Selected Paper prepared for presentation at the 2018 Agricultural & Applied Economics Association Annual Meeting, Washington, DC, August 5-7, 2018

The Role of Incidental Learning

on Reducing Household Food Waste in Free-Living Condition

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Abstract:

Food waste represents an inefficiency along the supply chain that can hamper food system productivity. As countries align national targets with the United Nations' Sustainable Development Goal to halve per capita food waste at the retail and consumer, addressing consumer food waste is regarded as one of the key channels to achieve these goals in developed countries. Acquisition of knowledge, such as organizational learning-by-doing, has been shown to be a significant source of productivity growth in a variety of industries. This paper investigates the role of incidental learning in reducing consumer plate waste during all eating occasions over approximately one week based on a unique data source with food-item level data collected from 50 adults from the United States using the Remote Food Photography Method.® Aligning with existing literature, we find subject behavior is consistent with significant incidental learning. As observed plate waste experience accumulates, subjects accomplished significant plate waste reduction by cleaning their plates, which also increased calorie intake. No evidence is found that learning from the past alters the amount of food that subjects' select. Given that habitual plate cleaning has been associated with overweight and obesity, social welfare maximizing public policy interventions should consider explicit information to help consumers switch the focus from the intentions not to waste (i.e., minimize food waste by cleaning plate after food was over-selected) to improvements in the ability to reduce food waste (i.e., selecting an appropriate amount of food).

Introduction

Nearly 40% of the food supply in the United States is eaten up by food loss and food waste. This motivated the United States administration in 2015 to announce the first-ever national goal to halve food waste by 2030 (USDA, 2015) by following United Nation's sustainable development goal. In 2018 the current U.S administration continues to prioritize food waste solutions throughout the entire food supply chain (USDA, 2018). As the final and arguably the key link in the food supply chain, consumers contribute most to food loss and waste in the U.S. as they waste 20% of the U.S food supply. Hence, reducing consumer food waste is one of the keys to achieving U.S. food waste reduction goals.

Difficulties remain to reduce consumer food waste in the long-run, especially when behavioral changes are required. Large-scale advocacy campaigns that aim to raise the awareness about food waste and educate consumer about ways to save money and prevent wasted food (Rethink Food Waste through Economics and Data (ReFED, 2016)) are regarded as promising ways to reduce consumer food waste, though the efficacy of such efforts is still to be verified as is the persistence of any such effects. Educational campaigns are an influx in information about how to change behaviors and/or information to motivate behavioral change that can decrease food waste. However, after initial campaigns, the effort to communicate to the target audience often declines and any behavior changes observed in response to the initial communications may not persist due to simple forgetfulness of the new behavior or due to reduced motivation to maintain new behaviors. We deem these as general forgetting effects and, in the context of food waste, postulate that efforts to maintain the low waste rate in the long-term decline after the initial event that stimulated behavioral change. For example, European countries including United Kingdom and the Netherlands witnessed stagnation or regression in progress towards a 50% food waste reduction after large-scale policy efforts including consumer education campaigns (Napel, 2014, WRAP, 2017). We argue that understanding the dynamics of behavioral change in the food waste space is important to helping craft improved interventions.

In this paper, we postulate that behavioral change with regards to plate waste – one key component of household food waste – can arise when consumers become aware of eating patterns through monitoring of food intake even in the absence of instructions about or attention to plate waste, food waste or related concepts. We postulate that this awareness stimulates learning by doing, a dynamic process that includes both learning to reduce the amount of food that is left as plate waste in daily dining situations as well as generalized forgetting effects where accumulated knowledge is lost or accumulated motivation to reduce waste declines. We seek to understand this process as a means to understanding how habits in this domain may emerge and develop and to assess behavioral stability through time.

Awareness of food waste is postulated to be an antecedent to consumer actions to reduce food waste and has been shown to be negatively correlated with self-reported food waste levels (Stancu, et al., 2016). Targeted informational interventions have been shown to reduce plate waste in school dining situations (Whitehair, et al., 2013). In other settings consumers made aware of behavioral monitoring or provided individualized informational feedback on key behaviors are documented to undertake pro-social behavioral change. For example, Faruqui, Segici and Sharif (2010) review the household energy conservation literature and find that real-time in-home feedback to consumers about energy usage and costs reduces energy consumption by about 7% compared to control households. Gosnell, List and Metcalfe (2016) find that airline pilots more frequently implement actions that improve fuel efficiency if they are either simply made aware that their actions will be monitored by academic team or if they are provided individual feedback about their fuel efficiency behaviors; in both cases there was no possible method for ascribing individual fuel efficiency activities of pilots to managers and pilots were aware that managers could not use study results to infer individual pilot performance. Levitsky et al. (2006) show that female college students who record daily weight and receive feedback about projected changes in weight based on daily weight measures are more likely to avoid weight gain than controls who do not monitor their weight.

Further, when the amount of food waste generated become salient, consumers may learn by wasting. Incidental learning, especially organizational learning-by-doing, has been shown to be a significant source of productivity growth in a great variety of industries (e.g,. semiconductor (Irwin and Klenow 1994), agricultural (Foster and Rosenzweig, 1995), aircraft (Benkard, 2000), shipbuilding (Thompson, 2007, Thompson, 2012, Thornton and Thompson, 2001), automobile (Levitt, et al., 2013), oil drilling (Kellogg,2010), and solar photovolatic (Bollinger and Gillingham, 2012). Management improves after trial-and-error processes and workers are more efficient as experience accumulates, both of which reduce production cost and increase productivity. In pharmaceutical markets, doctors discover the drugs that best match each participant's conditions by learning from the previous treatment experience (Crawford and Shum, 2005). Hence, as consumers become aware of food waste, we postulate that they could also learn by wasting and the accumulated experience helps improve the efficiency of food handling and selection behaviors that lead to reduced food waste.

The goal of this study is to test whether consumers incidentally learn to reduce plate waste based on previous plate waste experience. We choose the term incidental learning because food waste was never mentioned as a topic or focal interest to the study participants. We analyze food-item level data collected from 50 adults from the United States using the Remote Food

Photography Method® (RFPM) in free-living conditions during all eating occasions over approximately one week and estimate if subject plate waste varies with discounted cumulative plate waste. Aligning with the existing literature, we find subjects indeed learned from previous plate waste experiences and they generated significantly less plate waste as waste experiences accumulate. Research conducted with consumers in three U.S. cities documents that concerns about food waste may spill over to food consumption decisions as "…more than half of respondents…agree that it is important to them to finish all food put on their plates for a meal." (pg. 34, Hoover, 2017). Qi (2018) finds that subjects reduce food waste by cleaning their plate when they were informed of the social and environmental cost of food waste in a dining experiment. However, the habit of plate cleaning behavior is found to be strongly associated with overweight and obesity, which may induce health costs in the long term. Therefore, in this study, we explore the strategies consumers apply to reduce food waste and we find that, as subjects learn from previous wasting experiences, they reduce food waste by having higher calorie intake while selecting a similar amount of food to put on their plates.

The remainder of the article is organized as follows. First, we introduce the experimental methods and design and discuss summary statistics of the experimental data. Then, we introduce the estimation model and discuss the results. We end by discussing limitations of the experimental and empirical analyses and frame subsequent questions stimulated by the current work.

Measurement

Subjects collected their own food intake and plate waste data during all eating occasions over approximately one week via the Remote Food Photography Method®(RFPM) as implemented with the SmarkIntake^{TM} smart phone app, which has been previously described and validated (Martin, et al., 2012, Martin, et al., 2009, Martin, et al., 2014). Subjects started on different days of the week (i.e ., Day 1 could have been any day of the week except Sunday). Subjects used smartphones to capture images of their food selection before each eating episode and plate waste after each eating episode (also included are episodes that involve drinking beverages that contained calories). Compared to alternative approaches, such as paper and pencil diaries, participant burden is reduced as subjects are only responsible for capturing images, which are then sent wirelessly to a central server for analysis, while a research team uses a computer-assisted approach to identify a match for each food in a nutrient database and estimate portion size based on established and validated procedures. The analysts enter the portion size for food selection and plate waste, and the computer system calculates the energy and nutrient composition for food selection, plate waste, and food intake, where food intake is calculated as selection minus waste.

The study sample includes 50 adults age 18 to 65 years recruited from Baton Rouge, Louisiana region. Subjects were generally healthy and were not diagnosed with chronic health conditions or diseases, including diabetes, cardiovascular disease, and cancer. Subjects were also free of medication use that affected body weight and were weight stable (<0.5 kg weight change over one week). No information about the amount of plate waste or food intake was shared with subjects during the data collection period. Subjects were told the study's purpose was "…to test different methods of measuring energy balance, including food intake and energy expenditure." Hence, we expect the study design minimizes potential Hawthorne effects concerning plate waste.

Empirical Methods

Let $TakenGram_{nit}$, $KcalCon_{nit}$, $WasteRate_{nit}$ (= $WasteGram_{nit}$ / $TakenGram_{nit}$) denote the grams of food taken, Kcal of food consumed and percentage of the grams of a selected food item returned as plate waste for the *n*th item from participant *i* on day *t*. Each subject took multiple food items per day, though we can't identify the selection order of the food items within one day. We assume all the uneaten foods returned are plate waste.

We assume subjects' knowledge about their own plate waste accumulates as they throw away more food. The knowledges generated from the food they wasted in the previous days may improve their awareness about food waste and influence their decisions about food selection, intake and waste later. However, the knowledges obtained from the most recent plate waste experience may exert different impacts on current periods than the ones are more remote. Hence, the stock of plate waste knowledge accumulates at a discount rate $\delta \in [0,1]$ (or forgetting rate (1-δ)).

When $\delta = 1$ (or forgetting rate = 0), the subjects remembers everything learned from the past and, hence, the most remote experiences have the same impacts on decisions as the most recent ones. When $\delta = 0$ (or the forgetting rate =1), the subject remembers nothing from the experiences before yesterday (forgets everything experienced before yesterday). The experiences before yesterday exert no impact on his current decisions at all, and as a result only the most recent experiences matter. When $\delta \in (0,1)$, the subject still learns from remote experiences while these experiences influence the subject's decisions less than the more recent ones.

We assume selection, intake and waste decisions are informed by distinct discount rates (i.e., δ_T, δ_C, δ_W). In other words, the plate waste from, e.g., two days prior may influence today's selection, intake and waste differently. Since we can't identify the eating order of the selected food items within one day, we assume the knowledge of plate waste accumulates by day instead of by food item or by meal. The accumulated plate waste knowledge is measured based on the following:

$LearnT_{it} = \sum_n WasteGram_{ni(t-1)} + \delta_T LearnT_{i(t-1)}$ where $\delta_T \in [0,1]$ and $LearnT_{it} = 0$ when t=1.

$LearnC_{it} = \sum_n WasteGram_{ni(t-1)} + \delta_C LearnC_{i(t-1)}$ where $\delta_C \in [0,1]$ and $LearnC_{it} = 0$ when t=1.

$LearnW_{it} = \sum_n WasteGram_{ni(t-1)} + \delta_W LearnW_{i(t-1)}$ where $\delta_W \in [0,1]$ and $LearnW_{it} = 0$ when t=1.

The subject makes food selection, intake and waste decisions based on the types and the characteristics of the foods and based on the plate waste knowledge accumulated from previous days during the data collection period. The food-related decisions could also vary by individual and by the day of the study. Hence, we include individual and study day fixed effects to control time-invariant and time-variant factors. Learning effects specifically captures the changes caused by subjects' cumulative plate waste experience, while time fixed effects capture daily patterns that are homogenous across all subjects. Log transformations are applied to $TakenGram_{nit}$, $KcalCon_{nit}$ and $LearnT, LearnC, LearnW$ because the data are right skewed. An inverse hyperbolic sine (IHS) transformation is applied to analyze the food waste rate as a substantial fraction of the observations equal zero. The empirical food order, consumption and waste models are defined as follows:

$$Log(TakenGram_{nit} + 1) = \beta_0 + \beta_{LT} Log(LearnT_{it}(\delta_T) + 1) + \Gamma X_{nit} + \alpha_i Subject_i + \alpha_t Day_t + u_{nit}$$

$$Log(KcalCon_{nit} + 1) = \beta_0 + \beta_{LC} Log(LearnC_{it}(\delta_C) + 1) + \Gamma X_{nit} + \alpha_i Subject_i + \alpha_t Day_t + u_{nit}$$

$$\begin{aligned} &Log(WastRate_{nit} + (WastRate_{nit}{}^2 + 1)^{1/2}) \\ &= \beta_0 + \beta_{LW} Log(LearnW_{it}(\delta_W) + 1) + \Gamma X_{nit} + \alpha_i Subject_i + \alpha_t Day_t + u_{nit} \end{aligned}$$

where X includes servings of food taken, energy per serving, % fat, % protein, % fiber, vitamin C, calcium, and food code category. We estimate discount factors δ_T, δ_C, δ_W via grid search between zero and one; the δ_T, δ_C, and δ_W, that yields smallest sum square error (SSE) is presented. Bootstrapping methods are applied to estimate the standard error of δ_T, δ_C, and δ_W.

Analysis

Results are analyzed in Matlab R2016b and Stata (version 14.2). Key demographic variables includes gender, age, race, Body Mass Index (BMI); summary statistics for these variables are listed in Table 1 along with national averages. The sample aligns well with national averages on age, height and race (white and non-white). However, vast majority (88%) of subjects in this study are women and the average weight and average body mass index of the subjects in this study are higher than national average. Hence, to further control for these unbalanced characteristics and refine the representativeness of the sample, individual fixed effects are applied to all subsequent regression analyses.

Table 1. Characteristics of the study sample

		Study Sample (N=50)	U.S
Gender			
	Male (%)	12	49
	Female (%)	88	51
Age	18-29 (%)	26	22
	30-49 (%)	38	34
	50-64 (%)	34	26
	65+ (%)	2	19
Race	White (%)	62	62
	African American (%)	38	12

Height (cm)	Male	178.0	176.0
	Female	162.2	162.1
Weight (kg)	Male	99.4	88.7
	Female	82.0	75.4
BMI(kg/m2)	Male	30.9	28.6
	Female	31.2	28.7

In all the subsequent regression analyses, only solid food items are analyzed and subjects who generated zero food waste during the entire one week of study are excluded, which reduces the sample size to 1,599 food items. Summary statistics for food items analyzed are presented in Table 2. Food item variables include grams and Kcal of food taken, consumed and returned, solid food waste rate per item, number of servings selected, caloric density (calories per servings), the USDA Food and Nutrient Database for Dietary Studies (FNDDS) food group, and the percentage of energy from protein, fat, and carbohydrates. For each day, subjects selected on average 8 items with 134 grams per item, they ate vast majority of the food they selected and returned only 3.2% of the selected food. Excluding caloric liquids, subjects consumed 1847 Kcal of food per day.

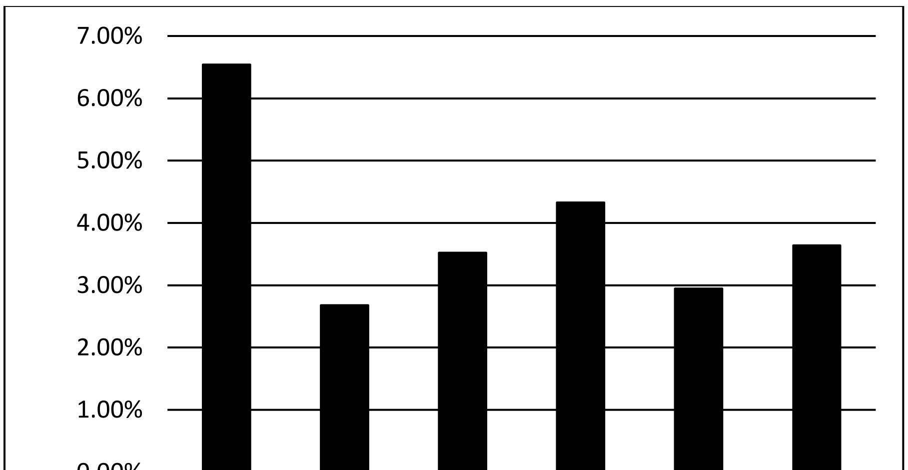
Table 2. Summary statistics

	N	Mean	SD	Min	Max
Per Day					
Average solid plate waste per day	205	3.99%	0.0053	0	43%
# of food items selected per person per day	205	7.8	0.25	1	23

Kcal of food consumed per person per day	205	1847.46	62.822	142.56	4263.70
Per Item					
# of servings taken	1599	1.88	2.53	0.2	50
Grams of food taken per item	1599	133.76	137.02	1.82	992.00
Grams of food consumed per item	1599	128.32	132.41	0.00	936.00
Grams of food returned per item	1599	5.44	26.22	0.00	372.00
Food waste rate per item	1599	3.20%	0.1281	0.00	100.00%
Kcal of food taken per item	1599	247.23	258.34	1.08	2785.86
Kcal of food consumed per item	1599	236.85	248.01	0.00	2785.86
Kcal of food returned per item	1599	10.38	50.65	0.00	609.84
Calories/serving	1599	166.80	151.28	0.78	1476.72
% Calories as Fat	1599	13.06%	0.1620	0.00	82.86%
% Calories as Protein	1599	8.16%	0.0791	0.00	41.82%
% Calories as Carbohydrates	1599	27.34%	0.2628	0.00	99.97%
Food code group (%)					
1. Milk and milk products	1599	8.88%	0.2846	0.00	100.00%
2. Meat, poultry, fish and mixtures	1599	22.01%	0.4145	0.00	100.00%
3. Egg	1599	1.31%	0.1139	0.00	100.00%
4. Legumes, nuts, and seeds	1599	2.44%	0.1543	0.00	100.00%
5. Grain products	1599	30.71%	0.4614	0.00	100.00%
6. Fruit	1599	6.32%	0.2433	0.00	100.00%
7. Vegetables	1599	17.70%	0.3818	0.00	100.00%
8. Fats, oils, and salad dressings	1599	5.25%	0.2232	0.00	100.00%

Results

Before we discuss regression results, first consider figure 1, which shows the average solid plate waste rate per day. We observe the highest solid plate waste rate on the first day of the study with 6.54% of selected food being wasted. Then the subjects achieved the lowest waste rate on day two with only 2.68% of selected food wasted. From Day 3 to Day 6, the average plate waste rate fluctuated between 3 - 4.5%. This trend is consistent with a pattern in which subjects learn from the high waste rate on the very first day and then achieve a very low plate waste rate the following day. After this achievement, what they learn from the following days are limited due to the relatively low waste rates and at the same time they begin to forget the waste experience from Day 1. As a result, the waste rates rebound again and fluctuate.

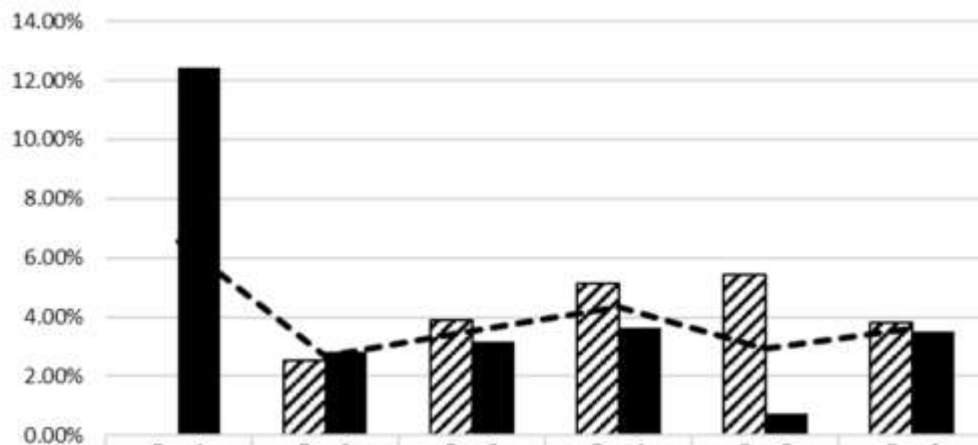


	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6
FW Rate	6.54%	2.68%	3.52%	4.33%	2.95%	3.64%

Figure 1: Average solid plate waste rate per day

Based on the suggested impacts of initial plate waste experiences on the later plate waste behaviors from figure 1, we compare the plate waste behaviors from the subjects who generated zero plate waste on Day 1 to subjects who wasted some of the selected food on Day 1 in Figure 2. The black bars in figure 2 presents the average plate waste rates of subjects who generated some plate waste on Day 1, and the bars with diagonal stripes show the average plate waste rates from zero initial waste subjects. The dotted line presents the average plate waste rate from the pooled sample.

Figure 2 shows that the two groups of subjects, i.e, zero initial waste subjects vs. non-zero initial waste subjects, present opposite plate waste patterns during the study period. The non-zero initial waste group threw away more than 12% of the selected on the first day which is 3 times of the average plate waste rate from the pooled sample during the study period (3.99%). However, their waste rate decreases dramatically on Day 2 to 2.84% which is only slightly higher than the average plate waste rate from the pooled sample on that day (2.68%). Starting from Day 3, the non-zero initial waste group maintained relatively low plate rates and generated lower plate waste rates than the sample average. The plate waste rate from subjects who generated zero plate waste on Day 1, on the other hand, keep rising from Day 2 to Day 5. After a relatively high waste rate on Day 5 (5.42%), plate waste rate dropped off slightly on Day 6 (3.80%). The different patterns between the two groups may further suggest the impacts of previous plate waste experiences on the current decisions.



	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6
Day 1: Zero waste	0.00%	2.52%	3.88%	5.15%	5.42%	3.80%
Day 1: Non-zero	12.43%	2.84%	3.17%	3.65%	0.75%	3.51%
Average waste rate	6.54%	2.68%	3.52%	4.33%	2.95%	3.64%
N	18	18	17	15	16	13
N	20	18	17	18	18	17
N	38	36	34	33	34	30

Fig 2: Group comparisons: Average solid plate waste rate

In table 3, we present the estimated learning effects on participants' food selection, intake, and plate waste behaviors when the types and the characteristics of the foods are controlled and time and individual effects are included. We find the estimated discount learning factor for plate waste δ_w for plate waste is 0.502. This suggests that there are significant forgetting effects and that the more recent plate waste experiences exert larger impacts on current decisions than the more remote ones. Though subjects forget some of the remote plate waste experience, the discounted stock of plate waste knowledges accumulated from these experiences is found to significantly decrease the subject's current plate waste rate.

We also estimate the impacts of the accumulative plate waste experiences on participants' food selection and food intake decisions to explore if incidental learning helps the subjects achieve plate waste reduction, i.e., if the accumulated plate waste experiences would encourage them to eat more food and/or clean their plate, or if the stock of plate waste knowledge could improve their food selection decisions and avoid over-ordering.

The results from table 3 suggest that subjects learned to reduce plate waste by eating more instead of selecting less. We find the previous plate waste experiences have almost no impacts on the subjects' food selection behaviors while discounted cumulative knowledge increases subjects' calorie intake. We also find the forgetting effects on selection behaviors are very limited, i.e., $\delta_C = 0.9475$, suggesting that almost all of the previous plate waste experiences would encourage the subjects to eat more.

Table 3. Estimated Model Parameters

	NLS	NLS	NLS
VARIABLES	Waste Rate-IHS	Log(TakenGram+1)	Log(ConsumedKcal+1)
$Log(Learn_W + 1)$ ($\delta_W = 0.5017$)	-0.012***		
	(0.003)		
$Log(Learn_T + 1)$ ($\delta_T = 0.0047$)		-0.006	
		(0.011)	
$Log(Learn_C + 1)$ ($\delta_C = 0.9475$)			0.045***
			(0.014)
# of servings selected per item	0.001		0.085***
	(0.001)		(0.030)
Calories/serving	0.000*	0.004***	0.005***
	(0.000)	(0.000)	(0.000)
Food code group (default group: egg)			

	NLS	NLS	NLS
VARIABLES	Waste Rate-IHS	Log(TakenGram+1)	Log(ConsumedKcal+1)
2. Fats, oils, and salad dressings	0.035	-0.051	-0.067
	(0.031)	(0.250)	(0.249)
3. Fruit	0.016	0.186	-0.166
	(0.017)	(0.192)	(0.209)
4. Grain products	0.039**	-0.233	0.127
	(0.018)	(0.159)	(0.181)
5. Legumes, nuts, and seeds	0.046*	0.205	-0.351
	(0.025)	(0.169)	(0.215)
6. Meat, poultry, fish and mixtures	0.025	-0.004	-0.220
	(0.017)	(0.168)	(0.186)
7. Milk and milk products	0.002	-0.166	0.095
	(0.018)	(0.202)	(0.195)
8. Sugars, sweets, and beverages	0.000	-1.710***	-0.369
	(0.016)	(0.274)	(0.221)
9. Vegetables	0.048**	-0.022	-0.503**
	(0.020)	(0.167)	(0.192)
% Calories as Fat	-0.024	-2.777***	0.442
	(0.032)	(0.321)	(0.329)
% Calories as Protein	-0.025	-0.958**	1.983***
	(0.050)	(0.427)	(0.655)
% Calories as Fiber	-0.453**	-10.041***	3.589*
	(0.185)	(2.096)	(1.816)
Vitamin C	-0.001***	0.005**	0.005*
	(0.000)	(0.002)	(0.003)
Calcium	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
Standard Error Clustered by Individual	Yes	Yes	Yes
Individual Fixed Effect	Yes	Yes	Yes
Study Day Fixed Effect	Yes	Yes	Yes

	NLS	NLS	NLS
VARIABLES	Waste Rate-IHS	Log(TakenGram+1)	Log(ConsumedKcal+1)
Constant	0.026	4.262***	3.454***
	(0.017)	(0.198)	(0.239)
Observations	1,599	1,599	1,599
R-squared	0.075	0.604	0.576

Note: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Discussion

As the food selection, intake and waste models show, subjects learned from previous plate waste experience when the use of SmartIntake raised the subjects' attentions to the amount of uneaten food. As the stock of plate waste knowledge accumulates, subjects learned to reduce plate waste. The subjects who generated any waste on Day 1 enjoyed a substantial plate waste reduction on Day 2 and maintained a relatively low plate waste rates during the rest of the week. On the other hand, the subjects who generated zero plate waste on Day 1 had few lessons to learn from, and hence have on rising plate waste rates on the following days. As a result, subjects with zero initial plate waste had similar plate waste rate as the subjects who wasted some on Day 2 (2.52% vs. 2.84%) and had higher plate waste rates than them since Day 3.

When subjects are aware of being observed and/or generate beliefs about researchers' expectations regarding the assessed behaviors, they tend to change their behaviors due to conformity effects and considerations of social desirability, which are usually defined as Hawthorne effects. The learning effects observed in this study are unlikely caused by direct Hawthorne effects as this was a nutrition study conducted in 2008 when there were limited news coverages of food waste. To conform with nutritionists' expectations or social desirability, we would expect a downward bias on food intake (i.e., subjects intentionally have lower calorie intake) which may lead to an upward bias on plate waste instead of decreasing amount of plate waste as was observed. Also, the SmartIntake app provides no data feedback on the amount of plate waste generated; all that subjects do is to take a picture of uneaten food in the end of the meal. Without explicit data feedback on food-related behavior, we argue there is limited evidence supporting traditional Hawthorne effects.

We continued to explore how the subjects achieved the plate waste reduction when they learned by examining the impacts of previous plate waste experiences on food selection and food intake behaviors. The subjects had higher calorie intake as the discounted stock of plate waste experience increased while food selection was not significantly related with the previous experience. This suggests that subjects learned to reduce food waste by over-eating instead of selecting less food at the beginning. This could worry public officials and nutritionists who aim to reduce health costs associated with overweight and obesity. We note that the average BMI of the subjects in this study is higher than national average and nutritionists found that plate cleaning behaviors are associated with higher BMI. Hence, it would be interesting to test the relationship among the habits of plate cleaning, food waste reduction, and the BMI of the subjects in future samples that may be large and diverse enough to provide adequate statistical power.

The results from the learning models also suggest a new avenue to help consumers reduce food waste. Current food waste education campaigns mainly work on deliberate learning, e.g., educating consumers on the social and environmental cost of the food waste and distributing tips about how to reduce household food waste. Our results suggest that consumers can reduce food waste via a dynamic incidental learning process, e.g., learning by doing in the presence of non-quantitative feedback. This may suggest tradeoffs among different strategies. Deliberate learning could work as an exogenous shock and help consumer achieve sudden large food waste reduction (e.g., zero food waste at the beginning), while the deliberate learning effects may decay over time and the amount of food waste generated will be on rise again if there are no continuous efforts in the long term. Learning by wasting, on the other hand, requires continuous efforts on food waste tracking, while consumers could adjust their behaviors dynamically and achieve low waste rate in the long term because any high waste rate induced by forgetting effects could increase the stock of knowledge and lead to food waste reduction in the future.

Limitations

In this study, we solely focus on subjects' plate waste due to the data constraints. However, plate waste only accounts for a portion of the total household food waste. Consumers waste food when they purchase too much, when they prepare food in a careless way, and when they prepare more food than is needed. Consumers could learn from the food wasting experiences in every stage of this process including plate waste, inventory waste and preparation waste. Further, the limited duration of consumer tracking with the SmartIntake app may limit subjects' ability to adjust their selection behaviors. For example, the subjects whose grocery shopping frequency is weekly or less frequently may have limited ability to adjust their food storage and meal plans during the study period, which may partially induce the observed insignificance of learning effects on food selection. A study that tracks the life cycle of the purchased food with a long enough study period would allow the subjects to adjust the grocery shopping and meal plans for multiple eating occasions and provide more insights on how consumers learn from their food waste experiences and adjust their food selection, storage, preparation, consumption and waste behaviors based on the accumulated stock of food waste knowledge.

Due to the lack of information regarding uneaten food management, we assume all the uneaten food left on plate is wasted. However, this is not necessarily true when the consumers can save the uneaten food for later use. Also, the cost generated by the uneaten food could be different when various waste management strategies are applied. According to the food waste recovery hierarchy from EPA, food waste that ends in landfill should generate higher societal costs than the re-used, recycled, or composted uneaten food. The perceived cost of throwing away food, when various waste management methods could be applied, may also provide consumers different motivations to learn and to adjust their future behaviors (Qi and Roe 2017).

Conclusions

There is an emerging idea that increasingly ubiquitous monitoring technologies or other policies can increase the salience of semi-autonomous everyday household decisions by illuminating how these decision affect metrics that consumers value such as dollars expended, energy units used, calories ingested or carbon footprint created. We take a key step in this literature by estimating the dynamics of consumer learning in such a situation. By enrolling subjects that agree to intensively monitor their food intake by using a smartphone app to take pictures of their plate before and after eating, we track how this monitoring activity alters the dynamics of the three constituent activities capture: food selection, food intake and plate waste. We document that the food intake and plate waste behaviors are consistent with a model of learning with different degrees of forgetting embedded in the process.

While documenting that consumer appear to learn is intriguing, it is but a first step to understanding the structure of consumers' dynamic behavior in response to new information. The current sample is not large enough to attempt to ascribe different learning rates to different types of consumers, nor have we explored how explicitly informational, persuasive, or punitive programs would differentially alter the learning dynamics. While using a week's worth of data is certainly a good first step, the current design did not allow for follow up evaluations that could establish of long-term behavioral changes persisted once monitoring was removed. Enriching future research designs in these directions could guide policy to emphasize approaches that subtly increase the salience of food waste (e.g., requirements to separate food and other organic waste before disposal) or provide informational campaigns (e.g., media awareness campaigns).

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