

# **An Explorative Data Analysis on Calorie Labeling**

Ling Dai

## **Abstract**

Considerable attempts have been made by policy makers in the United States to reduce obesity at the population level through targeting calorie consumption. While a lot of policy interventions around calorie consumption have been focused on calorie labeling, calorie labeling was found to have inconsistent effects in past research. In this study, through an explorative data analysis on a dataset collected by Goswami and Urminsky, I found that influencing food choice by providing additional information was not always the most efficient approach to affecting choices. Instead, the results suggest that the major mechanism of visually salient calorie labeling is through prompting people to consider nutrition and health. The findings suggest a potentially more effective approach of calorie labeling that stresses visual salience of calorie labels, to remind people to think about the calories in their food, instead of focusing on correcting inaccurate beliefs about calories. Moreover, the results further suggest that, like traditional calorie labels that provide benchmarking information, non-informational calorie labels are also subject to the limitations of their contexts and tend to be ineffective when the setting becomes irrelevant to their contents.

## **Introduction**

Obesity has long been a major concern for the U.S. population, contributing to numerous health risks such as heart disease. As a result, the U.S. government has made considerable attempts to prevent obesity through targeting calorie consumption, particularly in the Affordable Care Act. Many policy interventions around calorie consumption have been focused on calorie labeling. While many policy makers believed calorie labeling to be effective at reducing calorie overconsumption by providing people with necessary information, calorie labeling was found in past studies to have mixed effects on consumer food choices.

In this study, I aim to address the question of whether visual salience of the calorie labels, rather than merely information content or format, is the key to reducing calories in consumers' food choices. Our hypothesis, based on Goswami and Urminsky (2017), is that effective labeling needs to be more visually salient than standard industry disclosures and works primarily as a reminder, by prompting people to consider nutrition rather than by providing new information. To test the hypothesis that visually salient reminders to consider calories can reduce calories purchased, I conducted an explorative data analysis on a dataset originally collected by Urminsky and Goswami through a field experiment at four cafeterias on the University of Chicago campus. Through this study, I sought to test the hypothesis that both visually salient informative posters and completely non-informative "mere reminder" posters have similar effects on calorie choices, by increasing the likelihood for individuals to incorporate their beliefs about nutrition into their decisions. I also aimed to test whether effective calorie labeling changes people's level of spend on food, or affects consumer's choice structure. Finally, I also tested whether the effectiveness of non-informational calorie labeling is context-dependent.

## **Literature Review**

The rising level of obesity has been a growing concern worldwide (Finucane et al. 2011). In the United States, health issues caused by overweight and obesity, such as cardiovascular diseases and increased mortality rate (Kramer et al., 2012), account for approximately 20% of national medical spending (Cawley and Meyerhoefer, 2012). According to past research, the prevalence of obesity can be attributed to high calorie diets, popularized due to increasingly accessible and low-cost high calorie food (Swinburn et al., 2011; Gortmaker et al., 2011). Other factors, such as lack of knowledge (Krukowski et al., 2006; Elbel, 2011), automatic or habitual choice processes (Marteau, Hollands, and Fletcher, 2012; Wanskink, Just, and Payne, 2009), and preference for convenience (Rozin et al., 2011; Dayan and Bar-Hillel, 2011; Schwartz et al., 2012), were also found to contribute to unhealthy eating patterns and lead to weight gain.

In an attempt to reduce obesity at the population level, policy makers in the United States have made various efforts to target overconsumption of calories (Bray et al., 2012; Swinburn and Ravussin, 2009; Cutler et al., 2003), focusing on calorie and nutritional labeling. For example, the US Food and Drug Administration (FDA) released final regulations in December 2014, requiring restaurants with 20 or more locations to have calorie labels and a suggested daily total calorie intake on all menus (Federal Register, 2014). The focus on menu labeling policies have mainly relied on the assumption that obesity is largely driven by a lack of accurate information (Black, 2014), supported by the argument that the consumers often underestimate the calorie content of their food without correct information (Pomeranz and Brownell, 2008) and past evidence that some consumers choose healthier food when nutrition information is present at the point of purchase (Roberto, Schwartz, and Brownell, 2009). The popularity of menu calorie

labeling as informational interventions can also be explained by the fact that it is a relatively low-cost and easier to implement compared to other interventions such as taxes on unhealthy food or size restrictions on items (Goswami, Dai, and Urminsky, 2017).

However, the heavy reliance on calorie labeling also raises the question of whether such intervention is effective at reducing calorie consumption. First, calorie labeling based on providing persuasive information may be inconsistent as the effectiveness depends not only highly on recipients' literacy (Kutner et al., 2003; Williams, 2003), but also on interpretability of the messages. Moreover, the potential for information-based calorie labeling may be fundamentally limited because most human behavior is driven by automatic processes instead of deliberation upon the consequences of actions (Strack and Deutsch, 2004).

An alternative, non-informational approach of calorie labeling instead focuses on increasing individual's self-regulatory capacity to engage in healthier diet. According to psychological research, the fundamental conflict between hedonic short-term impulses and self-control cognitions involving goals and long-term consequences (Ainslie, 1975; Hoch and Loewenstein, 1991; Hoffmann et al., 2009) is a significant deciding factor on people's food choices. According to this account, identification of self-control conflicts (Bartels and Urminsky, 2015; Myrseth and Fishbach, 2009) and contextual influences on self-control (Ruderman, 1986), such as decision timing (Milkman et al., 2010), menu design (Parker and Lehmann, 2014) and convenience (Rozin et al., 2011), are two important influencing factors of calorie consumption. As a result, calorie labeling can reduce individuals' calorie intake by promoting cognitions and creating decision contexts that facilitate self-control.

There are four systematic reviews on the impact of calorie labeling on food choices in cafeterias and restaurants, but most of them showed inconsistent results for the effect of calorie labels on reducing calorie choices (Harnack and French, 2008; Krieger and Saelens, 2014; Swartz et al., 2011; Sinclair et al., 2014). The most recent meta-analysis reported a small but statistically significant inverse association between calorie labeling and calories purchased per meal or transaction (-18.13 kcal; 95% confidence interval [CI] = -33.56, -2.70;  $p = 0.021$ ), based on data from 23 comparisons across 19 studies (Long et al., 2014). However, the meta-analysis also found significant between-study heterogeneity. More specifically, studies conducted in non-restaurant settings showed a significant reduction in average calories purchased per transaction compared to control conditions (-58.16 kcal; 95% CI = -102.44, -13.87;  $p = 0.01$ ), whereas studies conducted in restaurants did not show a significant association between menu calorie labeling (-6.70 kcal; 95% CI = -20.21, 6.81;  $p = 0.331$ ) (Long et al., 2014).

Many different factors were proposed as potential sources of such heterogeneity. For example, although not significant, children and adolescents were found to have greater reduction in calories in response to calorie labeling. (Long et al., 2014; Roseman et al., 2013; Tandon et al., 2010; Tandon et al., 2011) In addition, some studies suggested that women tend to show stronger reduction in calories purchased compared to men in response to menu calorie labeling, although the relationship was not consistent across all the studies that presented results by gender. (Krieger, 2013; Bollinger, 2011) Moreover, race/ethnicity, BMI category, and neighborhood socioeconomic status may also play a role in determining the effect of calorie labeling.

In addition to the factors mentioned above, the way in which calorie labels are presented may influence the effectiveness of the labels in reducing calorie consumption. For example, warning labels were found to outperform calorie labels in many cases (Donnelly et al., 2018). Similar to calorie labels, warning labels aim to induce healthy behavior change by providing health-relevant information to consumers. In contrast to calorie labels, however, warning labels does not only convey information in a straightforward and easy to interpret way, but also communicate an explicit recommendation.

A potential explanation for warning labels having larger effects than common calorie labels is that people may have difficulty understanding the numbers on traditional calorie labels (Downs, Loewenstein, and Wisdom, 2009; Fagerlin, Zikmund-Fisher, and Ubel, 2011; Korfage et al., 2013), and the labels are therefore not as helpful as an aid to consumers in decision making. Indeed, some recent studies showed that calorie information presented in terms of physical activity equivalents (e.g., number of minutes of running to burn off the calories) are more effective in motivating consumers to choose healthier beverages compared to traditional calorie labels due to improved interpretability (Bleich, Barry, Gary-Webb, and Herring, 2014; Bleich, Herring, Flagg, and Gary-Webb, 2012).

There is evidence that graphic labels may have the strongest effects on behavior. Long before studies were conducted on calorie labeling, graphic labels were found to be more effective than text labels for smoking cessation across a variety of outcomes (Noar et al., 2017; Noar, Francis, et al., 2016; Noar, Hall, et al., 2016; Purmehdi, Legoux, Carrillat, and Senecal, 2017). To examine whether similar patterns generalize to food labels, Thorndike et al. conducted a field

study at Massachusetts General Hospital (MGH). The study used a traffic-light food labeling system based on the 2005 U.S. Department of Agriculture My Pyramid recommendations, labeling every item in the cafeteria as either red, yellow, or green. The study reported that, the proportion of red items purchased dropped from 24% to 21% ( $p < 0.001$ ) during the intervention period, while the proportion of green items increased from 41% to 45% ( $p < 0.001$ ) of all items. (Thorndike et al., 2014)

Another recent study conducted at a hospital cafeteria also showed that more evocative, graphic warning caloric labels on sugary drinks had a much stronger effect at reducing calorie choices, as compared to text warning labels. (Donnelly et al., 2018) While 21.4% of bottled drinks purchased were sugary drinks during the baseline/control period, the percentage was 21.5% during the calorie-label intervention ( $p = 0.84$ ) and 21.0% during the text-warning-label intervention ( $p = 0.66$ ), meaning that neither of these two interventions effectively reduced consumption of sugary drinks. In contrast, the share of sugary drinks was brought down to 18.2% during the graphic warning intervention ( $p < 0.001$ ), which is a 14.8% reduction compared to the baseline consumption.

Based on the inconsistent results of previous studies on calorie labeling and recent studies on graphic labeling, I try test in this study a novel explanation that the ineffectiveness of certain calorie labeling interventions may have little to do with interpretability of the information and may instead be explained by the effects of visual salience on decision making. (Goswami, Dai, and Urminsky, 2017). According to this account, visual salience plays an important role not only because it ensures information to be noticed, but primarily because it facilitates active

deliberation about cues (Shen and Urminsky, 2013) and incorporation of cues into decisions (Weber and Kirsner, 1997). My hypothesis is that visually salient information affects food choices primarily through a reminder effect, prompting people to consider nutrition rather than merely providing new information. If such hypothesis holds true, I expect to find that even non-informative “mere-reminders” yield similar results as salient new information.

## **Data and Methods**

The dataset used in this research was originally collected by Urminsky and Goswami through a 9-week field experiment in 2015 at four on-campus cafeterias at the University of Chicago, namely Gordon Cafe at the Gordon Center for Integrative Science, Harris Cafe at the Harris School of Public Policy, Law School Cafe at the University of Chicago Law School, and Stuart Cafe at the Stuart Hall. Because raw data were collected in the form of digital receipts, to make effective use of the data, I performed in this study subsequent data processing and analysis, including text parsing, data cleaning, coding of caloric information, and analysis of the causal effects of nutritional poster interventions.

In these cafes, many of the food items were already labeled with non-salient calorie information. During the experiment, four different signs, displayed at the entrance to the cafe, were tested. Two of the signs were informational and two were “mere reminders”. Specifically, Sign 1 showed “Do you know? Total Per-Meal (3 meals per day) Calories recommended is typically between 650-800 Calories.” Sign 2 displayed pictures of albacore tuna wraps, turkey and gouda wraps, and chicken Caesar salad, with their Calories per serving information listed. In contrast, Signs 3 and 4 had non-informational, mere-reminder content, with “Calorie information is



available for many of the pre-packaged items we carry in this cafe” and “Do you know how many calories are there in your lunch today?” printed, respectively. (Figure 1)

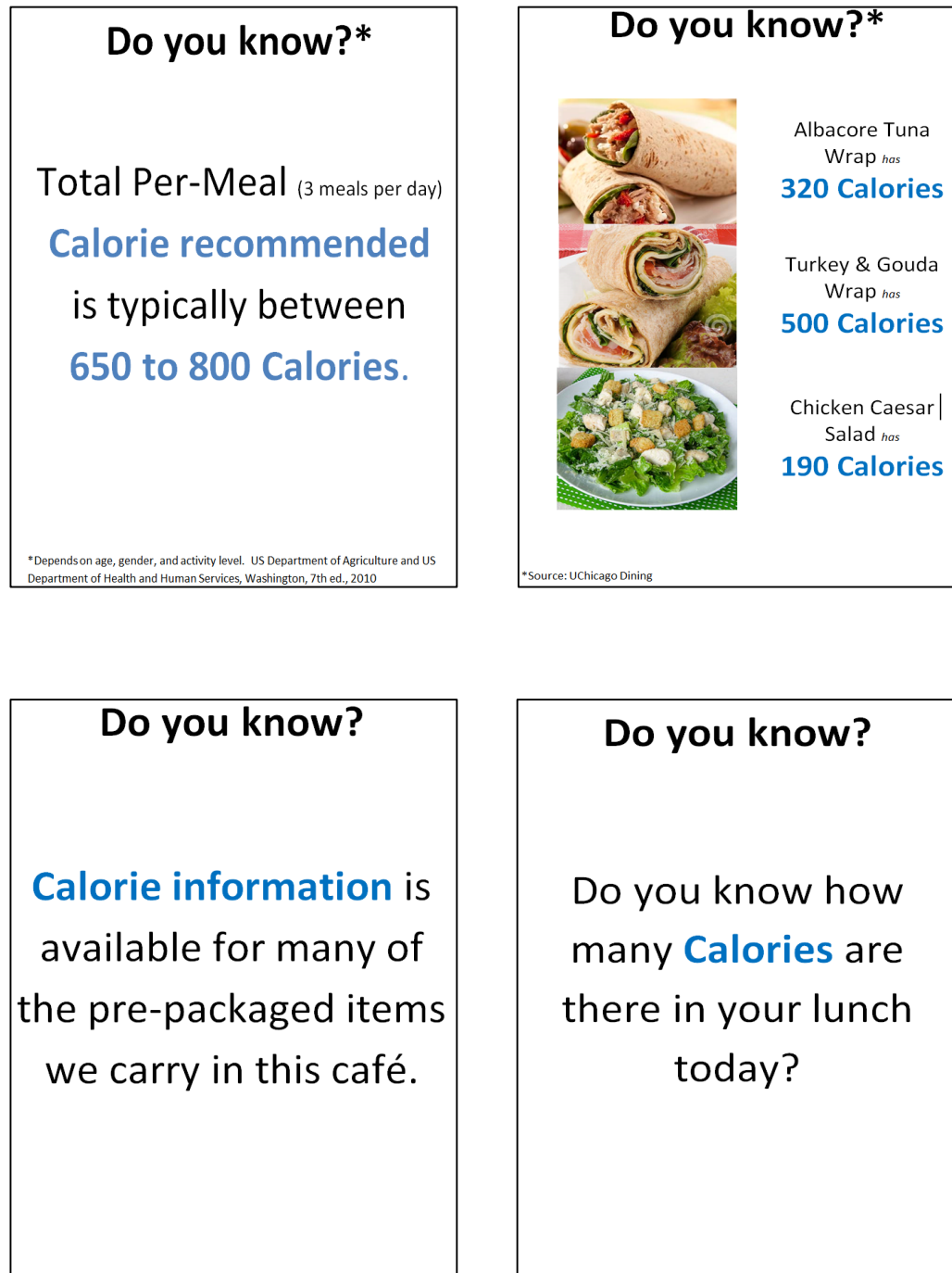


Figure 1: Treatment Conditions: Sign 1 (Upper-left), Sign 2 (Upper-right), Sign 3 (Lower-left), and Sign 4 (Lower-right).

Week of:	12th Jan	19J	26th Jan	2F	9th Feb	16th Feb (no signage)	19F	2nd March
	W1	W2	W3	W4	W5	W6 (Coupon Week)	W7	W8
<b>Law School Cafe</b>	<b>Signage 1</b> Do you know?*		<b>Signage 2</b> Do you know?*		<b>Signage 3</b> Do you know? Calorie information is available for many of the pre-packaged items we carry in this café.	\$1 off Grab-n-Go Wraps Today (Mon, Tues, Wed)		<b>Signage 4</b> Do you know? Do you know how many Calories are there in your lunch today?
<b>Harris School Cafe</b>	<b>Signage 4</b> Do you know? Do you know how many Calories are there in your lunch today?		<b>Signage 3</b> Do you know? Calorie information is available for many of the pre-packaged items we carry in this café.		<b>Signage 2</b> Do you know?*	\$1 off Lunch Today (Mon, Tues, Wed)		<b>Signage 1</b> Do you know?*
<b>Stuart Cafe</b>	<b>Signage 3</b> Do you know? Calorie information is available for many of the pre-packaged items we carry in this café.		<b>Signage 1</b> Do you know?*		<b>Signage 4</b> Do you know? Do you know how many Calories are there in your lunch today?	Eat Healthy! \$1 off Lunch Today (Mon, Tues, Wed)		<b>Signage 2</b> Do you know?*
<b>Gordon Cafe</b>	<b>Signage 2</b> Do you know?*		<b>Signage 4</b> Do you know? Do you know how many Calories are there in your lunch today?		<b>Signage 1</b> Do you know?*	Eat Healthy! \$1 off Salad Today (Mon, Tues, Wed)		<b>Signage 3</b> Do you know? Calorie information is available for many of the pre-packaged items we carry in this café.

Figure 2: Original Design of Interventions (Note: The interventions in red font color were not actually implemented).

The four different signs were displayed at the on-campus cafes on a rotational basis during the first, third, fifth, and eighth week, each followed by a week of washout period with no signs. However, at the Law School Cafe, the sign was only displayed in the first week, as the experiment was halted by the Law School administration in the second week. As shown in Figure 2, during the first week, Sign 1 was displayed at the Law School Cafe, Sign 4 was displayed at the Harris School Cafe, Sign 3 was displayed at the Stuart Cafe, and Sign 2 was displayed at the Gordon Cafe. Similarly, during the third week, Signs 3, 1, 4 were displayed at the Harris School Cafe, the Stuart Cafe, and the Gordon Cafe, respectively. Signs 2, 4, 1 were displayed at the Harris School Cafe, the Stuart Cafe, and the Gordon Cafe, respectively, during the 5<sup>th</sup> week. Finally, during the 8<sup>th</sup> week, we displayed Sign 1 at the Harris School Cafe, Sign 2 at the Stuart Cafe, and Sign 3 at the Gordon cafe. No signage was displayed at any of the cafeterias during 2<sup>nd</sup>, 4<sup>th</sup>, 6<sup>th</sup>, 7<sup>th</sup>, and 9<sup>th</sup> week. During the 6<sup>th</sup> week, coupons were handed out to promote sales of a selected collection of low-calorie products, displaying different messages at the different Cafes.

The original data in the form of electronic receipts were stored in 561 separate text files downloaded from the Café vendors' proprietary POS system and came in two different formats. The data were scraped and parsed into an aggregated receipt-level dataset, which contains 132,294 observations after dropping duplicate records. To effectively store and analyze the information of each electronic check, I used a data structure that is commonly found in natural language processing (NLP). Because there are 348 unique items in our item database, I created a vector of length 348 for each electronic receipt, with an integer on each position of the vector indicating the number of the corresponding item purchased in that transaction. This data structure

enables advantages in vector operations, thereby facilitating some important tasks such as calculating the number of items, summing up the total prices, as well as calorie lookup. The resulting aggregated dataset contains 49 days of sales data from the Spring of 2015, collected during the experiment, as well as 115 days of sales data from Spring and Winter of 2014 to serve as a baseline. For the remaining observations, a unique ID was created using the combination of date, cafe name, and the check number.

After data processing, the effectiveness of calorie labeling was evaluated by testing both average total Calories per transaction and average Calories per USD spent in the weeks when a sign was present to the same measures in the weeks when no sign was displayed. The calorie content for each sold item was matched using the databases at the cafeterias. Following that, data cleaning was performed to identify and exclude outliers and receipts that did not represent consumer purchases. Next, I compared average total calories per transaction during weeks with signage display to the average level during the baseline weeks, as well as the differences in food choices. Furthermore, for the Signs that are found to be effective, I also want to test if there is a spillover effect of calorie labeling. Last but not least, if the results suggest that the “mere-reminder” effect is a primary mechanism of effective calorie labeling, I would also like to test if such “mere-reminder” effect is context-intendent, in contrast to the context-dependent effect of the calorie labels with benchmarking information.

## **Analysis and Results**

Some key independent variables that were controlled for in the regression analyses include total value of the transaction in USD, without tax (*Subtotal*) and the cafeteria where the transaction

took place (*cafe*). The largest recorded single transaction has a *Subtotal* of 252.8 USD, compared to a mean *Subtotal* is 4.049 USD. The median, the 99th percentile, and the 99.9th percentile of *Subtotal* is 3.08, 12.78, and 21.41 USD, respectively. The small number of large transactions (e.g., above \$20) are a concern in the subsequent data analysis for multiple reasons. First, these transactions are statistical outliers that can have a disproportionate effect on the results. Second, I am skeptical that these transactions reflect actual purchases by consumers for their own consumption. While we are unable to get definitive confirmation, based on our understanding of the Cafes, we believe that the very large transactions are either individuals purchasing for multiple people (e.g., a student who is picking up lunch for their study group) or may represent catering orders.

To identify outliers for exclusion in a way that is relatively independent of the hypotheses being tested, we focused on the number of items per receipt. In the data, the number of items per receipt (*#Items*) has a median value of 1 and a 99th percentile of 4. Based on these statistics, we decided that the few ( $< 1\%$ ) of transactions with more than 5 items are very unlikely to be a single meal for an individual and thus should be excluded from our subsequent analysis. We will also discuss the robustness of the results to this assumption.

The primary intended dependent variable in this study is the total calories of the items on each receipt. However, many receipts reported “miscellaneous” as a product category. Each item was supposed to be rung up in the café by pressing one of the buttons on a large programmable keypad linked to that item (the Cafes did not use UPC scanning). Our understanding is that items were rung up as “miscellaneous” primarily when the cashier could not find the item on the

keypad and found it easier to just type in the price. When individual items could be uniquely matched to a price, we used the price to infer the item and assign the calories. Among all 130,891 transactions with a positive *Subtotal* value, 45,856 transactions contained at least one miscellaneous item that does have a corresponding calorie content in our database and thus require imputation.

To impute the calorie content of the miscellaneous items, I first calculated *Subtotal* and total Calories for each receipt after excluding all the miscellaneous items, and then fitted a linear model with no intercept to predict the calorie content of miscellaneous items based on their prices (Figure 3). The training set of the linear model consists of all the transactions that have positive *Subtotal* values after excluding miscellaneous items, and the resulting linear model had a slope of 69.142 (e.g., 69 calories per US dollar). The new variable that denotes the calorie content of each receipt after the imputation procedure is named as *Predicted\_Total\_Calories*. The median of *Predicted\_Total\_Calories* is 318 kcal, and the mean is 294 kcal. Other dependent variables to analyze include calories per dollar spent (*Calories\_per\_Dollar*), which is calculated as  $Predicted\_Total\_Calories / Subtotal$  for all transactions with positive transaction value (e.g., excluding reimbursement receipts).

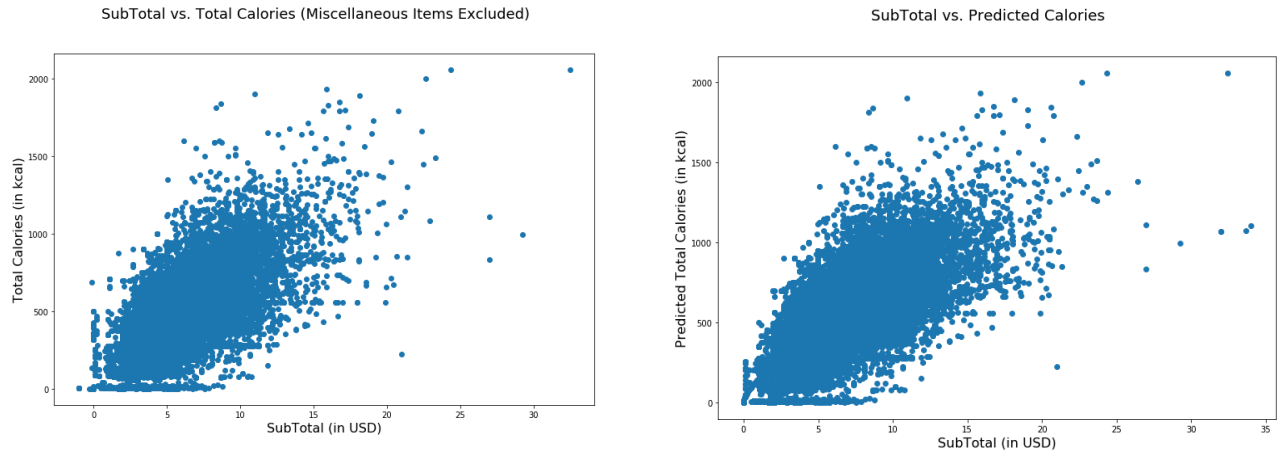


Figure 3: *Subtotal vs. Total Calories with Miscellaneous Items Excluded (Left); Subtotal vs. Predicted Total Calories (Right).*

Next, I aggregated the receipt-level data into a Café-date-level dataset, with each observation uniquely identified by the combination of date and cafeteria name. The resulting Café-date-level dataset contained 569 observations. For each observation in the Café-date-level dataset, *Predicted\_Total\_Calories* and *Subtotal* were calculated as the mean of the *Predicted\_Total\_Calories* and *Subtotal*, respectively, of all the recorded transactions of the corresponding observations. After that, *Calories\_per\_Dollar* was calculated as  $Predicted\_Total\_Calories / Subtotal$ . For each observation, we also created a variable *Count* to indicate the total number of recorded transactions that corresponds to the specific date and café. Within this dataset, the number of transactions per day varied substantially. For example, the observation with the least transactions (Law School cafe on March 3, 2014) has only 21 recorded transactions, and the observation with the most transactions (Law School cafe on Feb 13, 2014) had 431 recorded transactions. Because of this large discrepancy within the total number of transactions for each observation in the Café-date-level dataset, instead of fitting OLS models,

we choose to fit weighted least squares (WLS) linear models on the Café-date-level data, using *Count* as the weight.

Linear regressions were performed on the Café-date-level dataset using predicted total Calories per transaction as the outcome. Because the experiment was halted at the Law School cafe very early, we decide to first exclude all the observations at the Law School cafe completely from our regression analysis, and to later bring Law School cafe back into the analysis for the purpose of baselining and sensitivity analysis. The regression result suggests that there was a significant reduction in average total Calories per transaction during the display of Sign 1 and Sign 4 (Table 1, Model 5). Specifically, Sign 1 has an estimated effect of reducing total predicted Calories per transaction by 9.209 kcal ( $p = 0.013$ ), and Sign 4 has an estimated effect of reducing total predicted Calories per transaction by 8.734 kcal ( $p = 0.027$ ) (Appendix II, Table 1). According to the regression result, displaying Signs 2 and 3 was not associated with a significant reduction on calorie consumption during the experiment. However, it is noteworthy that the effects of Signs 1 and 4 are only statistically significant when we control for the fixed effect of week of quarter (as in Models 4 and 5). Because the estimated effects of the signs are confounded with week of quarter fixed effect, we believe that Models 4 and 5 yield more unbiased estimates of the poster effects compared to Models 1, 2, and 3. Furthermore, when we code the four signs as a single treatment called ‘Signage’, the regression results indicate the overall the Signs had a small but still significant impact on reducing the level of total Calories per transaction (-5.332 kcal,  $p = 0.041$ ) (Table 2).



Table 1: Summary of Linear Regression Results for Predicted Total Calories per Transaction  
(Café-date-level Data, with Law School Excluded)

Variable	Confounders				
	Model 1	Model 2	Model 3	Model 4	Model 5
	<i>Qtr</i>	<i>Qtr + café</i>	<i>café:Qtr</i>	<i>café:Qtr + WkofQtr</i>	<i>café:Qtr + WkofQtr + DayofWk</i>
<i>Intercept</i>	-12.126	-35.450***	-36.54***	-38.8123***	-39.071***
<i>SubTotal</i>	72.566***	78.6397***	74.647***	74.4841***	74.538***
<i>2014Spring</i>	1.315	2.0633	16.593***	15.1887***	15.193***
<i>2014Winter</i>	11.235***	12.5543***	18.912***	15.9747***	15.887***
<i>Signage1</i>	-5.906	-5.3032	-5.668.	-9.1235*	-9.209*
<i>Signage2</i>	-0.272	0.0196	-0.321	-1.2564	-1.442
<i>Signage3</i>	-0.845	-0.2728	-0.391	-1.7268	-1.855
<i>Signage4</i>	-7.081	-7.3593.	-6.669.	-8.5440*	-8.734*
<i>GCIS:Coupon</i>	3.274	0.5977	2.876	-0.0634	-0.224
<i>Harris:Coupon</i>	22.010*	21.8715***	10.441	7.8146	7.690
<i>Stuart:Coupon</i>	-1.886	4.2914	12.002	9.0801	9.905
<i>R</i> <sup>2</sup>	0.823	0.848	0.884	0.891	0.893

\**p* < .05 \*\**p* < .01 \*\*\**p* < .001

Table 2: Summary of Linear Regression Results for Predicted Total Calories per Transaction  
(Café-date-level Data, all Signs as a Single Treatment, with Law School Excluded)

Variable	Confounders				
	Model 1	Model 2	Model 3	Model 4	Model 5
	<i>Qtr</i>	<i>Qtr + café</i>	<i>café:Qtr</i>	<i>café:Qtr + WkofQtr</i>	<i>café:Qtr + WkofQtr + DayofWk</i>
<i>Intercept</i>	-12.02	-35.334**	-36.39***	-37.9716***	-38.208***
<i>SubTotal</i>	72.54***	78.610***	74.62***	74.4607***	74.508***
<i>2014Spring</i>	1.31	2.061	16.56***	15.1684***	15.170***
<i>2014Winter</i>	11.23***	12.552***	18.88***	15.9341***	15.843***
<i>Signage</i>	-3.52	-3.203	-3.26	-5.1863*	-5.332*
<i>GCIS:Coupon</i>	3.27	0.610	2.93	-0.0151	-0.177
<i>Harris:Coupon</i>	22.00*	21.846***	10.38	7.7448	7.620
<i>Stuart:Coupon</i>	-1.87	4.292	11.98	9.0652	9.889
<i>R</i> <sup>2</sup>	0.822	0.847	0.883	0.890	0.891

\**p* < .05 \*\**p* < .01 \*\*\**p* < .001

Linear regression models were also fitted to predicted Calories per USD spent as the outcome, using *TotalSales* as the weight for each observation in the Café-date-level data. According to the regression results, both Sign 1 and Sign 4 were both associated with a significant decrease in the level of predicted Calories per USD spent during the experiment (Table 3, Model 5). The final model reported an estimated effect of -2.100 kcal/USD for Signage 1 ( $p = 0.013$ ) and an estimated coefficient of -1.986 kcal/USD for Sign 4 ( $p = 0.027$ ), suggesting that the customers chose lower-calorie items during the display of Signage 1 and Signage 4 compared to the baseline level. Moreover, regression results predicting *Subtotal* finds no significant effects of any of the signs on the average level of spend or on the average number of items purchased per transaction. These results suggest that Signs 1 and 4 reduced the calories purchased primarily by prompting customers to purchase lower-calorie items, rather than reducing the amount they spent.

Table 3: Summary of Linear Regression Results for Avg. Calories per USD Spent  
(Café-date-level Data, with Law School Excluded)

Variable	Confounders				
	Model 1	Model 2	Model 3	Model 4	Model 5
	<i>Qtr</i>	<i>Qtr + café</i>	<i>café:Qtr</i>	<i>café:Qtr + WkofQtr</i>	<i>café:Qtr + WkofQtr + DayofWk</i>
<i>Intercept</i>	67.8412***	62.4739***	62.1328***	61.428***	61.39198***
<i>SubTotal</i>	0.4454	1.8349**	1.0286*	1.018*	1.02716*
<i>2014Spring</i>	0.2887	0.4298	3.4127***	3.111***	3.10699***
<i>2014Winter</i>	2.5482***	2.8269***	3.9261***	3.286***	3.25614***
<i>Signage1</i>	-1.3483	-1.2062	-1.2876.	-2.084*	-2.09962*
<i>Signage2</i>	-0.0515	0.0412	-0.0564	-0.233	-0.27285
<i>Signage3</i>	-0.2087	-0.0759	-0.0671	-0.279	-0.30826
<i>Signage4</i>	-1.5621	-1.6219.	-1.4540.	-1.943*	-1.98611*
<i>GCIS:Coupon</i>	0.7466	0.1538	0.6690	0.030	-0.00173
<i>Harris:Coupon</i>	5.4539**	5.4294**	2.7031	2.130	2.09100
<i>Stuart:Coupon</i>	-0.3495	0.7880	2.3417	1.695	1.89614
<i>R<sup>2</sup></i>	0.14	0.259	0.427	0.464	0.472

\* $p < .05$  \*\* $p < .01$  \*\*\* $p < .001$

While the analyses above that I carried out in my MA thesis confirmed our initial hypothesis that effective visually salient labeling mainly affects the level of calorie consumption through changing the food choices of the customers, I also did follow-up analyses and additional hypothesis testing to further our understanding of the mechanism of effective labeling. For example, while I assumed in these analyses above that there are no effects of the posters when the posters are absent, it is in fact possible that consumers remain affected by the posters that had been previously displayed after they are removed. Therefore, to test these potential spillover effects of the posters, I also recoded the weeks following an intervention period as the respective washout periods. However, it is worth mentioning that doing this inevitably reduces the precision of the estimates of the poster effects, since only Week 1 of Spring 2015 can be used as the baseline, when controlling for Quarter fixed effects.

In order to minimize the confounding effect of Week 1 on the estimates, it is thus necessary to introduce week of quarter (*WkofQtr*) as a covariate in the models. The regression results with washout periods is shown below (Table 4). While Signs 1 and 4 both had similar effects in reducing calorie consumption during the intervention period, Sign 4 seemed to have a stronger spillover effect compared to Sign 1. This may be explained by the fact that because Sign 4 only serves as a “mere reminder”, its effect may persist even when Sign 4 is no longer exhibited, whereas Sign 1 may have a relatively small spillover effect because few people remember the informational content of Sign 1 when it is no longer exhibited.

Table 4: Summary of Linear Regression Results for Predicted Total Calories per Transaction  
(Café-date-level Data, with Law School Excluded, with Washout Periods)

Variable	Confounders			
	Model 1	Model 2	Model 3	Model 4
	<i>Qtr</i>	<i>Qtr + café</i>	<i>café:Qtr</i>	<i>café:Qtr + WkofQtr</i>
<i>Intercept</i>	-6.08	-34.475***	-32.50***	-32.223***
<i>SubTotal</i>	72.30***	79.191***	74.51***	74.478***
<i>2014Spring</i>	-4.67	-4.307	8.77*	8.539*
<i>2014Winter</i>	4.60	5.604	9.44*	9.142*
<i>Signage1</i>	-13.89*	-14.130**	-15.56**	-15.848***
<i>S1 Wash-out</i>	-3.36	-3.388	-6.79	-7.022
<i>Signage2</i>	-5.96	-6.394	-7.69	-8.080.
<i>S2 Wash-out</i>	-5.18	-6.228	-8.57.	-8.745.
<i>Signage3</i>	-7.39	-7.368	-8.16.	-8.476.
<i>S3 Wash-out</i>	-6.21	-6.209	-8.60.	-8.813.
<i>Signage4</i>	-14.90*	-15.611**	-14.97**	-15.346**
<i>S4 Wash-out</i>	-8.83	-9.960.	-10.21*	-10.489*
<i>GCIS:Coupon</i>	-1.80	-5.739	-5.42	-5.852
<i>Harris:Coupon</i>	16.96.	15.551.	2.46	2.086
<i>Stuart:Coupon</i>	-7.02	-2.230	3.71	4.325
<i>R<sup>2</sup></i>	0.83	0.856	0.892	0.894

\* $p < .05$  \*\* $p < .01$  \*\*\* $p < .001$

Moreover, because the previous analyses results suggest that even non-informational calorie labels can reduce the average level of calorie consumption through reminding people of their health and diet, I am also curious about whether such effect is dependent on the context of labels. For example, while Sign 4 only asks people to think about the calorie content in their lunch, if the sign is able to make people aware of their diet, then people may also consume significantly less calories even when it is not lunch time. On the contrary, informational labels such as Sign 1 and Sign 2 should effectively reduce people's calorie intake in their matching contexts. According to my hypothesis, Sign 1 should only be effective around lunch time but Sign 4 should have relatively uniform level of effectiveness throughout a day.

To test my hypothesis above, I introduced the interaction term between the treatments and hour into my linear regression models. While the result suggests that Sign 1 indeed had a significant effect on reducing calorie intake around the lunch time (from 12:00 to 13:00), it also shows that Sign 1 significantly raised the average level of calorie intake between 9:00 and 10:00 (Figure 4). I think it might be caused by the fact that many students who have late breakfast during that time instead purchased more food after seeing the benchmarking data of Sign 1 (because it is about calorie content of a meal). Another surprising result is that, while Sign 2 was found to be ineffective in our previous analyses, it in fact strongly reduced the average level of calorie intake during dinner time (from 17:00 to 18:00). I believe it is due to the fact that people mostly purchase the hot food on Sign 2 during this time, but it needs to be confirmed in a follow-up analysis. Last but not least, the results also suggest that Sign 4 was effective only from 11:00 to 14:00, as opposed to what I theorized before. The result suggests that contrary to my hypothesis, even non-informational calorie labels are subject to the limitations of their contexts and tend to be ineffective when the context becomes irrelevant. Moreover, Sign 3 was found to be ineffective throughout the day.

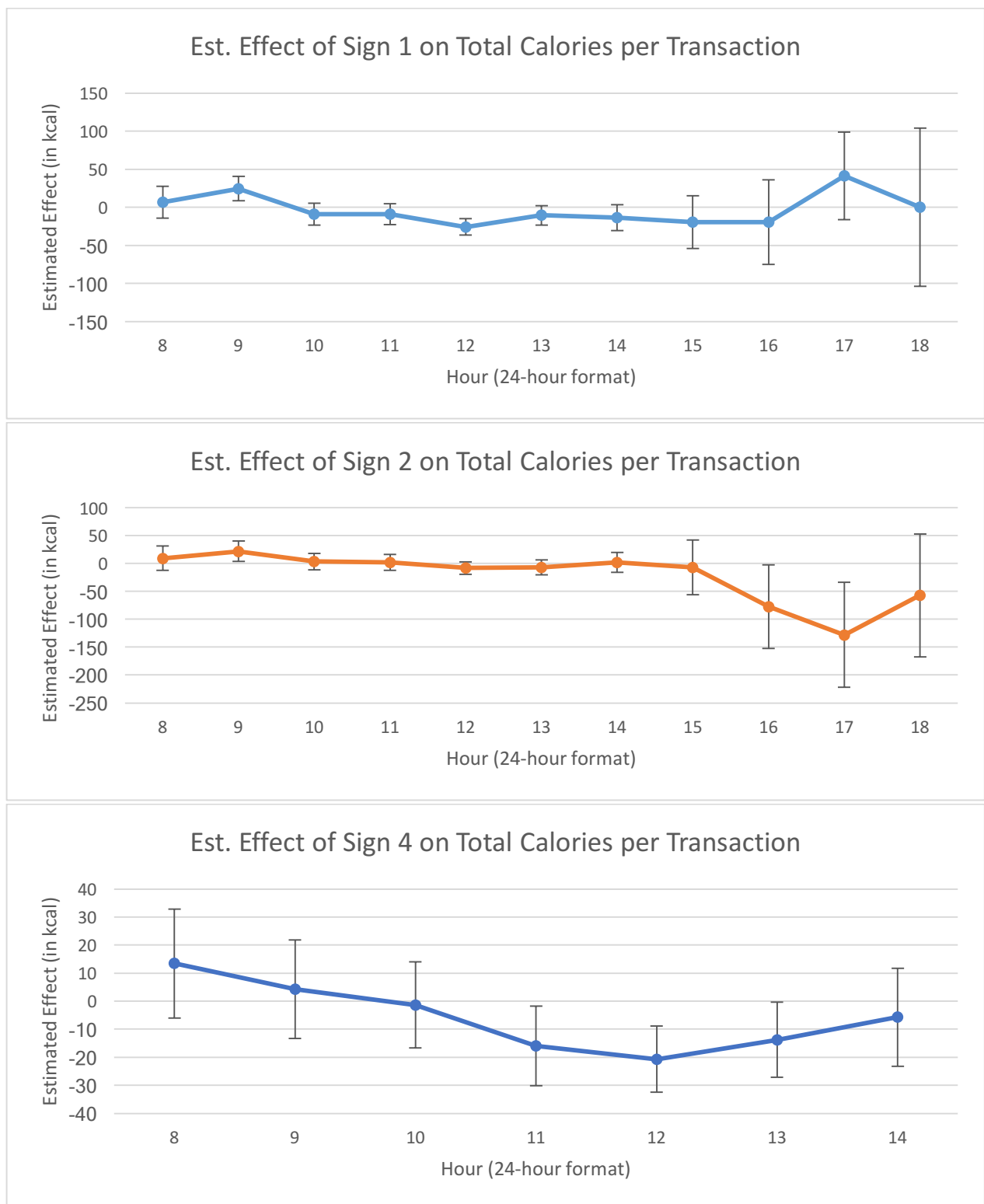


Figure 4: Estimated Effect of Signs on Average Total Calories per Transaction During Different Time of a Day: Sign 1 (Upper); Sign 2 (Middle); Sign 4 (Lower).

## **Discussion**

The analyses results confirm the first assumption that “mere-reminder” calorie labels and informational calorie labels yield similar effects on reduction of calorie consumption, suggesting that a primary mechanism of effective calorie labeling is through reminding people of a healthy diet. Signage 1 and 4 both have estimated effects that are comparable to the average effect of calorie labeling from past research conducted in restaurant settings (Long et al., 2014). The ineffectiveness of Sign 2 may be explained by the fact that providing information on specific menu items on Sign 2 was too specific to be relevant to most people’s purchasing decisions at the cafeterias, given that there were wide collections of foods and drinks offered at each cafeteria. Moreover, the ineffectiveness of Sign 3 may be due to the fact that it does not directly provide any informational content, nor does it strongly provoke people to think about their own diet. However, it is important to note that the estimated causal effects of the posters were not significantly different from each other.

Moreover, the results further suggest that effective calorie labeling affects the level of calorie intake mainly through changing the mix of foods that customers choose, instead of influencing their spending level. This result has an important implication: if these results generalize across contexts, compared to other public policies that targets the obesity problem on a population level, implementing calorie labeling has the advantage of being relatively risk-free for retailers and restaurants.

Furthermore, the results also indicate that the effectiveness of non-informational calorie labeling is still highly dependent on how relevant the context of decision making is to the content of the

label. This finding contradicts with the result from another field study conducted by Goswami and Urminsky that the “mere reminder” labels can help reduce the level of calorie consumption even when the context of decision making is irrelevant to the labels (Goswami, Dai, and Urminsky, 2017). A possible explanation for these seemingly contradictory results is that, people are more likely to be aware of the messages of the “mere reminder” calorie labels when the setting is more relevant to the content of the labels. Because participants were asked to evaluate the calorie content of some sandwiches and make a hypothetical choice after seeing the calorie labels in that study, salience of the “mere reminder” labels was thus assured. In this study, however, consumers who viewed Sign 4 in the morning were probably less aware of the message compared to those who viewed Sign 4 during lunch time. This hypothesis that relevance of the environment to the content of calorie labels can significantly influence the level of salience of the labels needs further confirmation through follow-up studies.

The results also suggest that the policy makers’ recent emphasis on providing information to correct consumers’ mistaken beliefs about calories may be misguided. For example, while the FDA had to push back the deadline for restaurants and retailer to post calories because of the time required to determine accurate calorie counts to post (Dennis, 2015), this study suggests that effective policies may need to focus on salience of disclosures because providing approximate but salient calorie information, or even just non-informative reminders, is likely to be more effective than an accurate but non-salient disclosure.

Like many previous studies on calorie labeling, however, the original field experiment conducted by Goswami and Urminsky has several noteworthy limitations. First, while the researchers tried



to make all the interventions visually salient by using relatively large font and poster sizes, because the nature of such experiment did not allow an attention check, there was no way of guaranteeing that consumers saw and read the posters. As a result, while visual salience may be a strong moderator of the effect of labeling on calorie consumption, there was in fact no way of observing or estimating the level of visual salience in the experiment. And the conclusions from this explorative data analysis also have to rely on the assumption that the level of visual salience is relatively consistent for all four signs, which might not hold given the fact that there are fundamental differences between the designs of the four posters, as well as differences between the designs of the cafeterias where the interventions took place.

Another limitation of the original field experiment comes from the fact that consumers were not randomly assigned to the treatments and that there is no background information of the customers to adjust for any potentially confounding covariates in my data analysis. While the researchers attempted to address this issue by rotating the posters across three different cafes and across weeks to control for simple effects of week or Café, during the test period, as confounds. However, the design cannot account for any week-specific Café effects as confounds. Therefore, the potential problem of unobserved confounders limits the inferences about the causal effects of the posters on the reduction in the average level of calorie consumption.

In sum, this explorative analysis provides evidence that visually salient nutritional posters can lead to small but significant reduction in the level of calorie consumption, and that such effective “nudges” can be achieved through merely reminding people of their health and diet. Moreover, the study also confirms the hypothesis that effective calorie labeling changes people’s calorie

consumption behavior through altering food choices instead of reducing the total amount of spend on food. Last, the results also suggest that the effectiveness of calorie labeling is context-dependent for both informational and non-informational labels. Because this finding is seemingly contradictory to the results of previous research on calorie labeling, potential follow-up studies should be conducted to test whether salience of a calorie label is dependent on the relevance of the environment to the content of the label.

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