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Learning about Our Vices from Devices: A Model of Individual Learning with an Application to Consumer Food Waste

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We formulate an empirical learning model suitable for understanding individual behavioral responses to personal devices and sensors. We estimate this model using data collected about personal decisions of food selection, intake, and waste during a study in which users photographed their meal selections and plate waste over the course of a week with a cell phone. We found substantial learning-by-doing effects in plate-waste reduction: Those who document greater plate waste in their photographs waste less on subsequent days. Further, we identified that participants reduced plate waste by learning to eat more rather than by learning to select less food.

Key words: behavior tracking, dietary intake, learning by doing, obesity

Introduction

The digital revolution has led to a proliferation of personal, household, and workplace sensors and devices that enrich individual environments with frequent purposeful and incidental feedback capable of altering behavior. This includes dedicated devices (e.g., accelerometer-based devices, smart thermostats, electrical outlet monitors) as well as extensions to multipurpose devices (e.g., smartphone cameras and apps, vehicle global positioning systems). Empirical modeling of behavioral responses to these rich emergent environments is limited but growing (Zhang et al., 2019). While such data has been used to predict aggregate outcomes such as influenza infection rates (Radin et al., 2020) and estimate relationships among factors (Li et al., 2017), little attention has been paid to modeling behavioral changes that are secondary to the use of such devices.

In this article, we investigate responses to the introduction of a method designed to track individual food intake (Martin, Correa et al., 2012) in which users are prompted to use their cell phone's camera to photograph daily meals over the course of a week. We identify a substantial learning-by-doing effect in plate waste reduction as those who document greater plate waste in their captured photographs waste less on subsequent days. While the current analysis is situated in a consumer household production setting, the role of learning by doing in shaping and driving

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productivity growth is well documented in the economics literature. Lucas (1988) suggests that learning by doing is as important as schooling in human capital investment and accumulation. Empirical studies confirm the presence of learning by doing in a variety of industries, including agriculture (Foster and Rosenzweig, 1995), manufacturing (Benkard, 2000; Levitt, List, and Syverson, 2013), and energy (Kellogg, 2011; Bollinger and Gillingham, 2012) by identifying significant improvements in working efficiency (Thompson, 2007, 2012) and decreases in defects as workers accumulate experience and learn through trial-and-error processes (Levitt, List, and Syverson, 2013).

However, few studies explore how households learn from daily life experiences and alter behaviors accordingly, mainly due the difficulty of tracking behavior in free-living conditions. Recent developments in digital technology can reduce the costs of tracking behavior and storing and transmitting data (Goldfarb and Tucker, 2019). For example, wearable accelerometer-based devices record second-by-second raw activity information in real time (Zhang et al., 2019). This enhanced ability to track individual activity allows researchers to conduct longitudinal research that could be used to provide novel insights about effects of interventions on subjects' behaviors (Hartman, Nelson, and Weiner, 2018), reveal individual health conditions on a daily basis (Seifert et al., 2017), and generate knowledge and predictions about public health in a more timely way (Radin et al., 2020). Further, some studies document the association between subjects' responses to interventions and their engagement with such devices. For example, in a randomized controlled trial, Hartman, Nelson, and Weiner (2018) identify a positive association between moderate-to-vigorous physical activity and both wearing and viewing output from a Fitbit®.

In this study, participants were asked to use their cell phone camera to capture images of food selection before each eating episode and plate waste after each eating episode to help validate the Remote Food Photography Method® (Martin, Correa, et al. 2012), a novel method of collecting food intake data. No feedback about the recorded data were provided either from their phone or by the researchers. Although participants were not instructed to reduce plate waste and did not receive any information about plate waste during the experiment, we found that—as the cumulative amount of plate waste captured by the participant increased—they responded with a statistically significant reduction in plate waste on both the intensive and extensive margins. This intraweekly pattern was captured with a learning-by-doing model that included both statistically significant learning and forgetting parameters, with accumulated experience with plate waste being forgotten over the course of several days. Reducing plate waste requires reducing the amount selected, increasing the amount consumed, or some combination thereof. We find accumulated experience with plate waste resulted in no significant change in the amount selected but a greater intake of the selected portion (i.e., plate cleaning),[1] a strategy associated with overweight and obesity (Robinson and Hardman, 2016).

To the best of our knowledge, this is the first study that explores the interactions between digital devices and individual behavioral responses with respect to food. The learning-by-doing model and the resulting estimates can be applied to other household behaviors. These insights stimulate discussion about the channels for nudging behavioral changes by providing nonspecific feedback from devices embedded in consumer daily routines.

Data and Study Design

We draw on data collected from 50 adults from the Baton Rouge, Louisiana, area that were previously assessed by Roe et al. (2018).[2] Participants were trained to use a smartphone app and then used the app to collect data for approximately 1 week in their normal, everyday setting. The

[1] Despite the change in the pattern of intake in response to accumulated plate waste, we note that average daily energy intake did not change significantly across the sample during the study (Table A3), which comports with results from Martin, Correa, et al. (Martin et al. (2012))2012).

[2] Roe et al. (2018) estimate and interpret associations between plate waste levels and the characteristics of food items and participants. They do not consider time trends or estimate learning or other explicit behavioral models.

Table 1. Study Sample Characteristics (*N* = 38)

	Percentage or Mean ± SE
Female (%)	89
Race	
White (%)	63
African American (%)	37
Age	
18–29 (%)	26
30–49 (%)	29
50+ (%)	45
Height (cm)	164.48 ± 7.37
Weight (kg)	84.50 ± 16.67
BMI (kg/m^2)	31.12 ± 5.30
Obesity (BMI ≥ 30) (%)	68

data were acquired via the Remote Food Photography Method (RFPM), which has been previously described and validated (Martin, Han, et al. 2008; Martin, Correa, et al. 2012). Briefly, participants used cameras on their cell phones to capture images of each food item that they selected before each eating episode and plate waste for each food item after each eating episode. A computer-assisted approach identifies a match for each food in a nutrient database and estimates the portion size selected and discarded based on established and validated procedures (Williamson et al., 2003; 2004; Martin, Han, et al. 2008; Martin, Correa, et al. 2012). Food intake is calculated as food selection less plate waste.

The purpose of the data collection was to test the efficacy of the phone-based photography approach to assessing dietary intake. Participants were informed of this purpose and received no explicit cues from researchers to reduce food waste. Specifically, subjects received no instruction concerning the types or amounts of food that they should or were recommended to select, eat, or discard. Respondents received no information or suggestions about food waste or reducing food waste during the entire study. Participants were informed that the purpose of this study was "to test different methods of measuring energy balance, including food intake and energy expenditure," which suggests no preferable direction in terms of food waste generation to the subjects.

While not assessed, participant awareness about food waste as a societal and environmental problem should have been lower when data were collected (2009) than current awareness levels. For context, compared to the term "obesity," the term "food waste" attracted little attention in 2009.[3] Therefore, we expect that, compared to obesity and energy intake control, reducing food waste was not at the top of participants' minds. If anything, we expect those suffering social desirability bias would have tried to reduce food intake by not cleaning their plates, leading to more food waste.

Our analysis sample consists of 38 participants who reported plate waste for at least one food item during the entirety of the study (Table 1).[4] Compared to the national average, a larger proportion of our respondents were female, and the average weight and average body mass index of the subjects in this study are higher than the national average. The former is not surprising as, during recruitment, participants were offered the opportunity to enroll in a weight loss treatment following the completion of the data-monitoring portion of the study, and women more frequently seek weight loss treatment (Roe et al., 2018).

[3] According to trends of Google searches for the keywords *obesity* and *food waste*, the topic of food waste attracted much less attention than obesity in the United States from 2008 to 2020 (Figure A1), with the volume of searches featuring *food waste* being only 1%–3% of the number of searches on obesity during the 2009 study period.

[4] The 12 participants who reported 0 grams of plate waste for the entire study week are removed because our model focuses on learning from cumulative plate waste experience, which results in a total sample size of 38.

Table 2. Summary Statistics for Food Items (*N* = 1,599)

	Mean or Percentage	SD	Min.	Max.
Food taken (g)	133.76	137.02	1.82	992.00
Food consumed (g)	128.32	132.41	0.00	936.00
Plate waste (g)	5.44	26.22	0.00	372.00
Food taken (kcal)	249.31	256.88	1.12	2,744.99
Food consumed (kcal)	236.85	248.01	0.00	2,785.86
Plate waste (kcal)	10.38	50.65	0.00	609.84
Calories/serving	168.39	150.09	0.87	1,431.31
Calories as fat (%)	36.33	25.78	0.00	99.50
Calories as protein (%)	15.62	15.09	0.00	90.71
Calories as carbohydrates (%)	48.04	30.52	0.00	100.00
Fiber taken (g)	2.01	2.81	0.00	43.09
Calcium (mg)	86.54	138.76	0.00	1,443.42
Vitamin C (mg)	7.79	22.12	0.00	338.69
Food group				
1. Milk and dairy products (%)	8.90			
2. Meat, poultry, fish and mixtures (%)	22.00			
3. Egg (%)	1.30			
4. Legumes, nuts, and seeds (%)	2.40			
5. Grain products (%)	30.70			
6. Fruit (%)	6.30			
7. Vegetables (%)	17.70			
8. Fats, oils, and salad dressings (%)	5.30			
9. Others (%)	5.40			

Food item variables include the number of servings taken, the caloric density of the food (calories/serving), the USDA Food and Nutrient Database for Dietary Studies (FDNNS version 3.0) food group, and the percentage of energy from protein, fat, and carbohydrates. Due to large differences in the nature of liquid and solid foods, only solid food items were analyzed, yielding a sample of 1,599 food items reported by the 38 participants during the study week. Table 2 presents summary statistics for food items analyzed.

Learning by Doing in Household Food Production

We postulate that participants maximize utility by combining their time and skills with purchased food in a household production function where wasted food represents a drag on the productivity obtained in this household production process (see Hamilton and Richards, 2019, for such a model). We argue that participants' training and use of the photo-based method induces a learning process that can increase the productivity of this household production process and enhance utility.[5] While no data are delivered to the participant as part of the measurement process, we hypothesize that the act of photographing meals prior to and upon completion of meal consumption heightens awareness of food selection, consumption, and waste patterns and stimulates learning. To capture this, we turn to economic models of learning by doing from the literature, which have largely focused on understanding the pattern of production unit costs in response to cumulative experience.

[5] We are silent on parameters of the utility function itself and note that participants in our study may have sought to reduce calorie intake, reduce food waste, or some combination of both.

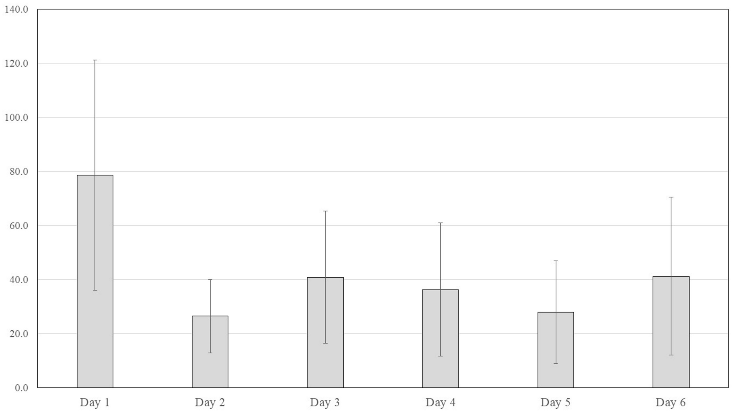

Figure 1. Average Plate Waste per Person (g/day)

Notes: 95% confidence intervals presented on bar figures.

Common sources of learning by doing that are documented in the literature include economic scale effects (Benkard, 2000), knowledge spillovers, and relationship development (Kellogg, 2011), each of which is unlikely in our context. However, Levitt, List, and Syverson (2013) also find that defect rates decrease at plants as workers accumulate production experience, which may be a more apt analogy for our household context. Hamilton and Richards (2019) characterize food waste as a consequence of imperfect food utilization, which may parallel the Levitt, List, and Syverson (2013) defect rate concept. Following that, we hypothesize that, like industrial productivity improvements, food utilization can also be improved as households accumulate knowledge of the food production experience by repeatedly photographing the food they select and discard, which results in a decrease in plate waste.

Some empirical patterns identified in our experiment support this hypothesis. For example, over the 1-week study period, we find that the average subject created significantly less plate waste in the later days of the study week. Figure 1 plots the average grams of plate waste generated per day per subject across the first 6 study days. The amount of plate waste was highest on day 1, when an average of 86.7 g of food was discarded. A substantial plate waste reduction was observed starting on day 2, when plate waste decreased by 65%, to only 30.1 g. Average plate waste remained relatively low level from day 2 to day 6, with an average around 40 g per day. The observed food waste improvement among our participants is consistent with productivity increases cited earlier, where a significant learning-by-doing relationship between productivity and production experience was identified (Levitt, List, and Syverson, 2013).

To model learning by doing in household food production, we follow Thompson (2001) and assume that household food waste production takes the following form:

$$FW_t = A f(e_t) Q_t^{\alpha}, \tag{1}$$

where FW_t is the amount of food discarded on study day t when Q_t grams of food are selected for a meal;[6,7] $f(e_t)$ is a learning curve describing the decrease of food waste and the improvements of food

[6] We choose day as the unit of time for two reasons. First, mealtimes were not uniformly captured during this study, rendering subday periods irrelevant. Second, even if such data were available, intermeal timing, and even the number of meals per day, may differ between participants. Aggregating to a daily level provides an even footing for pooling across participants.

[7] We choose grams of food wasted as the unit of analysis rather than, for example, percentage of food wasted because of the likely greater salience made available by the photography-based method about the level of waste versus the waste expressed as a percentage of the original amount of food served. Given that the choice of the amount of food served occurs before the amount wasted, we postulate that learning about the level of waste will be sharper than about the percentage of waste. Further, the level of waste has the added benefit of being more useful for analysis of policies and waste management practices.

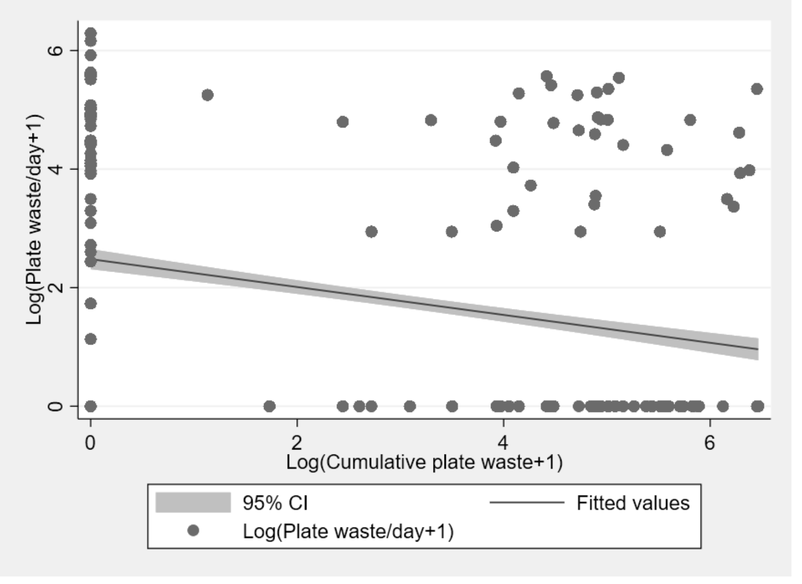

Figure 2. Association between Cumulative Plate Waste Experience and Current Plate Waste Generation

utilization as the food waste experience, e_t, that is accumulated before study day t increases; and A is the baseline efficiency of food utilization prior to any waste experience. Following Besanko et al. (2010), we postulate the learning curve as

(2) $$f(e_t) = e_t^{\log_2 \rho},$$

where $\rho \in (1,0]$ is the progress ratio and plate waste decreases by $100(1-\rho)\%$ as the waste experience doubles. Taking logs gives us an empirical description of the learning process:

(3) $$\ln(FW_t) = \beta_0 + \beta_1 \ln(e_t) + \beta_2 \ln(Q_t) + \varepsilon_t,$$

where $\beta_0 \equiv \ln(A)$ is a constant and $\beta_1 \equiv \log_2 \rho$ is the coefficient of interest. A negative β_1 suggests that participants learn from the past food waste experience and reduce food waste and improve food utilization as food waste experience accumulates.

In our study, a similar learning pattern suggested by the industrial organization literature is reflected in Figure 2, which plots the average logged plate waste generation (y-axis) against the logged cumulative food waste in the past (x-axis). When cumulative food waste experience was 0, many participants generated a large amount of plate waste. As they started photographing plate waste and accumulated food waste experience (though absent any numerical feedback), more learned to reduce food waste and more subjects generated 0 plate waste despite an absence of persuasive efforts from the study team.

Besides learning by doing, existing literature also documents nontrivial knowledge depreciation or forgetting effects that happen alongside learning (e.g., Benkard, 2000; Thompson, 2007; Levitt, List, and Syverson, 2013). Forgetting that happens during this process is well supported by psychology theories and experimental evidence. For example, human experiments reported by Wixted and Ebbesen (1991) suggest human forgetting follows a power function of time for name recall and facial recognition. In this study, to control for potential forgetting effects, we assume the food waste experience is accumulated based on a perpetual-inventory process, where experience declines over time and more recent food waste experience is more important in shaping the current food waste decisions than the more distant past waste. Following Benkard (2000) and Thompson (2007), we measure depreciated cumulative food waste experience with the following equation:

$$(4) \qquad e_t = \delta e_{t-1} + FW_{t-1},$$

where $\delta \in [0,1]$ and a δ close to 0 suggests a high depreciation rate, where more distant experience impose few impacts on current food waste decisions, while a δ closer to 1 suggests a low depreciation rate, where subjects rarely forget and more distant experience is nearly as important as the more recent food waste experience.

The theory of learning by doing suggests a causal effect of cumulative experience on the current productivities or inverse productivities (i.e., food waste generation). However, another alternative could be that learning is just a function of time rather cumulative experience; in that case, suffering from more food waste would not necessarily lead to more learning and rapid food waste reduction in the future, undermining the importance of the learning curve. Therefore, to identify the learning effect from previous experience rather than the alternative of a simple time trend, we control for the time trend in our model with study day fixed effects. Moreover, subject fixed effects and nutrition characteristics of the food items are also included to better control for unobserved factors at the subject level and the impacts of food type on waste generation. Given that a large proportion of food waste observations are 0, we adjust the measurement of food waste and learning as $\ln(FW_t + 1)$ and $\ln(e_t + 1)$. Therefore, our empirical model becomes

$$(5) \qquad \ln\left(FW_{jti} + 1\right) = \beta_0 + \beta_1 \ln(e_{ti} + 1) + \beta_2 \ln\left(Q_{jti}\right) + \beta_3 X_{jti} + I_i + Day_t + \varepsilon_{jti},$$

where Q_{jti} and FW_{jti} represent the amount of food item j that subject i selected and wasted, respectively, on day t. The model also controls for subject fixed effects (I_i), study day fixed effects (Day_t), and nutrition characteristics of the selected food item (X_{jti}).

Equation (5) can be estimated using ordinary least squares (OLS) if no significant forgetting effects take place. When subjects forget previous experiences and δ in $e_{ti} = \delta e_{t-1,i} + FW_{t-1,i}$ is positive, estimation via nonlinear least squares (NLS) is consistent and unbiased if ε_{jti} is *i.i.d.* and independent of the cumulative experience e_{ti} (Benkard, 2000). However, this would be a specious assumption as the existing literature identifies serial correlation in the unobserved portion of industrial activities (Benkard, 2000; Thompson, 2012; Levitt, List, and Syverson, 2013). In our case, we suspect that such serial correlation may also exist among households and hence assume that e_{ti} is correlated with ε_{jti}. For example, e_{ti} as a cumulative past food waste experience is correlated with unobserved factors in the past. Further, unobserved factors in the past are serially correlated with the unobserved factors in the current period. In that case, e_{ti} correlates with current unobservables ε_{jti} and the estimation of β_1 can be biased. Hence, it is necessary to instrument for these correlations to obtain consistent and unbiased estimates of the learning effect (Benkard, 2000; Thompson, 2012; Levitt, List, and Syverson, 2013). In this study, we use the average cumulative experience from all other subjects ($e_{t,-i}$) as the instrument for e_{ti}. We presume that other subjects' plate waste patterns over the study duration should be similar to individual i's behavioral pattern but independent of that individual's own experiences because study participants never interacted.

Results

Table 3 contains the estimates of the learning model without forgetting. Column 1 reports the results from the most basic specification estimated using OLS. We find that subjects generated significantly less plate waste as they accumulated plate waste experience. When subject fixed effects and the food characteristics are controlled for (column 2), the magnitude of the estimated learning effects increased. The results are robust when plate waste is measured in percentage terms (see Table S3 in the online supplement at www.jareonline.org).

To distinguish whether the reduction of food waste is a consequence of learning from past experience or just an outcome associated with the passage of time (Levitt, List, and Syverson, 2013), in

Table 3. Plate Waste as a Function of Nondepreciated Cumulative Plate Waste Experience (N = 1,599)

	OLS 1	OLS 2	OLS 3	OLS 4
Cumulative FW experience	−0.046*** (0.014)	−0.084*** (0.023)	−0.132*** (0.025)	−0.144*** (0.027)
No. of study days			0.077*** (0.025)	
Study fixed effects				
Day 2				0.116 (0.092)
Day 3				0.304** (0.124)
Day 4				0.384*** (0.138)
Day 5				0.323** (0.125)
Day 6				0.467*** (0.127)
R^2	0.011	0.098	0.105	0.107
Food controls[a]	No	Yes	Yes	Yes
Subject fixed effects	No	Yes	Yes	Yes

Notes: Robust standard errors clustered by subject in parentheses. Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level.
[a]Food Controls include the type, macronutrient content, and the energy density (kcal/g) of the selected food item. See the online supplement for a full presentation of regression results.

column 3 of Table 3 we control for the passage of time by including a time trend variable and in column 4 we include study day fixed effects to capture the behavioral patterns shared among all subjects over the study period in regardless of experience accumulation. The time trend is actually positive (column 3) rather than negative, which is mainly driven by the increase of food waste starting from the study day 3 (column 4). This suggests that, over the time, conditional on food waste experience, subjects tended to discard more food rather than less food. Therefore, the reduction of food waste observed among participants should be related to learning from the recorded past food waste experience instead of due to a simple passage of time.

The identified increasing time trend in plate waste also suggests the potential for forgetting effects (i.e., that subjects' food waste knowledge capital accumulated from previous recorded experience depreciates over time). Therefore, in Table 4, we report NLS estimates of the learning and forgetting models in which the cumulative food waste experience depreciates at a rate of δ each day. The results show a forgetting rate of 0.924, which refers to a 7.6% loss in food waste experience, which translates to about 38% loss of experience after a week.

Further, to control for potential serial error correlation, we instrument individual cumulative food waste experience with the average of all other subjects' cumulative experience in column 2 of Table 4. We assume that all subjects share some common patterns and therefore that the other subjects' cumulative experience should be correlated with this subject's experience. However, subjects in this study did not interact and therefore this subject's previous experience should not alter the other subjects' cumulative experience. Once the serial error correlation was corrected by the instrumental variable, the magnitude of the estimated forgetting and learning effects is larger (column 2). The estimated forgetting factor is about 0.223 in NLS-IV, suggesting that nearly 78% of the food waste experience recorded on study day 1 was forgotten by study day 3 and nearly all food waste that occurred on day 1 was forgotten

Table 4. Nonlinear Least Squares Estimations of Learning and Forgetting Models (N = 1,599)

	NLS	NLS-IV
Dependent Variable	**1**	**2**
Cumulative FW experience depreciated by forgetting factors	−0.144*** (0.027)	−0.229*** (0.046)
Forgetting factor[a]	0.924 (0.030)	0.223 (0.034)
R^2	0.107	0.099
Controls	Yes	Yes
Subject fixed effects	Yes	Yes
Day fixed effects	Yes	Yes

Notes: Robust standard errors clustered by subject in parentheses. Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level.

[a]The standard error of the forgetting factor is calculated via bootstrapping.

by the end of the week. Along with a greater forgetting effect, in the meanwhile, we also identify larger learning effects. The coefficient for the depreciated cumulative experience is −0.229. This translates to approximately 15% waste reduction when the plate waste experience doubles. We apply this model specification (column 2 in Table 4) in all the following analyses.

Mechanism to Reduce Plate Waste: Learning to Select Less or Learning to Eat More?

To reduce the amount of plate waste, a diner can select less food for a meal, consume a larger proportion of the prepared meal, or any mix of these two, though the social and environmental consequences from the different plate waste reduction strategies are distinct. While consuming a larger proportion of the selected food (i.e., plate cleaning) is a common bromide for limiting the generation of the plate waste, nutritionists have been long concerned about the potential health costs induced by excess energy intake or overeating (Thorpe et al., 2004; Lehnert et al., 2013). Reducing food waste by selecting less food in the beginning decreases the amount of food acquisition and, if accompanied by lowered purchasing, leaves more food available on the market, which could be transferred into societal benefits via improvements in food security. Food waste reduction achieved by insignificant changes in food selection but an increase in food consumption, however, does not result in less food purchased but could induce substantial health costs associated with overweight and obesity in the long run.

To understand the mechanisms that individuals applied while they learned to reduce plate waste, we estimate the impacts of the depreciated cumulative waste experience on participant food selection and food intake (Table 5, columns 2 and 3) along with the parallel parameters for plate waste (column 1). Instead of observing a significant reduction in food selection in response to accumulated experience with plate waste, we identify a significant increase in food intake as participants accumulated experience with plate waste.

The strategy of reducing plate waste by overeating is alarming and worrisome because the majority of participants in both groups were overweight or obese (Table 1). If the overweight and obese participants respond to accumulated experience with plate waste by learning to clean their plates, we would reasonably worry that such unguided learning could increase health costs through exacerbation of health conditions associated with overweight and obesity. We note that participant body mass index (BMI) is assumed to be constant over the 1-week study period and hence the impacts of BMI on the incidental learning are not identifiable when we have individual fixed effects controlled in the model. We find that obese subjects tended to generate less plate waste (Table A1, column 1) and were more likely to clean their plates, though such differences are not statistically different and should be interpreted cautiously as individual fixed effects were yet to be controlled (Table A1, column 2).

Table 5. Learning Effects: Food Waste, Intake, and Selection (N = 1,599)

Dependent Variable	Waste (grams) 1	Intake (kcal) 2	Selection (grams) 3
Cumulative FW experience	−0.229*** (0.046)	0.122*** (0.038)	−0.022 (0.034)
R^2	0.099	0.754	0.662
Controls	Yes	Yes	Yes
Subject fixed effects	Yes	Yes	Yes
Day fixed effects	Yes	Yes	Yes

Notes: Robust standard errors clustered by subject in parentheses. Cumulative FW experience depreciated by forgetting factors $\delta = 0.223$ (SE = 0.034). Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level.

Table 6. Linear Probability Model of Plate Cleaning Behavior (N = 1,599)

Dependent Variable	Plate Cleaned (yes = 1) 1
Cumulative FW experience depreciated by forgetting factors	0.055*** (0.012)
Study day 2	−0.082** (0.039)
Study day 3	−0.133*** (0.052)
Study day 4	−0.168*** (0.058)
Study day 5	−0.157*** (0.056)
Study day 6	−0.196*** (0.054)
R^2	0.074
Controls	Yes
Subject fixed effects	Yes
Day fixed effects	Yes

Notes: Robust standard errors clustered by subject in parentheses. Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level.

In fact, Robinson and Hardman (2016) find that excess energy consumption promoted by plate-clearing habits is strongly associated with greater body weight. Based on Table 5, we found that, even without any persuasion from the research team to reduce food waste, subjects who were already overweight and obese had a strong impulse to consume excess food to minimize plate waste generation. In Table 6, we continue to investigate if our subjects learned to adopt a habit of plate cleaning as Robinson and Hardman (2016) suggest. We estimated the relationship between returning a clean plate and plate waste experience that the subject accumulated. Conditional on cumulative plate waste experience, as time passed by, subjects were less likely to clean their plates (Table 6), which may be a consequence of fatigue effects. These results suggest that learning from previous experience could contribute to the development of plate-cleaning habits among our participants.

Discussion, Limitations, and Conclusions

We identify statistically significant and economically impactful participant learning and forgetting effects during the study, with accumulated experience with plate waste leading to reductions in subsequent plate waste levels. Further, we identify learning spillovers across linked behaviors as cumulative plate waste is estimated to drive subsequent food intake decisions. This points to the need for future research to consider how a device designed for one purpose (e.g., to measure food intake or track physical activity) may generate responses across the behavioral ecosystem in which that action is embedded. In our particular context, an intriguing question is whether learning about plate waste spilled over to other upstream (e.g., purchasing and menu planning) or downstream (e.g., keeping leftovers or beginning composting) behaviors. This then prompts questions about how the knowledge of such behavioral structures might inform active or passive monitoring strategies to address policies surrounding dietary choices or waste reduction.

While the purpose of this study is to estimate behavioral patterns once devices are deployed, this raises questions about whether this learning occurred prior to the commencement of measurement (in which case the study merely documented this preexisting process) or whether the deployment of the method triggered the documented patterns. We cannot know for certain because no data concerning participants' food selection, intake, or waste was captured prior to the study period.

Our conjecture is that deployment triggered the change in behavior because participation was preceded by formal training in which research staff worked to teach participants how to correctly take photos and to verify participants' mastery in documenting and transmitting the captured photos. This training, coupled with the photographs before and after each meal, could conceivably spur behavioral change be redirecting attention to the tasks that shape the input being gathered (food and intake choices). We also point to studies in workplace settings where performance data are often available before and after employees are made aware of monitoring. For example, Gosnell, List, and Metcalfe (2020) document that airline pilots' fuel use declined in a statistically and economically significant manner simply by learning of management's monitoring of several critical operational decisions made by pilots during each flight.

Our lack of prestudy data represents another limitation of this study. Further, it signals a challenge for consumer research in this domain and points to the need to creatively expand study designs in consumer contexts where such data are difficult to monitor prior to the deployment of devices without study subjects being aware of such monitoring. We also acknowledge that this study features a higher proportion of female participants (88%) than the national average. This could be attributed to the offering of weight loss treatment for overweight or obese subjects following the data collection portion; women are likely to be attracted by such opportunities (Roe et al., 2018). This suggests the estimations obtained from this study could be a lower bound of the observed incidental learning by doing if women attracted by weight loss treatment were to be more hesitant to adopt overeating and plate cleaning strategies to reduce plate waste.

Despite the several limitations of this particular study, we argue that consumer and workplace technologies that can trigger purposeful or incidental learning will continue to proliferate. Learning models such as the one described above provide an avenue to capture the ensuing behavioral responses and to inform the design of public policy and commercial products and practices.

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Online Supplement: Learning about Our Vices from Devices: A Model of Individual Learning with an Application to Consumer Food Waste

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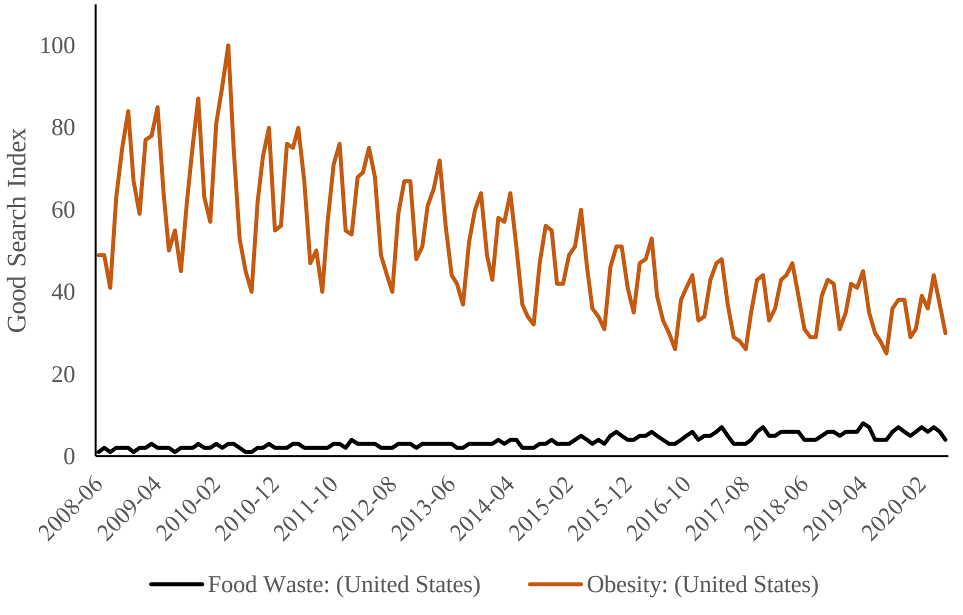

Figure S1. Google Search Trend on *Food Waste* and *Obesity* in the United States, 2008–2020

The material contained herein is supplementary to the article named in the title and published in the *Journal of Agricultural and Resource Economics* (*JARE*).

Table S1. Regression Estimations Without Individual Fixed Effects (*N* = 1,599)

Dependent Variable	**Waste (grams)** **1**	**Clean Plate (=1)** **2**
Cumulative FW experience	-0.038**	0.010**
	(0.016)	(0.005)
Individual characteristics		
Female	0.039	-0.010
	(0.084)	(0.021)
White	-0.155*	0.035
	(0.089)	(0.022)
Obese	-0.072	0.017
	(0.068)	(0.019)
Age (omitted: 18–29)		
30–49	0.131	-0.031
	(0.093)	(0.025)
50+	0.106	-0.020
	(0.088)	(0.022)
Food group (omitted: Others)		
Milk and dairy products	-0.373**	0.093**
	(0.165)	(0.041)
Meat, poultry, fish, and mixtures	-0.150	0.035
	(0.139)	(0.034)
Egg	-0.444*	0.114*
	(0.258)	(0.058)
Legumes, nuts, and seeds	-0.018	0.003
	(0.167)	(0.045)
Grain products	-0.057	0.014
	(0.102)	(0.030)
Fruit	-0.230**	0.062*
	(0.114)	(0.031)
Vegetables	-0.067	0.021
	(0.085)	(0.026)
Fats, oils, and salad dressings	0.045	-0.016
	(0.146)	(0.047)
Fiber taken (g)	-0.002	0.001
	(0.015)	(0.004)
Calcium taken (g)	0.338	-0.074
	(0.486)	(0.109)
Vitamin C (mg)	-0.004***	0.001***
	(0.001)	(0.000)
1000 Kcal per serving	-0.301	0.099*
	(0.216)	(0.056)
Percentage calories as protein (%)	0.008	0.006
	(0.255)	(0.063)
Percentage calories as fat (%)	0.089	-0.028
	(0.133)	(0.037)
Log (grams of food taken+1)	0.216***	-0.047***
	(0.042)	(0.010)

Dependent Variable	Waste (grams) 1	Clean Plate (=1) 2
Study day fixed effects		
Day 2	-0.136	0.028
	(0.107)	(0.030)
Day 3	-0.062	0.015
	(0.147)	(0.040)
Day 4	-0.066	0.020
	(0.146)	(0.037)
Day 5	-0.144	0.040
	(0.143)	(0.038)
Day 6	-0.052	0.016
	(0.152)	(0.041)
Constant	-0.295	1.036***
	(0.189)	(0.050)
R^2	0.063	0.052

Notes: Values in parentheses are robust standard errors clustered by subject. Single, double, and triple asterisks indicate significance at the 10%, 5%, and 1% level, respectively.

Table S2. Regression Estimation on Energy Intake

Dependent Variable	**Energy Intake** **1**	**Energy Intake** **2**	**Log (Energy Intake+1)** **3**	**Energy Intake** **4**	**Energy Intake** **5**	**Log (Energy Intake+1)** **6**
Study day (omitted: Study day 1)		*Joint* $p = 0.787$	*Joint* $p = 0.440$		*Joint* $p = 0.120$	*Joint* $p = 0.155$
Study day 2		-4.903	0.137***		10.939	0.174***
		(18.281)	(0.048)		(16.652)	(0.060)
Study day 3		-4.178	0.033		7.667	0.062
		(18.504)	(0.047)		(19.586)	(0.057)
Study day 4		-24.512	0.055		-11.523	0.073
		(18.601)	(0.056)		(20.326)	(0.068)
Study day 5		0.802	0.099*		20.525	0.133*
		(19.356)	(0.056)		(18.986)	(0.070)
Study day 6		-10.844	0.065		-15.497	0.082
		(19.077)	(0.048)		(20.813)	(0.058)
Study day	-1.825			-2.064		
	(3.233)			(3.517)		
Sample[a]	Full	Full	Full	Learn	Learn	Learn
Controls	No	No	Yes	No	No	Yes
Subject fixed effects	No	No	Yes	No	No	Yes
Cluster by subjec	No	No	Yes	No	No	Yes
No. of obs.	2,042	2,042	2,021	1,599	1,599	1,599
R^2	0.000	0.001	0.773	0.000	0.002	0.755

Notes: Values in parentheses are standard errors. Single, double, and triple asterisks indicate significance at the 10%, 5%, and 1% level, respectively.

[a] *Full* sample included food items recorded by all 50 subjects participated, which is consistent with the data analysis from Martin et al. (2012). *Learn* sample (=38) only included food items recorded by those who generated at least some plate waste during the entire study period, which is consistent with all other analysis presented in this article.

Table S3. Percentage of Selected Food Wasted as a Function of Nondepreciated Cumulative Plate Waste Experience (*N* = 1,599)

	OLS 1	OLS 2	OLS 3	OLS 4
Cumulative FW experience	-0.005***	-0.008***	-0.012***	-0.014***
	(0.001)	(0.002)	(0.002)	(0.002)
No. of study days			0.007***	
			(0.002)	
Study fixed effects				
Day 2				0.011
				(0.009)
Day 3				0.030***
				(0.009)
Day 4				0.038***
				(0.014)
Day 5				0.031***
				(0.011)
Day 6				0.040***
				(0.011)
R^2	0.013	0.078	0.084	0.087
Food controls[a]	No	Yes	Yes	Yes
Subject fixed effects	No	Yes	Yes	Yes
Cluster by subject	Yes	Yes	Yes	Yes

Notes: Values in parentheses are robust standard errors clustered by subject. Single, double, and triple asterisks indicate significance at the 10%, 5%, and 1% level, respectively.
[a] Food controls include the type, macronutrient content, and energy density (kcal/g) of the selected food item. See appendix for a full presentation of regression results.