contamination as well as the differences in composition of items between the bag and camera data sets.

Each item in each bin was coded for several characteristics, with the list of variables and their description shown in Table 3.4.1.

Table 3.4.1. Variable List

Variable	Description
Camday	Time period from camera set up to camera collection, days 1-27
Time	Time in hours and minutes
Matches bag	1 if matches the item found in the bag data
Dependent Variable	
Contam	1 if contamination
ContamFour	1 if item is a listed contaminant on the quality signage treatment (styrofoam, masks, plastic bags, candy wrappers)
ContamOther	1 if item is contamination other than four items in ContamFour Else 0 (not contamination)
Treat	1 if post-treatment period, Else 0 (pre-treatment period)
Treatment	
Quantity	1 if quantity treatment ("Geaux Recycle") shown in Figure 1 (Quantity1=bin2; Quantity2=bin6)
Quality	1 if quality treatment ("Don't Recycle") shown in Figure 2 (Quality1=bin3; Quality2=bin5) Else 0 (Control) (Control1=bin1; Control2=bin4)

First, we record the type of item with several categories: paper, bottle, can, SmallCC and other were used to identify which types of items contribute most to contamination rates. This identification is also the basis for coding the dummy variable 'Contamination', the dependent variable used in the subsequent analysis, with 1 indicating the item is not recyclable and inappropriately placed in the recycling bin and 0 indicating it is recyclable. This contamination variable included all items that were considered contaminated.

Because the sign in the quality treatment only focuses on reducing contamination of four specific items (food wrapper, mask, plastic bag, or Styrofoam) shown in Figure 3.4.2, we create a second dependent variable called 'ContamFour'. In this case, ContamFour equals 1 if the item was one of the four listed types of contamination (masks, Styrofoam, plastic bags, and food

wrappers), and 0 if it is not a contaminated item. This alternative analysis focuses on changes in the likelihood of contamination of only items specified by the signage treatment. Separately, 'ContamOther' is an additional dummy variable to denote the remaining items that are recycling contamination, but not the four types in ContamFour.

We recorded whether an item was smaller than a credit card (SmallCC) in both the bag and camera dataset. This is important because according to MRF used by the university where the experiment occurred, anything smaller than a credit card cannot be sorted out by their equipment. Therefore, we considered all such these items to be contamination. In our experiment, we measured SmallCC size by dimension. Therefore, although a mint container is larger in volume than a credit card, dimensionally it is the same size or smaller, and therefore coded as 1 for the SmallCC variable. Additional examples include a balled-up piece of paper or a crushed can flattened vertically. Other recycling facilities may have more advanced equipment that can handle the separation of small items, but in this case, it is automatically considered contamination. This has implications to diverting recyclable items to landfill since the cost of sorting out smaller items will be exponentially higher.

The ability to measure the time an item is placed in a recycling bin varies between the camera dataset and the bag dataset. Trail cameras can record the time a photo is taken and the corresponding item in the photo. This allows us to conduct a parallel trend assumption on hourly contamination data rather than daily contamination data for our camera data set. We also had an indicator for time frames in which an event was occurring. Event days were coded as 1 for whether events such as baseball games, basketball games, fall break, or midterms occurred on that day. We assume that the length of an Event includes one hour before and one hour after the

event, because people tend to arrive early to events and hangout afterwards. Importantly, coding for Event is precluded from the bag data analysis in which the hour of placement is unknown.

This is potentially important because this helps us to justify outliers in our data. Event days could lead to multiple issues. If the event is fall break, we know that there will be very few people on campus, if any, and we can therefore attribute low volume of items being recycled to this event. If the event, however, is a sporting event, we know that there will be a high volume of people who do not attend or work for the university, differing drastically from our targeted demographic. We can infer that these people's recycling behavior will differ from days in which no event is occurring. We can also assume that contamination levels may be higher in bins located closer to the event area will be higher. A list of dates and times of events are given in Table 3.4.2.

Table 3.4.2. Event name, date, and time

Event	Date (All in 2021)	Time
Fall break	Thursday, October 21st and Friday, October 22nd	All day
Women's basketball game	Thursday, November 4th	6:00pm
Men's basketball game	Tuesday, November 9th	7:00pm
Men's basketball game	Friday, November 12th	7:00pm
Men's basketball game	Monday, November 15th	6:00pm
Baseball game	Friday, November 19th	5:00pm

Lastly, we control for potential day-of-week effects with corresponding dummy variables for *Tuesday*, *Wednesday*, *Thursday*, and *Friday*.

3.5. Statistical/Econometric Approach

We estimate the impact of the Quantity and Quality signage treatments by comparing contamination levels across bins using a difference-in-differences (DiD) approach. DiD is a statistical technique that estimates the causal effects of independent variables on an outcome variable. The data is analyzed from a nonequivalence control group design, which helps to establish which variable is the cause and which is the effect (Wu, 2020). Non-equivalence control groups in our experiment refer to the differences in the types/demographics of people who were exposed to the control bins vs. the treatment bins throughout the experiment due to the bin locations. There is no way for us to guarantee that the same demographic of people was exposed to the control bins vs the treatment bins, therefore the experiment has non-equivalence in terms of who was exposed to what bins. It is particularly useful when the intervention being studied is not randomly assigned to individuals or groups, such as in quasi-experimental data, making it difficult to establish causality using traditional methods. The DiD approach involves comparing the change in the outcome variable between a treatment group and a control group, before and after the intervention. By comparing the change in the outcome variable between the two groups, the DiD analysis can estimate the causal effect of the intervention on the outcome variable. The key assumption of the DiD approach is that it requires a control group that is similar to the treatment group in all aspects except for the intervention being studied. This control group is used as a counterfactual, to estimate what would have happened to the outcome variable in the treatment group if the intervention had not been implemented. In summary, DiD analysis is a statistical method used to estimate the causal effects of an intervention by comparing the change in an outcome variable between a treatment group and a control group

before and after the intervention. It allows us to determine the effect of treatment by comparing the change in outcome within the treatment group to the change in outcome within the control group, thus controlling for any pre-existing trends.

The effect of the signage change was estimated as the coefficient of the interaction term between the intervention period and treatment (β_5 *and* β_6) . The identification strategy is expressed in equation (1):

$$\begin{aligned} Contam_{i,t} = \beta_1 \ + \beta_2 Quantity_i + \beta_3\, Quality_i + \beta_4\, Treat_t + \ \beta_5\, Quantity_i \\ * Treat_t + \beta_6\, Quality_i * Treat_t + \beta_7 Event_{i,t} \\ + \beta_8 Tues_{i,t} + \beta_9 Wed_{i,t} + \beta_{10} Thurs_{i,t} + \beta_{11} Fri_{i,t} + \mathcal{E}_{i,t} \end{aligned} \tag{1}$$

Contam is the dependent variable of interest and coded as a dummy variable, in which object *i*, is coded 1 if its contamination and 0 if it not contamination and a 1 for contamination. *Quantity* and *Quality* are indicator variables for the two bins per treatment that received the corresponding information, with the two Control bins excluded as the reference category. *Treat* is a dummy variable indicating the posttreatment period occurring from November 4 to November 19. *Quant***Treat* and *Qual***Treat* are interactions terms that tell us whether or not the intervention worked posttreatment. $\mathcal{E}_i$ is the error term. Lastly, Event and day-of-week dummy indicators are controls which appear in our full model specifications. Because Contam is a dummy variable, we use a logit regression.

As a robustness check, we run additional models of ContamFour to test the effects of the signs specifically for the four types of items and excluding all ContamOther observations. A multinomial logit model is better than two separate logit models when there are multiple categories of the dependent variable. If we were to run two separate logit models for each

category of the dependent variable, we would be ignoring the fact that the two categories are related to each other. Additionally, running two separate models may lead to loss of information and efficiency in the estimation of parameters, as the models do not account for the correlations and interactions between the outcomes. A multinomial logit model can simultaneously estimate the probabilities of all categories of the dependent variable, taking into account the interdependence between the categories. We run a multinomial logit of ContamFour and ContamOther to test whether signage treatments have a differential effect on likelihood of an item being contamination for the four types mentioned on the Quality sign versus all other forms of contamination. All analyses occurred in Stata 17.

3.6. Results

3.6.1. Summary Statistics

Over the course of the quasi-experiment, 1343 items were recorded in the bag data of all six bins. Of these, 1033 items were captured in photos with 964 (93%) of these items matching the items found in the bag dataset. Table 3.6.1.1 shows the composition of items per bin in the bag data and Table 3.6.1.2 shows the composition of items per bin in the camera data.

Table 3.6.1.1. Composition of Items per bin from bag data

	Total Bag Items (% of total)	Paper	Bottle	Can	Other	SmallCC	Contam ination	Masks	Styrofoam	Plastic bags	Food wrappers	Contam Four
Control1	599(45)	105	159	76	220	81	284	22	6	15	86	129
Control2	141(10)	8	38	38	49	8	44	0	8	0	8	16
Quantity1	110(8)	7	51	17	29	10	27	1	0	0	10	11
Quantity2	137(10)	12	47	28	43	9	33	0	1	0	4	5
Quality1	268(20)	52	96	50	51	50	96	3	2	4	15	24
Quality2	88(7)	5	33	13	30	12	15	0	1	0	6	7
Total (% of total)	1343	189 (14)	424 (32)	222 (17)	422 (31)	170 (13)	499 (37)	26 (2)	18 (1)	19 (1)	129 (10)	192 (14)

Table 3.6.1.2. Composition of Items per bin from camera data

	Total Camera Items (% of total)	Paper	Bottle	Can	Other	Small CC	Contam-ination	Masks	Styro-foam	Plastic bags	Food wrappers	ContamFour
Control1	433 (42)	60	137	62	174	27	158	19	4	11	45	79
Control2	117 (11)	10	32	30	45	4	42	0	5	0	5	10
Quantity1	91 (9)	8	49	13	21	5	26	1	0	0	9	10
Quantity2	113 (11)	12	46	25	30	5	26	0	1	0	3	4
Quality1	198 (19)	19	86	46	47	11	41	2	2	2	14	20
Quality2	81 (8)	9	32	12	27	6	19	0	1	1	5	6
Total (% of total)	1033	118 (11)	383 (37)	188 (18)	344 (33)	58 (6)	312 (30)	22 (2)	13 (1)	14 (1)	80 (8)	129 (12)

Per bin, 89-97% of items match the items found in the bag dataset. Because each item in the bag data is carefully and manually examined[2], it captures the true contents of items tossed, and we use it as our benchmark to assess validity of our camera results. Small items and paper items were often misidentified or unable to be identified in the camera results, as we found that the largest percent difference in composition of items between the bag and camera dataset occurred between paper and SmallCC items.

Table 3.6.1.3 shows the contamination level per bin based on the bag and camera data for the pre-treatment and post-treatment periods.

[2] Knowing the contents of the bag data are not perfect because during hand inspection, liquid sometimes degrades paper items such that identification becomes infeasible.

Table 3.6.1.3. Pre vs. Post-treatment Percent of Contam Items

	Bag			Bag excl. SmallCC			Camera			Camera excl. SmallCC		
Contam	Pre-treat # items	Post-treat # items	% Δ in contam	Pre-treat # items	Post-treat # items	% Δ in contam	Pre-treat # items	Post-treat # items	% Δ in contam	Pre-treat # items	Post-treat # items	% Δ in contam
Control1	166	118	-29%	119	98	-18%	84	76	-10%	66	67	2%
Control2	13	31	138%	10	29	190%	11	27	145%	8	26	225%
Quantity1	9	18	100%	8	14	75%	7	16	129%	5	13	160%
Quantity2	10	23	130%	8	19	138%	9	15	67%	8	11	38%
Quality1	52	44	-15%	29	26	-10%	27	18	-33%	18	16	-11%
Quality2	11	4	-64%	9	4	-56%	16	7	-56%	12	5	-58%
ContamFour												
Control1	75	54	-28%	66	47	-29%	42	37	-12%	36	36	0%
Control2	5	11	120%	4	10	150%	3	7	130%	3	7	133%
Quantity1	2	9	350%	2	9	350%	2	8	300%	2	8	300%
Quantity2	1	4	300%	1	4	300%	1	3	200%	1	2	100%
Quality1	18	6	-67%	17	5	-71%	15	5	-67%	13	5	-62%
Quality2	6	1	-83%	4	1	-75%	5	1	-80%	3	1	-67%

* % Δ in contaminated items calculated as (Post-treat# items – Pre-treat# items) / Pre-treat# items

Contamination levels in Control1 decreased in both the camera data and the bag data, but once SmallCC items were removed, it still decreased in the bag data, but slightly increased in the camera data. In Control2, contamination levels increased in both datasets, even when excluding SmallCC items. As we predicted, contamination levels increased in both Quantity treatment bins and decreased in both of the Quality treatment bins in the post-treatment period, even when excluding SmallCC items.

The bottom half of Table 3.6.1.3 shows the contamination level based on ContamFour. We see the same results in the bins as the contamination results above, including the same results when excluding SmallCC items. The only difference is that in Control1 bin, once SmallCC items were removed, we saw no change in contamination levels in the pre- vs. post-treatment periods.

3.6.2. Parallel trend assumption

A critical assumption for DiD to be valid is the parallel trend assumption. The parallel trend assumption states that the outcome variable of the treatment group and the control group would have followed the same trend in the absence of the intervention. In other words, the average outcome for the treated and untreated groups would have moved in parallel if the treatment of interest had not occurred (Ryan, et al., 2019).

The parallel trend assumption is important because it ensures that any changes in the outcome variable that are observed after the intervention are due to the intervention itself and not due to other factors such as pre-existing trends. For example, if the outcome variable of the treatment group was already increasing before the intervention, and it continues to increase after the intervention, it would be difficult to attribute the increase to the intervention. The parallel trend assumption allows us to control for these pre-existing trends and attribute any changes in the outcome variable solely to the intervention. To establish the parallel trend assumption, researchers typically examine the outcome variable for both the treatment and control groups

over a period of time prior to the intervention. If the outcome variable for both groups is trending similarly, it is evidence to support that the parallel trend assumption holds.

We conducted multiple parallel trends tests by comparing the percentage of items that are contaminated across bins in the pre-treatment period, with results shown in Table 3.6.2.1.

Table 3.6.2.1. Test on parallel trend assumption based on Contamination rates during the pre-treatment period.

	I: Bag: % contam per day		II: Camera: DV: % contam per hour		III: Camera: DV: % contam per day	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Constant	0.240***	0.051	0.206***	0.045	0.159***	0.061
Camday	-0.013	0.008	-0.005	0.008	0.001	0.010
Camday*Control1	0.040***	0.010	0.023***	0.008	0.018	0.011
Camday*Control2	0.002	0.010	0.013	0.011	0.013	0.012
Camday*Quantity1	-0.000	0.010	-0.000	0.011	-0.008	0.011
Camday*Quality1	0.033***	0.010	0.019**	0.009	0.018	0.011
Camday*Quality2	0.013	0.010	0.025**	0.011	0.019*	0.011
r^2	0.341		0.054		0.149	
N	75		294		76	
Total items	685		514		514	

N is the unit of observation. It represents contamination per bin per day in columns I and III and per hour per bin per day in column II. The discrepancy between I and III is due to eight instances in which camera data was unusable.

In the bag data, we are only able to test the proportion of contamination per day (represented by the variable Camday) per bin. In the camera data, we test the proportion of contamination both at a daily rate, to compare against the bag data, as well as at hourly rate because of the time stamps unique to the camera data.

The equation of this test is given by equation (2):

$$contam\ percent_i = \beta_1 + \beta_2 Camday_i + \beta_3\ Camday_i * Control1_i + \beta_4\ Camday_i * Control2_i + \beta_5\ Camday_i * Quantity1_i + \beta_6\ Camday_i * Quantity2_i + \beta_7 Camday_i * Quality1_i + \varepsilon_i \tag{2}$$

In the daily bag data Control1 and Quality1 violate the parallel trend assumption relative to the Quantity2 bin. In the hourly camera data Control1, Quality1 and Quality2 violate the parallel trend assumption, but in the daily camera data, we found that only Quality2 violated the parallel trend assumption. To further test the violation of the parallel trend assumption in these bins, we conduct post-estimation tests of contamination across camdaybin# in bag data, camera data per hour, and camera data per day shown in Table 3.6.2.2.

Table 3.6.2.2. P-value of post-estimation tests of contamination across camdaybin# in bag data, camera data per hour, and camera data per day

	Camday Quantity1	Camday Quality1	Camday Control2	Camday Quality2
Camday Control1	0.000, 0.021, 0.026	0.444, 0.538, 0.984	0.000, 0.277, 0.655	0.006, 0.861, 0.898
Camday Quantity1		0.001, 0.081, 0.027	0.779, 0.300, 0.080	0.158, 0.047, 0.021
Camday Quality1			0.002, 0.569, 0.670	0.040, 0.552, 0.882
Camday Control2				0.257, 0.318, 0.572

The significant p-values show that Control1 and Quality1 bins also violate the assumption relative to other bins and are therefore excluded from the analysis of Model I in Table 3.6.3.1. For models II and III in Table 3.6.3.1 we exclude Quantity1 and Quantity2 based on the results of the hourly contamination parallel trend test and significant p-values in the post-

estimation test. We use the hourly trend test over the daily trend test because it provides more data points and therefore a more accurate representation of the trend of contamination levels pre-experiment.

Table 3.6.2.3 shows the results of the parallel trend tests for daily bag data, daily camera data, and hourly camera data based on the ContamFour variable.

Table 3.6.2.3. Test on parallel trend assumption based on ContamFour.

	I: Bag: % ContamFour per day		II: Camera: DV: % ContamFour per hour		III: Camera: DV: % ContamFour per day	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Constant	0.093***	0.032	0.067*	0.035	0.022	0.042
Camday	-0.008	0.005	-0.005	0.006	-0.001	0.007
Camday*Control1	0.030***	0.006	0.020***	0.006	0.021***	0.008
Camday*Control2	0.007	0.006	0.012	0.009	0.008	0.008
Camday*Quantity1	0.005	0.006	0.005	0.008	0.004	0.008
Camday*Quality1	0.018***	0.006	0.018**	0.007	0.019**	0.008
Camday*Quality2	0.010	0.006	0.014	0.009	0.017**	0.008
r^2	0.3318		0.0647		0.2019	
N	74		259		74	
Total items	685		514		514	

ContamFour is defined as any of the four items listed on the quality signage.

In the daily bag data, we find that Control1 and Quality1 violate the assumption relative to the Quantity2 bin. In the daily camera data Control1, Quality1, and Quality2 violate the assumption, but in the hourly camera data only Control1 and Quality1 violate the assumption relative to the Quantity2 bin. To further prove the violation of the parallel trend assumption in these bins, we conduct post-estimation tests of ContamFour across camdaybin# in bag data, camera data per hour, and camera data per day shown in Table 3.6.2.4.

Table 3.6.2.4. P-value of post-estimation tests of ContamFour across camdaybin# in bag data, camera data per hour, and camera data per day

	Camday Quantity1	Camday Quality1	CamdayControl2	CamdayQuality2
Camday Control1	0.000, 0.050, 0.032	0.050, 0.668, 0.761	0.000, 0.262, 0.108	0.002, 0.461, 0.614
Camday Quantity1		0.026, 0.127, 0.063	0.650, 0.501, 0.674	0.397, 0.370, 0.109
Camday Quality1			0.075, 0.456, 0.184	0.167, 0.682, 0.835
Camday Control2				0.693, 0.800, 0.269

Control1 and Quality1 significant p-values in the bag data indicate that they also violate the assumption relative to other bins and are therefore excluded from Model I analysis in Table 3.6.3.2. We once again assume that hourly data gives more accurate results and therefore also exclude Control1 and Quality1 from the analysis of Model II and III in Table 3.6.3.2 based on the significance of the p-values relative to other bins.

For the multinomial logit regression results in Table 3.6.3.3, we exclude bins based on the parallel trend test in Table 3.6.2.1 and Table 3.6.2.2.

3.6.3. Model Results

The results of the DiD analysis appear in Table 3.6.3.1 using the bag and camera data, with the dependent variable ‘Contamination’.

Table 3.6.3.1. Model Results; D.V.= Contamination

	Model I- Bag DiD[1]		Model II- Camera DiD[2]		Model III- Camera DiD w Controls[2]	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Constant	-1.285***	0.313	-0.656***	0.126	-0.843***	0.211
Quantity	-0.248	0.403				
Quality	-0.146	0.459	-0.169	0.222	-0.177	0.224
Treat	0.807**	0.388	0.155	0.177	0.039	0.186
Quantity*Treat	-0.156	0.499				
Quality*Treat	-1.286*	0.742	-0.812**	0.337	-0.825**	0.340
Event					0.399**	0.170
Tues					0.156	0.247
Wed					0.185	0.247
Thurs					0.096	0.251
Fri					0.072	0.271
Marg. Effect of Quality*Treat	-0.233*		-0.174**		-0.175**	
Pseudo R2	0.029		0.0165		0.0227	
Log-likelihood	-259.83		-510.85		-507.634	
N	476		827		827	

Dependent Variable: Dummy of whether the item is (1) or is not (0) recycling contamination.
[1] Control1 and Quality1 fail parallel trend assumption in bag data and [2]Quantity1 and Quantity2 fail parallel trend in camera data. Excluded from DiD analysis.
Standard errors are reported in parentheses.
*,**, and *** indicate a p-value less than 0.1, 0.05, and 0.01, respectively.

Briefly recall that the hypothesis is that Contamination will increase in Quantity treatment and decrease in Quality treatment. Recall that based on failing the parallel trend assumption data from Control1 and Quality1 are excluded from the model of bag data (Model I) and Quantity1 and Quantity2 are excluded from the camera data (Models II and III).

In Model I the bins featuring Quantity and Quality information signage had no significant differences in contamination levels in the pre-intervention period. The Treat variable indicates that after the interventions took place there was a significant increase in contamination levels in the Control2 bin. The insignificance of Quantity*Treat indicates the treatment had no significant effect on contamination. Therefore, we do not reject the null hypothesis that the signage had no

significant effect on contamination levels. Quality*Treat is negative and significant, meaning that the Quality sign significantly decreased the probability of an item being contaminated, and we reject the null hypothesis that there was no significant effect on contamination.

Models II and III (run on the camera data set) both show insignificant coefficients for the Quality variable, meaning there were no significant differences in contamination levels in the Quality1 and Quality2 bins before the intervention took place. The treatment variable is also insignificant, meaning that neither of the control bins saw significant changes in contamination levels after the intervention took place. Quality*Treat is positive and significant, indicating that bins featuring the Quality signage had a decreased probability of contamination levels.

Model III also included additional explanatory variables (Event and days of the week). We could only account for event days in the camera data set, since there was no way to account for the time in which items were thrown into the bin in the bag data. The coefficient of Event in Model III was positive and significant, meaning that event day had increased probability of contamination in the bins. The coefficients of Tues, Wed, Thurs, and Fri were all insignificant, indicating that days of the week had no effect on the probability of contamination in the bins.

With the Quality*Treat coefficient being negative and significant across all three models, we tested the marginal effect of the quality treatment to further identify the effects of the signage on contamination levels.

$$Marginal\ Effect = \frac{\Delta P(y=1)}{\Delta x_j} = \frac{exp(x\beta)}{[1+exp(x\beta)]^2} \times \beta_j$$

Recall that the Quality sign only discouraged the placement of four types of items. We examine how contamination changes for only these four items using ContamFour, which is a dataset including recyclable items and these four item types but excluding all other forms of contamination. The corresponding DiD model results appear in Table 3.6.3.2.

Table 3.6.3.2. Model Results; D.V.= ContamFour

	Model I- Bag DiD[1]		Model II- Camera DiD[2]		Model III- Camera DiD w Controls[2]	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Constant	-2.241***	0.470	-2.539***	0.599	-2.304***	0.743
Quantity	-1.138	0.752	-0.732	0.840	-0.776	0.850
Quality	0.204	0.640	0.593	0.767	0.730	0.782
Treat	0.727	0.576	0.771	0.726	0.926	0.767
Quantity*Treat	0.632	0.874	0.541	0.988	0.542	1.000
Quality*Treat	-1.986	1.248	-1.821	1.344	-1.961	1.364
Event					-0.360	0.468
Tues					0.016	0.590
Wed					-0.283	0.601
Thurs					-0.134	0.594
Fri					-0.897	0.736
Marg. Effect of Quality*Treat	-0.172		-0.151		-0.161	
Pseudo R2	0.0462		0.0375		0.0520	
Log-likelihood	-121.430		-95.921		-94.476	
N	395		321		321	

[1]Unit of observation: each item placed in the recycling bin (Model I) or captured on camera (II & III)
Dependent Variable: Dummy of whether the item is (1) or is not (0) recycling contamination.
Parallel trend assumption fails for Control1 and Quality1 in bag data and camera data. Excluded from DiD analysis.
Standard errors are reported in parenthesis.
*,**, and *** indicate a p-value less than 0.1, 0.05, and 0.01, respectively.

Each of these models exclude data from Control1 and Quality1 due to failing the parallel trend assumption in Table 3.6.2.3. Model I is run using the bag data set and Model II is run using the camera data set. Model III is also run on the camera data set but includes additional explanatory variables (Events and days of the week). None of the coefficients across the three models are significant, indicating that neither the Quality nor Quantity treatment had a significant effect on levels of contamination as it pertained to the ContamFour variable. In Model

III this also indicates that event days and days of the week had no significant effects on the probability of ContamFour in the bins.

Table 3.6.3.3 shows the results of a multinomial logit regression to measure how the likelihood of contamination changes both for the four main types of contamination (ContamFour) and all other types of contamination (ContamOther). The model results using bag data exclude observations from Control1 and Quality1 and the camera data excludes observations from Control1 due to failing the parallel trend analysis.

Table 3.6.3.3. Multinomial Logit Model Results[1]

	I- Bag[2]		II- Camera[3]		III- Camera w Controls[3]	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
ContamFour						
Constant	-2.241	0.470	-1.403***	0.166	-1.467***	0.172
Quantity	-1.138	0.752				
Quality	0.204	0.640	-0.186	0.296	-0.197	0.296
Treat	0.727	0.576	0.052	0.237	-0.050	0.247
Quantity*Treat	0.632	0.874				
Quality*Treat	-1.986	1.248	-1.371**	0.540	-1.367**	0.540
Event					0.342	0.230
Marg. Effect of Quality*Treat	-0.134		-0.147**		-0.147**	
ContamOther						
Constant	-1.771	0.382	-1.297***	0.160	-1.382***	0.172
Quantity	0.066	0.469				
Quality	-0.448	0.607	-0.154	0.280	-0.169	0.296
Treat	0.854	0.465	0.239	0.219	0.106	0.228
Quantity*Treat	-0.367	0.579				
Quality*Treat	-0.832	0.899	-0.544	0.403	-0.538	0.404
Event					0.440**	0.201
Marg. Effect of Quality*Treat	-0.085		-0.045		-0.043	

(Table cont'd.)

	I- Bag[2]		II- Camera[3]		III- Camera w Controls[3]	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Pseudo R2	0.031		0.016		0.0199	
Log-likelihood	-333.62		-690.34		-687.41	
N	476		827		827	

[1]Unit of observation: each item placed in the recycling bin (Model I) or captured on camera (II & III)
Dependent Variable: Categorical dummy variable of whether the item is ContamFour, ContamOther, or neither (not contamination; recyclable).
Control1 and Quality1 fail parallel trend assumption in bag data and Quantity1 and Quantity2 fail parallel trend in camera data. Excluded from DiD analysis.
Standard errors are reported in parentheses.
*,**, and *** indicate a p-value less than 0.1, 0.05, and 0.01, respectively.

Model I shows the result of the bag data. None of the coefficients in this model for either ContamFour or ContamOther are significant, leading us to believe that the signage interventions had no significant effects on contamination levels in the bins.

Models II and III show the results of the camera data. The treatment variable is insignificant for both ContamFour and ContamOther in both models, indicating no difference in the probability of contamination in either of the control bins after the intervention took place. The Quality variable for both ContamFour and ContamOther in both models is insignificant, meaning that bins featuring Quality signage had no significant differences in contamination levels in the pre-intervention period. Quality*Treat is negative and significant for ContamFour in both models, meaning that the Quality treatment decreased the probability of the four types of contamination listed on the signage in the bins. The Quality*Treat variable for ContamOther, however, is insignificant across both models, meaning that the Quality signage had no significant effect on the probability of other types of contamination not listed on the signage. Model III also includes an additional explanatory variable (Event). The event variable is only significant for

ContamOther, meaning that there was an increased probability of 'other' types of contamination in the bins on event days.

In the multinomial logit, we also tested the marginal effect of the Quality*Treat variable, which was insignificant across all models for ContamOther, as well as for ContamFour in Model I. It was, however, negative and significant for ContamFour in Models II and III, indicating that ContamFour levels decreased by about 13%.

As a robustness check, we ran several additional models to relax assumptions implicit to the results shown in Tables 3.6.3.1, 3.6.3.2, and 3.6.3.3. Specifically, logistic regression relies on (1) no outliers in the data, (2) no multicollinearity, and (3) homoskedasticity. We relax assumption 1 by checking the Cook's D values of each observation, all of which were close to a value of zero. To test for assumption 2, we created correlation matrices of each of the independent variables of the model, none of which showed high correlation to another. Lastly, we re-ran each of the models with robust regressions, clustering by bin type/number to test assumption 3. The results of each of these auxiliary models (not shown) provide qualitatively similar outcomes to those previously reported.

3.7. Discussion and Conclusions

Contamination is a problem and studying recycling behavior is difficult. This study tests the efficacy of a behavioral nudge through a signage change to reduce rates of contamination in recycling bins while also using trail cameras as a means of collecting data.

Using quasi-experiment data collected among recycling bin users at a large public university, we estimate that the signage change in the Quantity treatment had no significant effect on the probability of contamination. We also estimate that the signage change for the Quality treatment decreased the likelihood that an item was contaminated by 13%. Given the

high levels of contamination found in recycling bins and the issues it causes recycling facilities, we demonstrate a successful use of signage to reduce these levels of contamination.

Our findings show that signage can effectively reduce recycling contamination. Because all three models generate similar conclusions, we conclude that the use of trail cameras in recycling contamination studies is a feasible alternative to hand sorting and counting. Using this nudge to encourage the correct behavior is an effective strategy to reduce contamination that is likely to be attractive due to its low cost of implementation nor unnecessarily burdensome to end-users.

A more formal Benefit-Cost Analysis (BCA) would be useful to estimate whether the recycling facilities accrue positive net benefits from the reduction in contamination. This analysis could also consider the benefits of the reduction in contamination levels such as reduced labor costs, reduced machinery maintenance, etc. 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, our analysis has little individual-specific information on bin users to explain behavior. Second, our experiment occurred in the restricted context of a university campus with predominantly student patrons. Future work should be conducted in a public area such as a public park, where users are more representative of the general public. Such a strategy will enhance the external validity of our analysis framework by using real-world recycling bin users and the explanatory power of user characteristics on recycling behavior. Another opportunity for improvement in the future is to examine both the recycling rate and the contamination levels simultaneously to see how they move in conjunction with each other. This is something that to our knowledge has only previously been done by one study, Catlin et.al. 2010. Additionally, the average daily temperature during our experiment was

about 72 degrees, which could have resulted in the melting of certain objects like frozen foods, candies, or chocolates that could have cross contaminated other items in the bin. This would have made items reported as non-contamination at the time the photo was taken become contaminated afterwards, resulting in that item being coded as contamination in the bag data set at the end of the day. This creates additional discrepancies between the contamination variable in our bag and camera data sets.

Acknowledging that our experiment was not completely random, and we had a relatively short pre-intervention period, we recommend future studies with a random experiment design containing a relatively longer pre-intervention period. Moreover, despite our effort to reduce overlapping users, the possibility exists for patron spillover which may lead to a biased estimate of the true effect of the signage intervention. Individuals who pass more than one of the experimental bins, but were exposed to a certain signage intervention first, may be influenced by their previous signage observation in their decision at another bin. For example, if an individual passes a bin with the Quality treatment signage, they may be more likely to throw away one of the four items listed on the signage rather than recycle it, even if they are located at a Quantity treatment bin later in the day.

Appendix A. Pre-Experiment Test of Trail Cameras

Pre-Experiment Protocol

We tested seven models, with varying photo resolution (i.e., megapixel) and photo-capture setting (i.e., timelapse, motion capture, or both), with full model names and details shown in Table A1. We tested a Cabela, Muddy, Reconyx brand, Stealth, and three different Wildgame models. Each camera was tested using its highest resolution settings. The only thing comparable across cameras was the selected timelapse time-interval used for the experiment.

Table A1. Camera Models, Resolution, and Mode

MODEL	MSRP	Maximum MP	TIMELAPSE, MOTION SENSE, OR BOTH
Cabela	99.99	30	Both
Stealth	129.99	32	Both
Muddy*	99.99	24	Both
Reconyx	399.99	30	Both
Wildgame Innovations	149.99	20	Motion Sense
Wildgame Innovations	119.99	30	Motion Sense
Wildgame Mirage	93.29	22	Motion Sense

*Camera used in lab and field trials

Each camera captured photos using a time-lapse setting, motion sense, or both. Motion sense mode means that any time the camera senses motion, i.e., an item being thrown into the bin, it can be set to either one photo or a ‘burst’ of multiple photos. Timelapse mode sets the cameras to take a photo at set intervals throughout a designated period of time. The shortest time interval among the six cameras for timelapse feature was 1 minute apart.

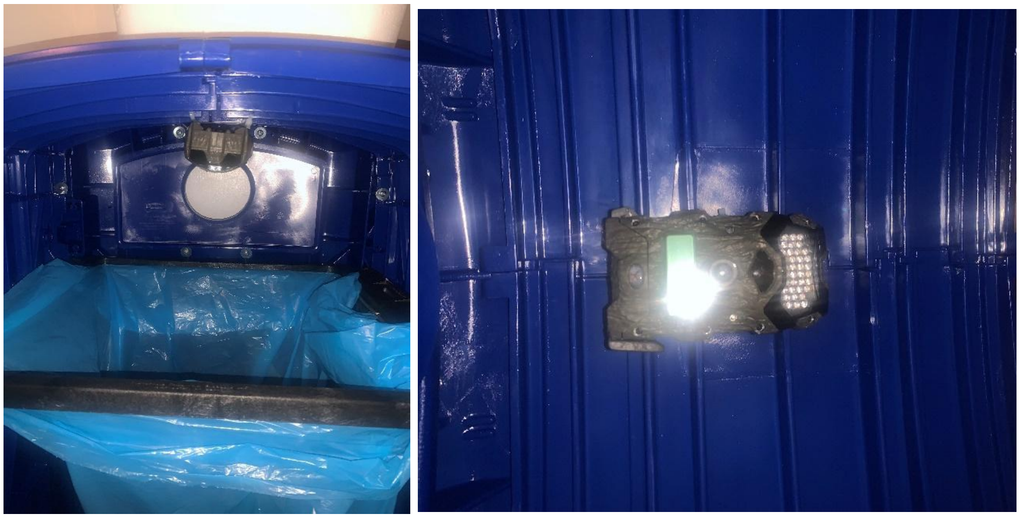


Figure A1. Images of the trail camera attached to the recycling bin.

Each camera was set up by zip tying it to the top of a recycling bin as shown in Figure A1. These are multi-bins, meaning they accept multiple recyclable materials, specifically paper, plastics 1-7, glass, aluminum cans, and cardboard. The bin used on the university campus where the trials occurred is the Rubbermaid FG396873BLUE. While the bin had a round slot about 5x5inches around located on the front and back side of the bin in which to throw the items away. This was the same bin as the ones located on the university campus.

For motion sense, 50 randomly selected items from local recycling bins were thrown into the bin each at 30 seconds apart to give the camera enough time to capture each item. Only 30 of the 50 items were used to test the timelapse feature of the cameras because the smallest time interval between photos was a minute each and because of the fact that photos of each item were taken each time, there was less of a chance that an item was missed. These items appear in Table A2.

Table A2. Camera Test trial item list

ID	MOTION SENSE	TIMELAPSE
1	plastic cereal bag	plastic cereal bag
2	Powerade bottle	Powerade bottle

(Table cont'd.)

ID	MOTION SENSE	TIMELAPSE
3	Ziploc bag	Ziploc bag
4	Sour Patch Kid bag	Sour Patch Kid bag
5	Fanta bottle	Fanta bottle
6	Tampax box	Tampax box
7	cup lid straw	cup lid straw
8	red Solo cup	red Solo cup
9	dryer sheet	dryer sheet
10	cake wrapper	cake wrapper
11	Truly can	Truly can
12	paper towel	paper towel
13	plastic bag	plastic bag
14	cran juice	cran juice
15	piece of paper	piece of paper
16	Milky Way wrapper	Milky Way wrapper
17	plastic lid	plastic lid
18	water bottle cap	water bottle
19	receipt	receipt
20	Red Bull	Red Bull
21	yogurt lid	yogurt lid
22	piece of styrofoam	piece of styrofoam
23	lid/straw	lid/straw
24	plastic spoon	plastic spoon
25	green solo cup	green solo cup
26	Cayman Jack	Cayman Jack
27	Crystal Light wrapper	Crystal Light wrapper
28	ketchup packet	ketchup packet
29	Coke can	Coke can
30	lighter	lighter
31	clear plastic cup	
32	another piece of styro	
33	another plastic bag	
34	Dove chocolate bag	
35	water bottle	
36	Big Shot soda	
37	protein bar wrapper	
38	Oralta paper	
39	plastic knife	
40	taco sauce packet	
41	Diet Coke can	
42	Red Bull can	
43	Sprite	

(Table cont'd.)

ID	MOTION SENSE	TIMELAPSE
44	Smushed water bottle	
45	utensil wrapper	
46	milk jugs lid	
47	Coffee Mate	
48	piece of styrofoam	
49	grits box	
50	plastic bag	

We had five paper items, six aluminum cans, eight plastic beverage bottles, and five items smaller than a credit card included in the variety of items tested. Items that were smaller than a credit card were used because it was important to distinguish how smaller items appeared on camera in comparison to larger items. Items smaller than a credit card tended to be harder to identify on camera and typically got buried under larger items in the bin. We also made sure to include common forms of contamination such as plastic bags, Styrofoam, candy wrappers, and items contaminated with food waste in our selection. Little formal research exists documenting the forms of contamination but several informal sources support these common contaminants, such as rubicon.com, recyclops.com, and cleanaway.com, as well as reports from universities such as the University of Colorado Boulder Environmental Center (https://www.colorado.edu/ecenter/2021/04/15/recyclings-most-common-contaminants).

Pre-experiment Camera Results

Results using motion sense and timelapse for each camera appear in Table A3. Motion detection was ruled out for all cameras because it failed for almost all items smaller than a credit card and translucent items such as small plastic wrappers or pieces of paper. The Cabela camera had the lowest percentage of items caught on camera between all of the tests at only 50%, and only captured four photos, so it was immediately eliminated and not tested a second time. The Wildgame Silent 30 MP caught 84% of items in the first test, but only 68% of items in the second test. The Wildgame Silent 20 MP caught 71% of items in the first test, and 76% of items in the second test. The Wildgame Mirage caught 84% of items on its first test as well, but only

74% of items on its second test. n motion sense test 1 the Muddy camera caught 66% of the items and in motion test 2 it caught 70% of items. The Stealth brand camera caught 70 %of items in its first motion sense test and 60 % of items in its second motion sense test. Reconyx brand camera caught 76 %of items in motion sense test 1 and 66 %of items in motion sense test 2.

None of the Wildgame cameras had the timelapse feature, so the only cameras tested using timelapse were the Muddy, Stealth, and Reconyx brands. In timelapse mode, the Muddy camera showed great improvement with 93% of items captured in both tests, which not only conveys its accuracy, but its consistency as well. Stealth brand also improved in timelapse mode. It captured 86 % of items thrown into the bin in trail mode test 1 and 90 % of items in trail mode test 2. Reconyx's improvement by using timelapse mode varied, with trail mode test 1 resulting in 73 %of items being caught on camera and 86 %of items being caught on camera in test 2.

Since timelapse mode outperformed motion sense mode across all tests except for Reconyx test 1, we decided to select a camera with timelapse mode for our official experiment. The muddy camera did best in camera testing, therefore it became our camera used for the lab and field.

Table A3. Percentage of items photographed using motion sense and timelapse.

Camera	% items photographed using motion sense	Total pictures taken using motion sense	% items photographed using timelapse
Cabela 1	50%	4	
WG Silent 30MP 1	84%	16	
WG Silent 30MP 2	68%	8	
WG Silent 20MP 1	71%	20	
WG Silent 20MP 2	76%	17	
WG Mirage 1	84%	30	
WG Mirage 2	74%	12	
Mud 1	66%	8	93%
Mud 2	70%	11	93%
Stealth 1	70%	14	86%
Stealth 2	60%	10	90%
Reconyx 1	76%	26	73%
Reconyx 2	66%	12	86%

Appendix B. Lab Experiment

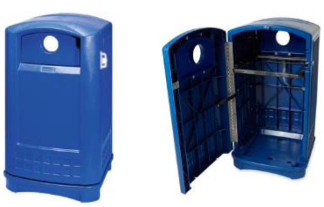
The objective of this experiment is to compare camera data to a real dataset to test the camera's efficacy to detect all items tossed and what types of items they are.

Lab Experiment Setup

Materials

In order to conduct the lab experiment, the following items are needed:

- Recycling bin: Rubbermaid FG396873BLUE
- trail camera
- zip ties
- scissors
- drill
- trash bags
- recyclable items
- non-recyclable items



Camera Setup: Attachment to the recycling bin

For the trail camera model (MUD-MTC24VK V2) used in this study, and for our bin type this was done by:

1. Drill four holes, two on each rib of the top of the bin.

   Thread a long zip tie through the back of the trail camera, and then through the holes and pull it tight. The camera should be facing down. See figure A1.

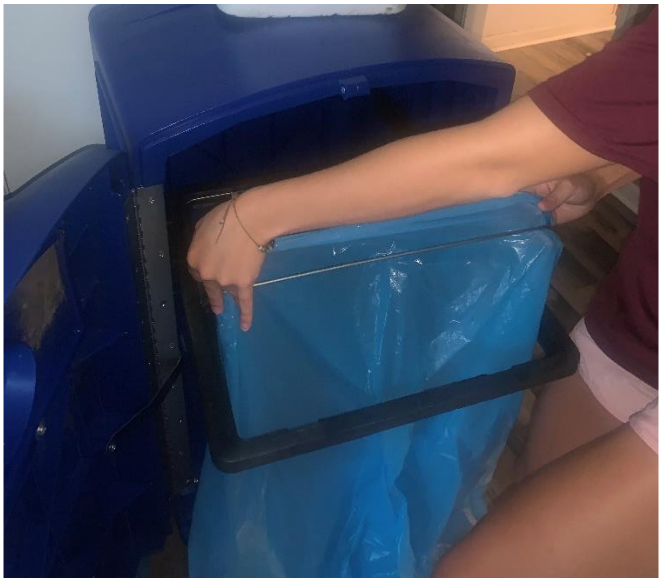
Camera Setup: Camera Settings

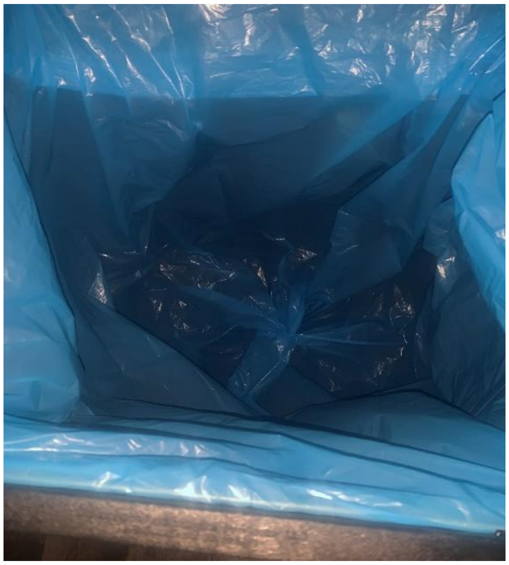
The following camera settings should be used to replicate the lab and field trials. More detail and screenshots are available upon request.

- Mode: Timelapse
- 24MP resolution
- Timelapse Delay: 2 minutes 00 seconds
- Timelapse Start: 9am
- Timelapse End: 7pm
- Blur Reduction: Advanced
- NOTE: Some camera settings are not changeable and should be inspected before the experiment occurs. Trail cameras typically have an infrared (IR) flash that allows them to take photos at night or in low-light conditions without spooking animals with a bright flash of light. These cameras have two types of IR flash: a low-glow flash and a no-glow flash. When a trail camera is set to use the low-glow flash, it will typically capture color photos during the day and black and white photos at night or in low-light conditions.

Bag and Bin Setup

1. Place a blue trash bag in the bin. Based on preliminary trials, we found that blue reflects the least amount of light from the camera. Make sure it is evenly spread out with a clear view of the bottom of the bag.

a. 

b. 

2. The experiment may be conducted indoors or outdoors as long as there is some source of lighting available.

Item Collection

1. Collect 150 items, half from a recycling bin and half from a trash bin, making sure there are a variety of recyclable and non-recyclable items in the mix such as bottles, cans, paper, food waste, Styrofoam, and candy wrappers.

a. Note: Some items should be half full, such as a half full bottle of water and some items should have food residue on them. It should be recorded whether or not this was detectable on the camera to compare this to real life scenarios.

Lab Trial Experimental procedure

1. Randomly select 50 of the 150 items to use in the experimental trial.
2. Person A will randomly pick and discard one, two, or three items in the bin every 2 minutes, recording in an excel sheet the order in which the items were thrown away and the time, until all 50 items are in the bin.
    a.

Placement Order[1]	Time	Item Description
1	2:00pm	Taco Bell cup with lid
2	2:02pm	green Lacroix can
2	2:02pm	piece of paper
3	2:04pm	water bottle
4	2:06pm	Reign energy drink can
4	2:06pm	glass bottle
4	2:06pm	Dasani water bottle
5	2:08pm	piece of paper

[1]The same number indicates that two or three items were discarded at the same time.

3. A second person B is responsible for reviewing photographs of the items without knowing what items were thrown in at all or in what order.
4. After all photos are sorted through, the excel sheets will be combined into one, with the true order that they were thrown away in column A, and the order in which they were observed on camera in column B for comparison.

Item thrown away	Item observed on camera
Water bottle	Water bottle
Water bottle	Water bottle
McDonald’s bag	Plastic bag
Chip bag	Chip bag
Black monster energy can	can
Soda bottle	Soda bottle
Chewy protein bar wrapper	Piece of paper

5. In column C, a 1 or 0 will be recorded for whether or not the observation on camera matches the order in which the items were truly thrown into the bin. 1 = match, 0 = no match.

Item thrown away	Item observed on camera	Match = 1
Water bottle	Water bottle	1
Water bottle	Water bottle	1
McDonald’s bag	Plastic bag	0
Chip bag	Chip bag	1
Black monster energy can	can	1
Soda bottle	Soda bottle	1
Chewy protein bar wrapper	Piece of paper	0

6. Conducts 3 more trials of the experiment.

Note: The 50 items will fill up the bag about a quarter of the way. As the bags become more full, new items that are thrown away will be harder to detect. Except for recycling bins with extremely high use, this is rarely an issue because bags can be changed out often enough to avoid this problem.

Table B1. composition of items for lab experiment per trial X

	TRIAL 1		TRIAL 2		TRIAL 3
1	essential water bottle	1	coffee cup	1	Starbucks plastic cup
2	plastic bag	2	Redbull can	2	small plastic Powerade bottle
3	sushi container	2	plastic water bottle	3	plastic water bottle
3	Lacroix can	2	diet coke bottle	4	piece of cardboard
4	gallon freezer cardboard box	3	Redbull sugar free can	4	Gatorade bottle with water in it
5	diet Dr. Pepper bottle	4	green sour sop juice can	5	poptart wrapper
5	Coca Cola can	5	black Reign energy drink can	6	piece of cardboard
5	coffee cup Dunkin Donuts	6	Atkins protein shake	7	Dasani bottle
6	Summer Shandy glass bottle	6	Aquafina water bottle	8	cardboard piece
7	Virginia Slims cigarette box	7	balled up paper	9	folded piece of paper
8	small Diet Coke can	8	balled up paper	10	V8 energy drink can
9	green Lacroix can	9	Jarrito's coconut water with pulp	11	Coca Cola can
9	Great Value water bottle	10	plastic Panera bread fountain drink cup with drink residue	11	Sprite bottle
10	small Diet Coke can	11	Mentos gum container	12	plastic water bottle
11	plastic food container	12	Community Coffee cup	13	Dr. Pepper bottle
12	Pure Life water bottle	13	Ozark plastic water bottle	14	Liquid Death can
13	Zeelool paperboard box	13	Sam's plastic water bottle	15	plastic coffee cup lid
14	cherry Coca Cola bottle	14	water bottle	16	straw
14	green Lacroix can	15	Diet Coke can	16	plastic coffee cup lid
14	water bottle	16	naked juice bottle	17	Dasani bottle
15	macaroni box	17	plastic Chic Fil A milkshake cup	18	Liquid Death can
16	Gilbert name tag	18	balled up paper	18	Pellegrino can
17	monster energy can	19	Dr. Pepper bottle	19	laminated paper
18	PowerAde bottle	20	water bottle	20	piece of cardboard
19	ginger beer glass bottle	20	large smoothie king cup	21	Funyons chip bag

(Table cont'd.)

	TRIAL 1		TRIAL 2		TRIAL 3
20	charged plastic cup with lid and straw	21	shiny coated piece of paper	22	half full plastic water bottle
20	green Lacroix can	22	coffee sleeve	23	water bottle cap only
21	protein bar wrapper	23	coffee cup with lid and straw	24	coffee cup with lid and straw
22	protein shake cardboard box	24	coffee sleeve	24	piece of paper
23	polar pop styrofoam cup	25	water bottle	24	V8 energy drink can
23	Alkaline large water bottle	26	naked juice plastic mini bottle	25	Sunkist soda can
24	Gatorade small water bottle	27	Fiji water bottle	26	vitamin water plastic bottle
25	bio steel paperboard bottle	27	crushed water bottle	27	Jimmy John's paper cup
26	red bull sugar free can	27	plastic lid	28	straw and lid
27	water bottle	28	Frito-Lay bag	29	V8 energy drink can
28	Panda Express paper cup	29	plastic fork	30	black plastic bag
28	yogurt container	30	cardboard coffee sleeve	31	Fiji water bottle
28	small PowerAde bottle	31	ripped cardboard piece	32	crushed piece of paper
29	coffee cup Panera bread	32	balled up paper	33	Fritos chip bag
30	red bull sugar free can	33	newspaper sheet	34	Redbull can
31	Nature Valley protein bar wrapper	34	plastic utensils wrapper	34	smoothie king styrofoam cup
32	Ziploc plastic bag	34	crushed water bottle	35	coffee cup
32	green Lacroix can	35	plastic water bottle	36	naked juice bottle
33	ginger beer glass bottle	36	straw	37	coffee sleeve
34	Reese's wrapper	37	plastic knife	38	cardboard piece
35	monster energy can	38	coffee cup with lid	39	coffee cup with plastic lid
35	Oreo mini wrapper	39	clear plastic cup	40	Sour Sop juice drink can
36	Dasani large water bottle	40	glass kombucha bottle	41	Febreze plastic packaging
37	peach red bull can	41	Febreze plastic car freshener packet	41	piece of paper
38	plastic bag	42	black plastic bag	42	plastic lid

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