HELPING CONSUMERS USE NUTRITION INFORMATION

Effects of Format and Presentation

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ABSTRACT
Recent policy efforts aimed at curbing obesity rates in the United States have focused primarily on mandated posting of calorie information. However, the research to date suggests that such interventions have relatively little impact on consumer choices. This paper explores whether alternative approaches to communicating nutrition information might increase its impact on consumer choice as well as whether the presence of calorie information affects the effectiveness of other policy approaches. Study 1 tests a variety of methods for conveying nutrition information to promote choice of lower-calorie snack items, including basic numerical information, contextualized numeric information, and heuristic cues such as traffic lights and letter grades. Results suggest that using heuristic cues to communicate the information holds special promise for changing behavior. Study 2 examines the interactive impact of calorie labeling and choice architecture (presenting options in caloric sequence), and shows that calorie information has a beneficial impact, but only when organization of snacks by caloric content facilitates use of the information. These results speak to the importance of understanding how combinations of policy approaches can trigger nonobvious consumer responses, activating different psychological processes when implemented together or individually. They suggest that novel policies to enhance the effectiveness of existing legislation deserve further investigation.

KEYWORDS: menu labeling, nutrition, nudge
JEL CLASSIFICATION: C93, D83, I12, I18

I. Introduction

Since the 1980s, rates of obesity have risen dramatically in the United States (Flegal et al. 2010; Ogden et al. 2013), with profound consequences for public health and health-care spending (Wang et al. 2011). Although different policy levers have been applied to the problem, such as programs to improve food served at schools (Gortmaker et al. 2011), the most significant policy aimed at the obesity problem has been the enactment of regulations mandating posting of calorie information at chain restaurants. These regulations are being implemented nationwide as part of the Affordable Care Act (ACA) of 2010.

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Early introduction of calorie posting requirements in New York City and King County (Seattle) served as "natural experiments" that social scientists used to study the impact of the policy, in part to predict the likely impact of national posting. Most of these studies have not found that calorie posting had much of an impact on diners' selections (Kiszko et al. 2014; Swartz, Braxton, and Viera 2011). For example, in a study of 14 different fast food chain restaurants in low-income New York neighborhoods (and control restaurants in New Jersey) before and after menu labeling went into effect, Elbel et al. (2009) found that patrons reported noticing and responding to the labels, but did not find a drop in the calorie content of orders, even among those who self-reported paying attention to the labels. Nor do the labels appear to lead customers to avoid fast food dining, as evidenced by a lack of drop in sales figures (Finkelstein et al. 2011).

The largest and most careful study (Bollinger, Leslie, and Sørensen 2011) examined drink and food purchases at Starbucks before and after labeling went into effect in New York City, using a data set that contained 100 million transactions, thus enabling the detection of extremely small effects. The effects were, indeed, small but systematic: a 14-calorie reduction in food purchases per transaction, but no impact on drink calories. About three-quarters of the reduction in food calories arose from choices to forego food options altogether, rather than switching to lower-calorie options. Data from the same study showed that individual consumers who changed their behavior in New York City also did so when they frequented locations outside of New York where labeling was not in place, suggesting that the effect was driven by learning or habit, and not by the immediate presence of the information.

Behavioral economists have explored alternative approaches to changing behavior, focusing more on directing behavior through subtle, noncoercive changes in the decision-making environment (e.g., Thaler and Sunstein 2008). Just as behavior in the physical environment can be affected by subtle changes in physical architecture, so can cognitions be guided by carefully structuring how options present themselves through so-called choice architecture (Thaler and Sunstein 2008; Johnson et al. 2012). An early observation of the power of structuring choices came from the comparison of rates of consent for organ donation in countries that require citizens to opt in (ranging from 4 percent to 28 percent), relative to much higher rates in countries that require citizens to opt out (86–99 percent), with six out of seven countries achieving consent rates at 98 percent or higher (Johnson and Goldstein 2003). This finding, confirmed experimentally, shows a very strong effect of simply changing the default outcome of a choice. Although citizens in these countries have identical options—to consent or not consent for organ donation—the way in which the choice is presented simply "nudges" them toward one option, while leaving the other option available to them.

Such nudging often capitalizes on known biases in decision making, such as the tendency to stick with the default response in the case of organ donation. Regulatory processes can be designed to take advantage of a range of such biases (see, e.g., Volpp et al. 2011), structuring decisions so that succumbing to known biases will favor choices favored by the "choice architect," while not restricting the freedom of choice of those who have well-established preferences (Camerer et al. 2003).

Nudges appear well suited to changing eating behavior (Downs and Loewenstein 2011; Liu et al. 2014), including strategies such as trayless dining (Just and Wansink 2009), decreased portion sizes (Schwartz et al. 2012; Wansink and Kim 2005), physical arrangement of foods (Sobal and Wansink 2007), and making healthful options easier to choose than less healthful ones (Rozin et al. 2011; Thorndike et al. 2014; Wisdom, Downs, and Loewenstein 2010).

Although several of these approaches are found to alter consumer choices in lab and field settings, none holds much promise of being mandated by government policy. As a result, despite its apparently limited impact on behavior, calorie labeling remains, for the short run, the best hope for changing behavior on a mass scale (Kersh 2009). Thus, in this paper, we examine format and presentation of calorie labels, examining both presentation of the information and how the information may interact with aspects of choice architecture aimed at changing behavior.

Presenting information in more effective ways is one of the key applications of behavioral economics to public policy, along with nudges and using insights from psychology to "supercharge" economic incentives (Downs and Loewenstein 2011). Policies mandating information disclosure are widespread, not only in the domain of food but also in a wide range of other areas such as health and safety, and privacy. Although research has yielded numerous insights into how information disclosure can be made more effective, most empirical investigations of information disclosure policies have found that disclosure is ineffective in changing the behavior of those who receive it (see Loewenstein, Sunstein, and Golman 2014), or even that, in certain situations, it backfires, producing the opposite of its intended effects (see, e.g., Loewenstein, Cain, and Sah 2011; Loewenstein, Sah, and Cain 2012 in the context of conflict of interest disclosures).

Given widespread implementation of calorie posting, despite its apparently limited effectiveness, tests of alternative ways to enhance its impact may be of value. We report results from two such tests. The first compares the effectiveness of different ways of expressing calorie information. Prior research has drawn attention to the difficulties consumers have in making sense of nutrition information (Feunekes et al. 2008). Calorie information, alien to many consumers in any form (e.g., when provided on packaged goods), is often even more difficult for consumers to make sense of when posted in restaurants, where consumers order multiple items (the calories of which should, logically, be summed); where some items, such as drinks, often have ranges of calories that depend on portion size and whether the item is "diet"; and where some items are customizable (e.g., toppings for pizza, mayonnaise on sandwiches) (Auchincloss et al. 2013; Cohn et al. 2012). Given the challenges for consumers of using raw calorie numbers to make decisions, we investigated whether alternative approaches to communicating nutrition information might increase its usefulness or impact for consumers, similar to how presenting smokers with lung volume measurements as "lung age" was found to achieve better quit rates than presenting smokers with more conventional pulmonary function measurements (Parkes et al. 2008).

A range of alternative formats have been explored for presenting nutrition information, typically by providing calorie labels and adding additional guidance, such as color coding analogous to traffic lights (Liu et al. 2012; Morley et al. 2013), and highlighting the exercise required to burn off an item's calories (Dowray et al. 2013). However, most formats have been studied in hypothetical or laboratory settings where experimental demand might lead to exaggerated estimates of effect sizes; there have been few field investigations of alternative strategies for presenting calorie information (Hawley et al. 2013).

Two field studies do, however, provide limited support for nonnumeric information formats. One study found that color-coding items by amalgamating multiple nutritional criteria led to a shift toward generally healthier items, especially among drink choices (Thorndike et al. 2012). Another study found that a variety of labeling approaches that highlighted the unhealthy nature of sugar-sweetened beverages led to a shift toward choosing water (Bleich et al. 2012).

Our second test examines the interaction of calorie information and choice architecture, addressing an issue of great importance in the current policy environment in which the simultaneous implementation of different policies runs the risk of producing unexpected and unintended interactions. Prior research has, in fact, documented interactions between calorie labeling and other types of interventions. One study (Giesen et al. 2011), for example, found that both labeling calories and taxing high-calorie options led to calorie reductions in hypothetical food purchases, but that the effects were sub-additive. Another, focusing mainly on the impact of voluntary downsizing of side dishes in fast food lunch orders (Schwartz et al. 2012), found not only that calorie labels alone did not lead to a reduction in calories purchased, but also that the downsizing offer was less likely to be accepted when calorie information was provided.

Both of the studies reported in this paper examine the impact of different labeling and nonlabeling policy approaches on a common and relatively simple choice facing many consumers: a midday snack. Snacking is of substantial importance, given that, as obesity levels have increased, consumption of snack foods has increased faster than any other category of food (Cutler, Glaeser, and Shapiro 2003). In Study 1 we evaluate various numeric approaches to conveying nutrition information, testing the efficacy of both basic and contextualized numeric information as well as heuristic approaches to conveying that information. In Study 2 we examine the impact of calorie information when combined with an alternative approach intended to nudge consumers toward healthier choices—presenting lower-calorie items earlier on the menu—which prior research has found to boost item selection (Ditmer and Griffin 1994).

II. Study 1

A. METHODS

A.1. PARTICIPANTS. Participants were 921 pedestrians recruited from busy public locations, aged 18 to 87 (mean = 31), 45 percent female, 66 percent white, 12 percent Asian, 10 percent African American, and 34 percent overweight or obese based on self-reported height and weight.

A.2. PROCEDURE. A mobile research lab was stationed in shopping and recreational neighborhoods around Pittsburgh. Passersby were offered a free snack in return for completing a short survey. We attached our study to a variety of different studies that were conducted using the mobile lab, none of which pertained to food. After completing whatever study was being run, participants were randomly assigned to one of 10 experimental treatments of the current study. These varied the information provided about the calorie content of a list of seven snacks, ranging from 40 to 470 calories.[1] In a control group, the seven snacks were depicted with photographs, but with no nutritional information. Nine other treatments presented the same photos along with calorie information as basic numeric information (three techniques), contextualized numeric information (three techniques), or heuristic cues (three techniques). All menu options were listed in the same arbitrary sequence across all treatments. Finally, participants provided basic demographic information.

A.3. BASIC NUMERIC INFORMATION. We included three formats offering simple raw calorie numbers for each item: one with *calorie labels* for each snack, one with calories plus a reference guideline for recommended *daily intake* of 2,000 calories per day, and the last with calories plus a recommended daily *snack intake* (assuming 10 percent of intake devoted to snacks) of 200 snack calories per day. The use of a daily calorie guide has been generally recommended (Kiszko et al. 2014; Nestle 2009), and has shown mixed results in controlled laboratory experiments and hypothetical choice studies (Morley et al. 2013; Prins et al. 2012; Wisdom, Downs, and Loewenstein 2010), but disappointing results in a field study (Downs et al. 2013). Recommendations appear to work by providing cues to behavior, not by facilitating use of calorie information (Downs et al. 2013; Wisdom, Downs, and Loewenstein 2010).

A.4. PARTICIPANTS CONTEXTUALIZED NUMERIC INFORMATION. Three additional formats were tested using values that we expected to be more meaningful to consumers than the raw numbers alone: the snack's calculated *percentage of daily calories* recommended, the snack's calculated *percentage of snack calories* recommended, and the number of minutes running on a *treadmill* required to burn the item's calories. Percentages have shown benefits in some contexts (Bleich et al. 2012), and interference in others (Morley et al. 2013). Exercise time showed promise in one study (Bleich et al. 2012) but not another (Jue et al. 2012), and is popular among consumers (Dowray et al. 2013), perhaps because people are surprised at how long one needs to exercise to burn a relatively small number of calories.

A.5. HEURISTIC INFORMATION. We included three formats using symbols to categorize the snack options based on caloric content: a *letter grade* (from A to F), expected *body size* images (Stunkard, Sørensen, and Schulsinger 1983) associated with routine eating of each item, and *traffic light* ratings (green, yellow, or red). We expected that the heuristic information would be more intuitive and more easily processed by consumers (Borgmeier and Westenhoefer 2009), as no computational processing was required.

Participants were randomly assigned to one of these ten treatments, with the sample size for basic calorie information doubled relative to the other labeling treatments, to be sure that this popular policy approach was sufficiently powered for comparison with other treatments.

1 Another two treatments collected at the same time varied the ordering of the snacks; these ended up serving as a pilot study for Study 2 reported in this paper, and are not reported here.

A.6. STATISCAL ANALYSES. The effectiveness of each category of intervention was tested using an ordinary least squares (OLS) hierarchical linear regression predicting snack calories from the three categories, with no calorie information controls as the referent group, and Šidák-corrected post-hoc comparisons between the intervention categories. An additional regression, using a dummy code for each of the nine interventions, provides explanatory value at a more detailed level, although the individual interventions had relatively small sample sizes, so the study was not powered to observe what we expected to be small differences between individual treatments. For both regressions, we also tested a separate model including demographic controls, to assess the robustness of effects; sample size is slightly reduced for these analyses due to missing data.

B. RESULTS

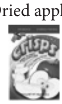
The top row of Table 1 shows the mean snack calories consumed in each experimental treatment; the remaining rows show the distribution of snacks chosen in each treatment. Compared with controls, participants consumed fewer mean snack calories when given either the contextualized numeric information (24 fewer calories, $t(917) = 2.06$, $p = .039$), or the heuristic information (30 fewer calories, $t(917) = 2.56$, $p = .011$). These results remain significant when controlling for demographics ($p = .047$ and $p = .007$, respectively). Basic numeric information was not significantly different from controls (16 fewer calories, $t(917) = 1.51$, $p = .131$), nor were any of the three categories of intervention different from one another in post-hoc tests (all $p > .70$).

Table 2 presents results breaking these categories down into individual strategies. The coefficients for all nine treatments are negative, although not all interventions were statistically significantly different from controls. Calorie labeling achieved a decrease of 22 calories, which was only marginally significant ($p = .093$) without controls and not significant when demographic controls were included ($p = .217$). Percentage of recommended daily snack calories led to a 44-calorie decrease ($p = .006$) and traffic light images led to a 34-calorie decrease ($p = .031$), both of which remained significant after controlling for demographics. Letter grades led to a 33-calorie decrease ($p = .038$), but this effect was not significant after controlling for demographics ($p = .095$). None of the other formats, individually, approached significance (all $p > .20$).

C. DISCUSSION

The results of this first study indicate that labels translating caloric content into easier-to-use formats, such as heuristic representations or numbers in context, encourage healthier snack choices. Although the effects aren't large in absolute value, they are relatively large relative to average snack calories, and also relative to the 14-calorie reduction found in the prior study that found a significant impact of calorie labeling (Bollinger, Leslie, and Sørensen 2011). In contrast, basic numeric information did not perform as well, and recommendations appear to do little to promote use of posted calorie information. Traffic lights and, to a lesser degree, letter grades both emerged as promising approaches. Most policy instantiations of traffic lights have used them to designate nutrient levels per 100 g of calories, or as a combination of multiple factors (Sonnenberg et al. 2013), rather than as an indication of caloric content (Hawley et al. 2013). Attempting to convey calorie

TABLE 1. Snack choices and average calories by treatment

		Basic information			Contextualized information			Heuristic cues		
	M = 222	M = 206 (SD = 112), *n* = 293			M = 198 (SD = 118), *n* = 221			M = 192 (SD = 118), *n* = 222		
Snack	Control	Calorie labels	Daily intake	Snack intake	Percentage daily calories	Percentage snack calories	Treadmill time	Letter grade	Body size	Traffic light
Mean (SD) calories of selection	222 (117) *n* = 185	200 (112) *n* = 145	207 (109) *n* = 75	214 (117) *n* = 73	214 (124) *n* = 74	178 (117) *n* = 74	203 (113) *n* = 73	189 (120) *n* = 75	201 (120) *n* = 72	188 (114) *n* = 75
	Percentage of participants choosing each snack, by treatment									
Dried apples  40 calories	16	20	15	14	20	30	18	25	21	23
Baked chips  130 calories	12	9	13	12	11	8	14	11	17	17
Mint candy  140 calories	11	17	20	22	12	16	15	17	11	13
Potato chips  230 calories	9	11	7	5	9	16	12	9	10	8
Candy bar  280 calories	31	31	28	31	28	15	27	21	26	29
Cookies  340 calories	15	8	15	10	12	12	10	12	10	5
Apple Pie  470 calories	5	3	3	7	7	3	4	4	6	4

Note: Shifts downward in mean caloric intake in each treatment compared with controls correspond to slightly different distributions of snack selections.

information alone using a three-point scale (green, yellow, red) or a five-point scale (A through F) necessitates drawing thresholds. In this study, with snack choices spanning a wide array of caloric content, participants could successfully differentiate the options

TABLE 2. Regression predicting calories in snack choice from each label format (Model 1), controlling for demographic predictors to assess robustness (Model 2)

	Model 1: Main effects	Model 2: Covariates
Constant	222.05[a] (8.54)	255.97[a] (13.01)
Numeric: Calories	−21.64[c] (12.88)	−16.18 (13.11)
Numeric: Daily intake	−14.72 (15.90)	−5.35 (16.46)
Numeric: Snack intake	−8.08 (16.06)	−10.82 (16.33)
Contextualized: Percentage daily calories	−8.54 (15.98)	−9.20 (16.22)
Contextualized: Percentage snack calories	−43.95[a] (15.98)	−38.49[b] (16.24)
Contextualized: Treadmill time	−19.04 (16.06)	−16.51 (16.22)
Heuristic: Letter grade	−32.99[b] (15.90)	−27.08[c] (16.22)
Heuristic: Body size	−22.08 (16.14)	−19.47 (16.62)
Heuristic: Traffic light	−34.32[b] (15.90)	−40.64[b] (16.30)
Female		−19.90[b] (7.99)
Age		−0.20 (0.27)
White		−35.57[a] (8.56)
Overweight		9.73 (8.50)
	$N = 921$ $F(9,911) = 1.35$, $p = 0.207$ $R^2 = 0.013$	$N = 864$ $F(13,850) = 3.28$, $p < 0.001$ $R^2 = 0.048$

Note: [a]$p < 0.01$, [b]$p < 0.05$, and [c]$p < 0.10$.

using these labels. However, it is important to note that in many consumer settings the options may be clustered at one end of this range, and it is important to consider the potential effects on behavior of either truncating the labels available for use (e.g., only yellow and red light items may be available) versus rescaling the labels depending on the range of options available (e.g., so that the lowest-calorie item is always given a green light, no matter how indulgent it truly is).

The only numeric information format to have a significant and robust effect on behavior was the presentation of calories as a percentage of daily snack calories. This effect may be driven in part by the fairly conservative snack calorie recommendation (i.e., denominator) we chose, somewhat arbitrarily, of 200 daily calories for snacks, creating a range of 20 percent for apple crisps up to 235 percent for the apple pie. Translating calorie information into such stark numbers may provide sufficient shock value to shift behavior (Burton et al. 2006), although if it works by grossly misrepresenting the sinfulness of the snacks, this strategy is unlikely to have long-term benefits. Indeed, the anticipated "sticker shock" of calorie labels emerges repeatedly in policy analysis of menu labeling among consumers, restaurant owners and policy makers (Britt et al. 2011; Jones 2010; McColl 2008), although anecdotally consumers tend to report such effects to be short-lived (Jones 2010).

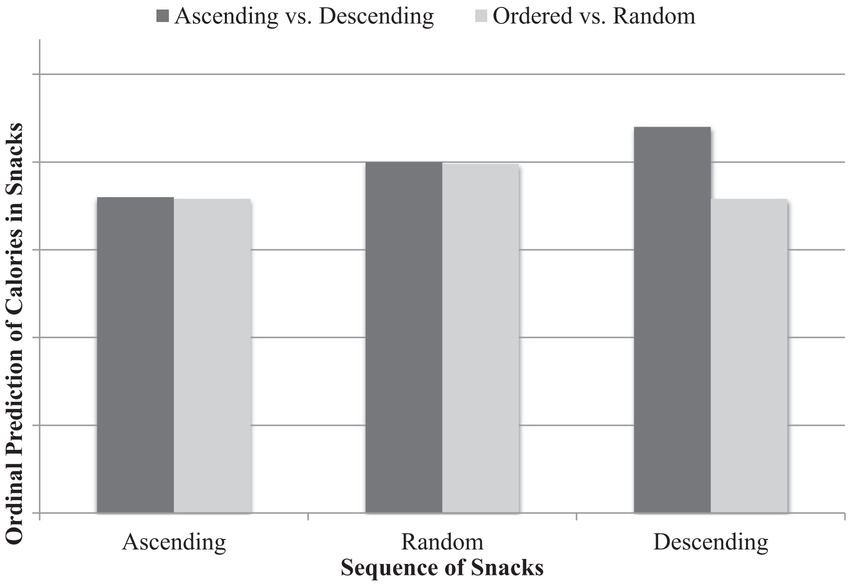
III. Study 2

In contrast to the explicit labeling of Study 1, the use of choice architecture can guide choices more subtly. However, because calorie information is becoming dramatically more prevalent as a result of the ACA's calorie-posting provisions, it is important to understand how the provision of calorie information both affects, and is affected by, the implementation of alternative approaches.

The alternative approach we examined was a "nudge" in which low-calorie snacks were listed first. Organizing food choices so that healthy items come first (albeit in a cafeteria lineup rather than in a list of options) is the first example of a nudge proposed in the book by that title (Thaler and Sunstein 2008), and research has, in fact corroborated the efficacy of such an approach (Wansink and Just 2011; Wansink and Hanks 2013). Dayan and Bar-Hillel (2011) found, in lab studies, that items near the top (and, interestingly, also the bottom) of randomly ordered food menus were chosen more frequently, and the effect of coming first replicated in the field. Likewise, Liu et al. (2012) found, in a laboratory experiment, that presenting menu items rank-ordered by, and also labeled with, caloric content, reduced calories ordered, again suggesting a primacy effect. Consistent with this literature, we first hypothesize that presenting the snacks in an ascending sequence, from low calorie (on top) to high calorie (on the bottom) of a list of choices, would promote choice of the former, irrespective of calorie labels.

However, there have been no studies to date informing how the presence of calorie information may affect the impact of a nudge. Because the traditional nudge (best-to-worst ordering) and labeling with calorie information are both likely to promote the same items, including only random and ascending sequences cannot inform how the two approaches may interact to affect decision making. If the nudge works merely by convenience, then early items would be selected irrespective of information. However, the nudge may also interact with calorie information by making it easier for participants to make sense of the calorie information and to rapidly choose a desirable low-calorie snack (if that is what they desire). To test for this mechanism, we included a treatment in which the snacks were listed

FIGURE 1. Predictions corresponding to orthogonal planned contrasts



in a descending sequence: from highest to lowest calorie. Here we expected to observe a particularly dramatic effect of calorie information. The descending sequence nudge alone should encourage participants to select high-calorie snacks, through mere convenience. With calorie labels, however, the ranking by calorie content should facilitate the use of calorie information beyond the simple presentation of numbers, thus discouraging choice of the top-listed, highest-calorie snacks, even relative to the random sequence.

We thus anticipated two patterns to emerge, depending on calorie labeling (Figure 1). When no labels were present, we expected the primary finding to be a divergence between ascending sequence (which should lower overall calories) versus descending sequence (which should raise calories), represented by the dark gray prediction line. In contrast, when labels were provided, we expected a pattern consistent with a facilitation effect, represented by the light gray prediction line, in which either order (ascending or descending) would lead to lower mean calories compared with a random order in which calorie information is typically difficult to use, as suggested by the literature on menu labeling (Kiszko et al. 2014; Swartz, Braxton, and Viera 2011) and Study 1.

A. METHODS

A.1. PARTICIPANTS. Participants were 610 pedestrians aged 18–87 (mean = 36), 53 percent female, 74 percent white, 12 percent African American, and 29 percent overweight or obese.

A.2. PROCEDURE. The same procedure was followed as in Study 1. Participants were recruited off the street and brought onto our research truck, where they completed a study focusing on an unrelated topic and then chose which of the seven snacks to receive as a thank-you for participating. The snack list faced by an individual participant was determined by random assignment to one of the six treatments defined by (1) the presence or absence of numeric calorie information and (2) the sequence of snack options, which were ordered in ascending sequence (with the lowest calorie item on top), descending sequence (with the highest calorie item on top), or in an order that was randomized for each individual participant.

A.3. STATISCAL ANALYSES. We analyzed the results using an OLS hierarchical multiple regression predicting snack calories. We tested for the patterns in Figure 1 using planned orthogonal parametric contrasts (Rosenthal and Rosnow 1985), in which weights are applied to each level of a variable to test for each predicted pattern using a single degree of freedom rather than relying on simple pairwise comparisons. The first contrast tests for the convenience effect by comparing ascending versus descending (linear weights: ascending = −1, random = 0, descending = 1), and the second tests for a facilitation effect comparing the random sequence with both ordered sequences (quadratic weights: ascending = −1, random = 2, descending = −1). These weights correspond to the general pattern displayed in Figure 1, constrained by the need to be orthogonal to one another.

In step 1 of the regression, the two planned contrasts are entered as main effects (using the two degrees of freedom in the sequence manipulation) along with a main effect for calorie labels (one degree of freedom). In step 2, interaction terms between presence of calorie labels and the two planned contrasts are entered (accounting for the final two degrees of freedom from the manipulations), to test for the differential emergence of each pattern depending on the presence of calorie labeling. We predict the first pattern (ascending versus descending) to emerge when no information was provided, corresponding to a simple nudge. When calorie information was present, however, we predicted the second pattern (ordered versus random) to emerge, corresponding to a facilitation of the use of calorie information by the layout of the options. Demographics are entered in step 3.

B. RESULTS

Table 3 reveals that both of the interactions between calorie labeling and the planned contrasts were significant, and there was also a marginally significant main effect of providing calorie information ($p = .062$). As Figure 2 illustrates, the interaction between calorie information and the ascending versus descending planned contrast ($p = .051$, weakening slightly to $p = .056$ when controlling for demographics) indicates that arranging the snacks in ascending order of calories reduced calorie consumption when no calorie information was provided.[2] The interaction between calorie information and the ordered versus random planned contrast ($p = .042$, remaining significant at $p = .034$ when controlling for

2 Simple effects tests, in which each treatment is analyzed separately, were performed to confirm that the interaction represents the pattern emerging in one treatment but not the other. As anticipated, the ascending versus descending contrast was significant when calorie information was absent ($B = 18.39$, $p = .045$), but not when information is present ($B = -6.68$, $p = .456$).

TABLE 3. Calories in snack choice as a function of information, convenience, facilitation, and interactions between them

	Step 1: Main effects	Step 2: Interaction	Step 3: Covariates
Constant	219.75 (7.40)	219.78 (7.36)	268.95 (17.04)
Calorie information	-19.61^{c} (10.47)	-19.57^{c} (10.42)	-20.30^{b} (10.34)
Contrast: Ascending vs. descending	5.86 (6.43)	18.39^{b} (9.04)	19.00^{b} (8.94)
Contrast: Ordered vs. random	3.76 (3.69)	−3.71 (5.19)	−3.64 (5.17)
Information × convenience		-25.07^{b} (12.80)	-24.20^{c} (12.65)
Information × facilitation		14.88^{b} (7.35)	15.48^{b} (7.29)
Female			-34.07^{a} (10.50)
Age			−0.39 (0.35)
White			-26.05^{b} (11.91)
Overweight			5.84 (10.94)
	$N = 610$ $F(3,601) = 1.78$, $p = 0.151$ $R^2 = 0.009$	$N = 610$ $F(5,599) = 2.68$, $p = 0.021$ $R^2 = 0.022$	$N = 610$ $F(9,595) = 3.62$, $p < 0.001$ $R^2 = 0.052$

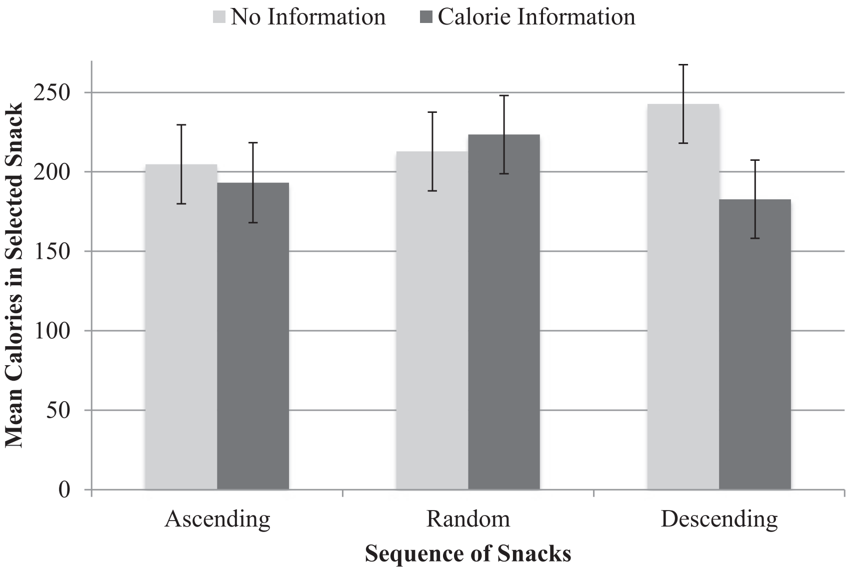
Notes: Regression predicting calories in snack choice from presence of calorie information and the two predicted patterns associated with different sequences (step 1), followed by interaction terms between calorie information and these two sequences (step 2), adding demographic predictors for robustness check (step 3). $^{a}p < 0.01$, $^{b}p < 0.05$, and $^{c}p < 0.10$.

demographics) reveals that, when information is provided, both systematic orderings lead to lower calorie consumption than does random order.[3]

Both predicted patterns therefore emerged as predicted. In the treatment with descending sequence and no calorie information, the nudge propelled choices toward high-calorie snacks, and there was no information-facilitation effect because calorie information was not present. However, when calorie information was present, calories were

3 Simple effects tests confirmed that the ordered versus random planned contrast was significant when calorie information was present ($B = 11.17$, $p = .030$), but not when information is absent ($B = -3.71$, $p = .480$).

FIGURE 2. Estimated marginal means of chosen snack's calories by presence of calorie Information and Sequence of snack presentation. Bars indicate 95% confidence intervals



similarly low for both organized orderings, indicating that the effect of providing an organizing principle for interpreting calorie information completely counteracted the simple nudge effect.

C. DISCUSSION

The beneficial impact of calorie labeling on snack choice emerged only when the sequence of snacks facilitated use of the information. And the convenience effect of promoting items listed earlier—even high-calorie items—emerged only in the absence of calorie information. In essence, ordering the options appears to help guide the consumer to use the posted calorie information in a different way, facilitating its use in making a selection.

The qualitative difference in the effect of ordering, depending on whether information was present, warrants caution in predicting effects of nudges in a complex environment. Successful instantiations of choice architecture tend to focus on relatively simple decisions, such as taking the stairs instead of the elevator (Soler et al. 2010). For more multifaceted decisions and behaviors, especially those with more inherent trade-offs, the effects have been more varied (Skov et al. 2013). Although eating behavior is a popular topic for application of choice architecture, and many positive effects have emerged, there has been little attention paid to the mechanisms of behavior change (Hollands et al. 2013). Here we show evidence that the mechanism can vary markedly depending on other factors in the decision space.

IV. General Discussion

Nudges have been hailed as a simple tool to leverage great benefits with a minimum sacrifice of liberty (Thaler and Sunstein 2008; Galizzi 2012), but also attacked as a manipulative approach that depends on lack of transparency (Blumenthal-Barby and Burroughs 2012). Information provision appears benign and philosophically desirable in its emphasis on transparency, and serves a useful purpose for accountability (Dawes 2010), but, in its raw form, appears to yield little benefit in changing consumer behavior (Howells 2005). These arguments play out in numerous domains, but food choice is a domain that is particularly well studied.

Prior research on calorie posting suggests that provision of simple calorie information does little to reduce intake. Here, in Study 1, we test alternative ways of providing such information, of which few have been tested in field studies, to assess whether information may have greater impact if presented in formats that are easier to use. Although our results do suggest that simpler ways of conveying calorie information might have a greater impact on behavior, before implementing them on a broad scale, policies of these types should be tested much more carefully—in realistic settings, on large and diverse populations, and over extended periods of time.

Future research on interventions intended to change behavior should also seek to obtain a more comprehensive view of the behavior being addressed. Studies of policy approaches using either information provision or nudges have tended to focus on near-term behavioral consequences, with largely unmeasured impacts on longer-term sustainability or unintended compensatory effects. For example, a nudge may increase enrollment in employer retirement plans (Thaler and Benartzi 2004), but it is largely unstudied whether the slimmed-down paychecks might result in, for example, increased credit card debt. Compensation has been observed in some cases, and, indeed, specifically in the case of dietary choices (Wisdom, Downs, and Loewenstein 2010) even in decisions immediately following the nudge.

The findings of Study 2 further underscore the pitfalls of implementing untested policies by showing that multiple interventions may interact in nonadditive ways, potentially facilitating one another, but also potentially interfering with one another. We show here that consumers can better use posted information when we provide an organizing principle for them to do so, so this particular instantiation of choice architecture facilitates the use of information. At the same time, what appears to be a straightforward nudge may be greatly affected by details in the environment; here, the simple primacy nudge that otherwise leads consumers to pick earlier options is completely reversed when calorie information is posted, leading them to pick later ones.

Predicting whether policies will have their intended effects is a challenge. Information-provision policies that have seemed encouraging, and even shown promise in laboratory studies, often haven't panned out as expected. Nudges, in particular, are vulnerable to failures to generalize from lab and even field studies to the real world. To the extent that different environments may differ subtly in ambient cues, they may activate different biases that could alter the effects of a nudge. For example, trayless cafeterias have been implemented to reduce calorie consumption, but when side salads and fruits were available primarily as side dishes, consumers skipped them in favor of larger, less nutritious main dishes (Just and Wansink 2009).

Although nudges and enhanced approaches to information provision are often treated as examples of behavioral economic approaches to public policy, there is nothing inherently economic in the approaches tested in the two experiments reported here. The difficulties of communicating information and changing behavior are issues as central to psychology as they are to economics. Yet, the interventions reported in this paper certainly do lie squarely in the realm of the types of policies tested by behavioral economics. Just as behavioral economics itself has come to signify a more open-minded approach to economics that embraces multiple empirical methods (e.g., lab experiments, field studies, genetics, and neuroscience methods) and multiple foundational inputs (e.g., psychology and sociology), behavioral economics and public policy have become associated with an eclectic, creative approach to public policy, and a belief in the importance of (ideally, experimental) testing.

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