WP 2020-01
April 2020

Working Paper

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Date Labels, Food Waste, and Implications for Dietary Quality

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Abstract: Recent research suggests that the variety of date labels found on food and beverage products (e.g., Use by, Best by, Sell by) is a leading culprit of food waste in the United States, and there have been calls to harmonize date labels. However, little is known about how the implementation of standardized date labels will affect food markets. We developed a survey to collect information on consumers' intentions to discard 15 food products when exposed to different date labels. The survey data were used to estimate how shifting to a specific date label would affect the likelihood to discard food, and then in second step we simulated how such changes would affect food prices and food purchases. Results show that the adoption of certain date labels has the capacity to reduce food waste, but the reductions would happen differentially across food groups. When we examine the caloric and nutritional implications, we find that these reductions in food waste would decrease the relative availability of carbohydrates and sugar in the household and lead to an increase in the relative availability of fats, cholesterol, and protein.

Acknowledgments: The authors would like to thank Anjali Narang for assistance with designing and implementing the survey, as well as Norbert Wilson, Aaron Adalja, and seminar participants at Purdue University, the University of Rhode Island, and the National Academy of Sciences for helpful comments and discussions. All remaining errors are the responsibility of the authors. The project was supported by Agricultural and Food Research Initiative Competitive Grant no. 2016-67023-24817 from the USDA National Institute of Food and Agriculture (NIFA), and through USDA Hatch project NYC-121864. Any opinions, findings, conclusions, or recommendations expressed in this publication are those of the authors and do not necessarily reflect the view of NIFA or the United States Department of Agriculture (USDA).

Key words: date labels, food waste, nutrition, simulation, survey.

JEL classification: I18, Q13, Q18

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Food waste continues to be one of the most pressing global issues having implications for the environment (Hall et al. 2009, and see Halloran et al. 2014 for a nice overview), food security (e.g., Coleman-Jensen et al. 2015) and human health (Conrad et al. 2018). Much attention focuses on the quantity and value of food that is wasted, and some work has also calculated the calories that are wasted each year. Earlier reports suggest that food waste is substantial across all food groups, but that it is particularly high for meats, dairy products, and fruits and vegetables (Buzby, Wells, and Hyman 2014). In terms of calories lost due to food waste, Buzby, Wells, and Hyman (2014) show that nearly 50% of lost calories are in the form of added fats and added sugars. Although many have recommended policies and ways to reduce food waste for several years, there has been surprisingly little effort devoted to understanding how reductions in food waste will affect food purchases, caloric intake, and nutrient consumption.

A recent surge in research in economics examines the causes and consequences of food waste, highlighting the potential effects of policies and initiatives that could potentially reduce food waste. Economic research examining food waste is not new, and it is a topic that has long been viewed as important by agricultural economists (e.g., Kling 1943). Economic research in this arena can largely be grouped into one of four areas. First, a growing body of work is primarily interested in the measurement of food waste and authors here argue that proper measurement is needed before policies are developed and implemented (e.g., Bellemare et al. 2017; Yu and Jaenicke 2020). Second, several articles address the question of the optimal amount of food waste, and some of this work has stressed the economic implications of a zero-waste policy (see Lusk and Ellison 2017; Katare et al. 2017; Bellemare et al. 2017). A third research area offers empirical evidence on the effectiveness of policies or initiatives that may be used to mitigate food waste (e.g., Wilson et al. 2017; Roe et al. 2018; Reynolds et al. 2019). Some studies in this area advocate using policy instruments like taxes to incentivize producers to reduce waste and subsides to encourage consumers to better manage their waste (Hamilton and Richards 2019). The fourth area of research examines the market effects of food waste as well as the market implications associated with less food waste (e.g., see Rutten 2013; Ellison, Muth, and Golan 2019; de Gorter et al. 2020). This research recognizes that consumers will either consume more food or will purchase less food, and both of these scenarios will affect prices and quantities in both food and agricultural markets.

Our research is focused on shedding new light on the fourth area of research identified above. Specifically, we quantify the market effects for farmers and consumers of reductions in food waste for a specific mitigation initiative, and trace these effects on the nutritional content of food purchases. We first measure the effect of harmonized date labels on consumer food waste because significant research suggests that date labels create confusion and lead to a non-trivial amount of food waste (see Neff et al. 2015). Data are collected in a survey to assess the likely reductions in waste for different date labels across a range of products. Based on the survey results, we estimate the likely changes in purchase patterns for different food groups. In the second step, we use the estimated changes in purchase patterns (for a given change in date label usage) to simulate the changes in prices and quantities in food and farm markets. The changes in purchased quantities of food groups are also used to simulate changes in per capita availability of key micro- and macro-nutrients.

Surveying Consumers about Their Likelihood to Discard Food

We designed a survey that was distributed to 579 subjects in the United States to elicit consumer response on their likelihood to discard different food products. The subjects were asked their likelihood of discarding 15 selected food items using a Likert scale between 1 (Extremely unlikely to discard) and 5 (Extremely likely to discard). Figure 1 showcases the way we presented the questions to our subjects. We decided not to use pictures when we introduced the products to subjects but rather described the size of the product.

The survey was both a within-subject and a between-subject design. For the within-subject component, each subject was first presented the 15 products with a date (but no date label) and then subsequently presented the same 15 products with a date and a date label. In each case (with or without the date label), the product was presented as one day past its stated due date. The between-subject component of our design altered the date label that was presented, and was randomly drawn from one of 10 date label treatments. Four of the treatments included date labels that are commonly found on food products in the United States: i) Best if used by, ii) Best by, iii) Use by, and iv) Sell by.

The other six treatments focused on the use of a biosensor to indicate the freshness of the food product. Biosensors are a relatively new technology that provide consumers with a visual indication of specific food quality parameters. An example of a biosensor adopted for the marketplace is a simple front-of-package image that responds to the temperature and atmospheric conditions for a packaged food item (for additional details, see Vanderroost et al. 2014). To date, biosensors have been used for select packaged food products in select markets, but interest is growing among consumers and retailers for wider use of this technology. In our survey we presented consumers with either “Best if used by” or “Use by” coupled with additional information from a biosensor that reported to detect the “freshness” of the product. In the treatments that involved a biosensor, we showed subjects an image with one of three color codes to describe the freshness of the product. The color code was explained to change as the freshness of the product deteriorates whereby: a) green indicates “fresh”, b) blue indicates “less fresh”, and c) purple indicates “past fresh”. In addition to the four date label treatments outlined above, we also have the following six treatments: v) Best if used by + Green biosensor, vi) Best if used by + Blue biosensor, vii). Best if used by + Purple biosensor, viii) Use by + Green biosensor, ix) Use by + Blue biosensor, and x) Use by + Purple biosensor.

We used 15 food products including: bread, cookies, chicken, ham, eggs, fruit salad, packaged salad greens, milk, yogurt, juice, soda, butter, mixed nuts, canned soup, and jam. Our simulation model was designed to consider purchasing (and substitution) patterns among nine food groups (following Okrent and Alston 2012); these include cereal and bakery, meat, eggs, fruits and vegetables, dairy, non-alcoholic beverages, other food, alcoholic beverages, and food away from home (FAFH). Therefore we included these 15 food products in our survey in order to have representation of items in seven of the nine food groups. In the simulation exercise we focus only on food and non-alcoholic beverages consumed at home, and we will assume that date labels will not have any important effects on the likelihood of discarding alcohol and FAFH products.

Data and Empirical Estimation

Our online survey was completed by 579 U.S. subjects and we have data from approximately 55 subjects in each of the 10 treatments. The average age of our respondents was 33.8 years, 46% were single, 29% households included children, 84% lived in an urban or suburban region, 34% were female, and 54% had earned a bachelor degree or higher. Each subject provided us with their likelihood to discard for each product in the control treatment (without a date label or biosensor) and then their likelihood to discard each product in one of the 10 treatments.

We show the average responses across the five likelihood groups for the control treatment and for each of the ten date label/biosensor treatments (table 1). The share of subjects that say they are “extremely unlikely” or “somewhat unlikely” to discard the food and beverage products is relatively high in the two treatments that use the green biosensor and relatively low in the two treatments that use the purple biosensor. The summary statistics for the four treatments that use date labels but do not use biosensors are less conclusive. However, there is some indication that the use of these date labels does increase the percent of subjects that select “extremely unlikely” or “somewhat unlikely” relative to the control group.

To examine the treatment effects more carefully, we estimate the likelihood to discard for each of the 10 date labels/biosensor treatments (relative to the control) and for each of the food items (relative to soda). Following Ellison and Lusk (2018), we used an ordered logit model to estimate these effects following the specification shown in equation (1):

$$(1)\quad LTD_{ita} = f(Treatment_t, Item_a, Treatment_t \text{ x } Item_a; \mathbf{Z}_\mathbf{i}),$$

where LTD_{ita} denotes the likelihood to discard item *a* under treatment *t* for subject *i*, and $\boldsymbol{Z_i}$ is a vector of variables that describe the socio-economic and purchase pattern characteristics (collected in our survey) for *i*. The dependent variable is the subject’s response to the question shown in Figure 1 that uses a 5-point Likert scale between 1 (extremely unlikely to discard) and 5 (extremely likely to discard).

Table 2 presents the regression results in models that include only treatment effects, treatment and item effects, and treatment, item and treatment-item interaction effects. In line with the summary statistics presented in Table 1, we find that the treatments with a purple biosensor (with either the “Use by” or the “Best if used by” date label) led to a positive and statistically significant effect on the likelihood to waste whereas the use of a green biosensor led to a negative and statistically significant effect on the likelihood to waste. As expected the use of a blue biosensor did not lead to a statistically significant effect on the likelihood to waste (relative to the control). Table 2 also shows that the use of “Use by” and “Best if used by” (without the biosensors) labels did not have a statistically significant effect on the likelihood to waste, yet the “Best by” and Sell by” date labels did have a negative and statistically significant effect on the likelihood to waste (in the first two specifications). This finding largely agrees with earlier work showing that date labels suggestive of food safety (e.g., labels such as “Use by”) are more closely linked to higher levels of food waste relative to date labels that are more suggestive of food quality (e.g., labels such as “Best by” or “Sell by”). In this analysis, the presence of the “Use by” or “Best if used by” labels both include the phrase “use by”, and both these treatments do not lead to a statistically significant decrease in subjects’ likelihood to waste relative to the control treatment (without a date label). However, the two treatments with a date label that is suggestive of food quality (“Best by” and “Sell by”) do lead to a statistically significant decrease in the likelihood to waste relative to the control.

The latter two specifications in Table 2 present item-specific results. Estimate results with and without interaction terms are similar in direction and magnitude; the positive results indicate that the likelihood to waste each food item is greater relative to the likelihood to waste the omitted item (soda). More importantly, the results highlight that the likelihood to discard patterns vary, in non-trivial ways, across the 14 food items. We see a relatively low likelihood of discarding bread, cookies, jam, and butter and a relatively high likelihood to discard chicken, fruit, ham, milk, salad, and yogurt. The nutritional content of items in these two groups is also different, and therefore any change in consumption patterns induced by a change in date labels may have implications for diet quality.

In Table 3 (and in the subsequent results and discussion) we focus on the estimation results from the “Best by” treatment (without the interaction terms). The larger effects based on treatments using biosensors indicates that this may be a promising tool to reduce food waste in the future. However, the results from the “Best by” treatment may be more reflective of how changes in date labels might impact markets and dietary quality patterns in the short run. Table 3 presents the estimated margins for each food product for the “somewhat likely to discard” and the “extremely likely to discard” options from the “Best by” treatment. The final column is the sum of the marginal effects, which indicates the total change in the likelihood to discard each product in the presence of the “Best by” date label. This calculated total change in the likelihood to discard is i) for the “Best by” date label relative to the control, or relative to no date label, and ii) for the situation whereby consumers are making a decision about a food item that is one day past the posted date.

In Table 4 we use the results from Table 3 to create a measure of the likelihood to discard for seven food categories, which is a simple average of the margins for individual food items within each category. The items bread and cookies belong to the cereal and bakery category, chicken and ham belong to the meat category, eggs comprise the egg category, milk and yogurt belong to the dairy category, fruit salad and packaged salad greens form the F&V category, butter, mixed nuts, canned soup, and jam fall into the other category, and juice and soda comprise the non-alcoholic beverage category. To calculate the net effect of the “Best by” date label on retail demand we use the product of the estimated margins (from the first column in Table 4) and the share of food that is currently wasted in each category (shown in the second column in Table 4). The share of food that is currently wasted has been estimated by various sources in the United States and elsewhere, and there is substantial range in the estimates. We employ the shares reported in Buzby, Wells, Hyman (2014) which have a narrow range around 20% for the food categories used in our analysis.

The final column in Table 4 represents the net effect of the date label on the retail demand for each food category. Any decrease in the likelihood to discard could plausibly lead to an increase in food consumption or a decrease in food purchases. In our survey we asked subjects how they expect to respond to a general decrease in their level of food waste, and nearly 60% selected the option stating that they would decrease their subsequent purchases. Therefore, we introduce the estimated decreases in the likelihood to discard food as proportional shifts (in the quantity direction) for the retail demand for food categories in our simulation model.

Simulation Model

Here we develop a partial equilibrium model to simulate the economic and nutritional implications associated with changes in food demand for the consumer behavior observed in our survey to the date label “Best by”. The model simulates changes in quantities and prices in both food and agricultural markets, and considers the linkages between food categories and between the food categories and the agricultural inputs. Following Okrent and Alston (2012) and Rickard, Okrent, and Alston (2013), our framework includes markets for nine food categories and eleven agricultural inputs. However, we offer a substantial extension to these earlier models by also simulating the changes in nutrient purchases. This contribution allows us to weigh in on how changes to date label language affect food waste, food and agricultural markets, caloric intake, and dietary quality. Food waste levels vary across food categories and decreases in food waste are also expected to vary across food categories; our framework enables us to carefully examine trade-offs across food categories for a specific food waste reduction strategy, and then to quantify the effects on nutrient purchases.

The model introduced here extends a model with one output product with L inputs, as presented by Alston, Norton, and Pardey (1995), to N output products with L–1 farm commodities and one composite marketing input (representing an aggregate of labor, materials, energy, capital and other inputs used in the food processing, manufacturing, and marketing sector, in conjunction with farm commodities). The market equilibrium for this system can be expressed in terms of N demand equations for food products, N total cost equations for food product supply, L supply equations for input commodities and $L \times N$ equations for competitive market clearing. The market equilibrium for this system is expressed as:

(1) $Q^n = \mathrm{Q}^n(\mathbf{P}, A^n), \forall n = 1,..,N$

(2) $P^n = \mathrm{c}^n(\mathbf{W}), \forall n = 1,..,N,$

(3) $X_l = \sum_{n=1}^{N} \mathrm{g}_l^n(\mathbf{W})Q^n, \forall l = 1,...,L,$

(4) $X_l = \mathrm{f}_l(\mathbf{W}, B_l), \forall l = 1,..,L.$

Equation (1) represents the demand for nth food product in which the quantity demanded, Q^n, is a function of an $N \times 1$ vector of product prices, $\mathbf{P}$, and an exogenous demand shifter, A^n. Equation (2) is based on the assumption of constant returns to scale at the product industry level and competitive market equilibrium, where the price of the nth product is set equal to the marginal cost of producing product n, $\mathrm{c}^n(\mathbf{W})$, which is a function of an $\mathrm{L} \times 1$ vector of commodity prices, $\mathbf{W}$. Equation (3) is the Hicksian demand for commodity l, X_l, which is derived by applying Shephard's lemma to the total cost functions of the N products (i.e., $\partial C^n / \partial W_l = \mathrm{g}_l^n(\mathbf{W})Q^n$), and then summing across the N product industry demands for commodity l. Equation (4) is the supply function for commodity l, which is a function of all of the commodity prices and an exogenous supply shifter, B_l.

Totally differentiating equations (2) to (5), and converting to elasticity form yields equations for proportionate changes in quantities and prices of retail products (i.e., $\mathrm{E}Q^n = \mathrm{d}Q^n/Q^n$ and $\mathrm{E}P^n = \mathrm{d}P^n/P^n$ where d is the total differential operator) and farm commodities (i.e., $\mathrm{E}X_l = \mathrm{d}X_l/X_l$ and $\mathrm{E}W_l = \mathrm{d}W_l/W_l$) in equations (6) to (9):

(5) $$\mathrm{E}\,Q^n = \sum_{k=1}^{N} \eta^{nk}\,\mathrm{E}\,P^k + \alpha^n, \forall n = 1,..,N,$$

(6) $$\mathrm{E}\,P^n = \sum_{l=1}^{L} \frac{\partial\,\mathrm{c}^n(\mathbf{W})}{\partial W_l}\frac{W_l}{P^n}\mathrm{E}\,W_l, \forall n = 1,..,N,$$

(7) $$\mathrm{E}\,X_l = \sum_{n=1}^{N} SC_l^n \sum_{m=1}^{L}\left(\eta_{lm}^{n*}\,\mathrm{E}\,W_m + \mathrm{E}\,Q^n\right), \forall l = 1,...,L,$$

(8) $$\mathrm{E}\,X_l = \sum_{j=1}^{L} \varepsilon_{lj}\,\mathrm{E}\,W_j + \beta_l, \forall l = 1,...,L,$$

where

(9)	$\eta^{nk} = \dfrac{\partial\,\mathrm{Q}^n\left(\mathbf{P}, A^n\right)}{\partial P^k}\dfrac{P^k}{Q^n}$	is the Marshallian elasticity of demand for retail product *n* with respect to retail price *k*,
(10)	$SC_l^n = \dfrac{X_l^n W_l}{X_l W_l}$	is the share of the total cost of commodity *l* used in the production of retail product *n* (farm commodity use share),
(11)	$\eta_{lm}^{n*} = \left(\dfrac{\partial\,\mathrm{g}_l^n(\mathbf{W})Q^n}{\partial W_m}\right)\dfrac{W_m}{X_l^n}$	is the Hicksian elasticity of demand for commodity *l* in industry *n* with respect to commodity price *m*,
(12)	$\varepsilon_{lj} = \dfrac{\partial\,\mathrm{f}_l\left(\mathbf{W}, B_l\right)}{\partial W_j}\dfrac{W_j}{X_l}$	is the elasticity of supply of commodity *l* with respect to commodity price *j*,
(13)	$\alpha^n = \dfrac{\partial\,\mathrm{Q}^n\left(\mathbf{P}, A^n\right)}{\partial A^n}\dfrac{A^n}{Q^n}\mathrm{E}\,A^n$	is the proportional shift of demand for retail product *n* in the quantity direction,
(14)	$\beta_l = \dfrac{\partial\,\mathrm{f}_l\left(W_l, B_l\right)}{\partial B_l}\dfrac{B_l}{X_l}\mathrm{E}\,B_l$	is the proportional shift of supply of commodity *l* in the quantity direction.

In our analysis, we use this framework to simulate how proportional shifts in demand for retail products, due to the estimated consumer response to the presence of the "Best by" date label, affect the prices and purchase patterns of the nine food categories. We then convert our simulated changes in purchases of food categories to changes in calories purchased and ultimately to nutrients purchased. The effects in markets for eleven agricultural input markets are also calculated to better understand the upstream farm-level effects of this particular food waste mitigation strategy.

Our simulation model requires parameters to describe (i) elasticities of demand for the food categories, (ii) agricultural input supply elasticities, (iii) farm-retail cost shares, (iv) farm-commodity cost shares, (v) our estimates of consumer response to the "Best by" date label for each food category, (vi) food quantity-to-calorie conversion rates, and (vii) food quantity-to-nutrient conversion rates. We adopt the elasticity of demand parameters reported in Okrent and Alston (2011), and the other elasticity and share parameters have been updated and follow those used in Okrent and Alston (2012). Also, following Davis and Espinoza (1998) and Zhao et al. (2000), we apply prior distributions to the baseline elasticity parameters to conduct a robust sensitivity analysis. Our results outline the empirical posterior distributions for the effects of interest, and we report the means from the posterior distributions in our results. Measures of consumer response to the "Best by" date label for the seven food categories are based on our econometric estimates presented in Table 4.

We calculated the average daily food, calorie, and nutrient intake for a nationally representative sample of individuals aged 18 and older using 24-hour dietary recall data from the National Health and Nutrition Examination Survey (NHANES). Data in the surveys categorize foods based on the USDA food classification system, which includes the following food categories: dairy, meats, eggs, beans, seeds and nuts, cereals and bakery products, fruits, vegetables, fats, sweets, nonalcoholic beverages and alcoholic beverages (for more details see NHANES 2018). We aggregated the food categories so that they closely match the food products included in our simulation model; we were also able to identify whether the food consumed was FAH or FAFH, based on survey questions.

Table 5 summarizes the nutrient intake information derived from the NHANES data. The data include a detailed list of food products reported by individuals interviewed in a two-day period throughout the continuous two-year survey cycle and the accompanied energy and nutrient intake information for each specific product consumed. The average intake level for the selected micro- and macro-nutrients is first calculated by averaging the total intake across two days for each individual. The intake level for all the food items is then summed up under each of the nine food categories. Applying the sampling weight, the nutrient and energy intake levels are averaged across the entire pool of interviewed subjects to derive the per-capita per-day nutrient profile for each of the food categories.

Results

Our simulation was conducted to better understand how the implementation of a harmonized "Best by" date label across all food categories would affect food and agricultural prices and quantities purchased. We then calculated the changes in annual nutrient and caloric intake per capita based on the simulated changes in food purchases.

Table 6 summarizes our results of the simulated changes in prices and quantities in both food and agricultural markets. Our results show that, in the presence of the "Best by" date label, the quantity and prices of foods purchased will fall, however, the magnitude of the decrease varies across food categories. The purchased quantity of FAFH declines the least (0.01%), followed by modest decreases for cereal and bakery (0.54%), and other foods (0.57%). Purchased quantities and prices decline more for meat, eggs, dairy and fruits and vegetables.

Given the price elasticities used in the model, the decreases in prices for most food categories (other than meat, eggs, and dairy) are relatively small.

The results in the bottom portion of Table 6 describe the simulated effects for eleven agricultural markets. Similar in magnitude to those in food markets, we find decreases in quantities of agricultural inputs (between –0.61% and –1.05%), with the largest decreases in the agricultural markets for fruits and vegetables. However, it should be noted that the simulated decreases in prices in the agricultural markets are larger in magnitude than those simulated in the food markets. The simulated results show an average change of approximately –0.50% in the prices of the agricultural commodities (but the simulated price change is substantially higher in the fish market).

Using the results from Table 6 and the conversion rates shown in Table 5, we subsequently calculate the simulated changes in caloric and nutrient purchases. In the first row in Table 7, we show a simulated decrease of 4,085.9 calories (per year) associated with consumer response to a harmonized "Best by" date label. Given an average per capita daily intake of 2,107.1 calories, this reduction is equivalent to approximately a 0.5% decrease in annual purchased calories (or 1.94 calorie days per year). As we move across the columns we see how this change in caloric purchases is distributed across the various food categories. The following rows in Table 7 provide details on the simulated changes for annual nutrient purchases across the food categories. The penultimate column in Table 7 shows the annual total change in per capita consumption of the nutrients; overall, the simulated results indicate modest decreases in purchases for most of the nutrients. Here we see that protein purchases fall by 208.5 grams, vitamin A purchases fall by 1,781 milligrams, and calcium purchases fall by 2,205.7 micrograms.

The final column in Table 7 is changes in nutrient intake for an average U.S. consumer (based on data from the NHANES) from a 4,085.9 calorie reduction per year, holding consumer product choice as fixed. This defines a benchmark of average nutrient consumption changes associated with a reduction of 4,085.9 calories per year. Comparing our simulated changes to these benchmark levels allows us to calculate the relative changes in reduced nutrient purchases (purchase reductions given consumer response to the "Best by" date label relative to an average reduction in consumption). Purchases are reduced in the presence of the "Best by" date label because less food is wasted and more food remains available for the consumer. Therefore, we could also refer to the relative change in reduced nutrient purchases as the relative change in per capita nutrient availability. For example, we compare the decrease in the consumption of a particular nutrient, denoted as *b*, stemming from the response to the "Best by" date label with a decrease in that nutrient due to a more general change in purchases (following average consumption levels). In this case, we would say the "Best by" date label led to a change in the relative per capita availability of that nutrient. When the values in the benchmark column in Table 7 are larger (are closer to 0) than those in the column with total simulated changes from the labeling treatment, there is an increase in the per capita availability of that nutrient; otherwise, there is a decrease in the per capita availability of the nutrient. In equation (16) we define the change in the relative per capita availability of a nutrient, denoted as A_b, as:

$$(16) \qquad A_b = \frac{SCP_b - BM_b}{BM_b} \ ,$$

where SCP_b is the simulated change in purchases of nutrient b given the presence of the "Best by" date label and BM_b is the benchmark change in consumption of nutrient b following observed patterns of consumption.

In Figure 2 we illustrate the direction and magnitude of changes in per capita nutrient availability. Here we see that the availability of many nutrients increases, while for other nutrients it falls. The “Best by” date label disproportionally decreases waste for products that are relatively high in protein and fat; therefore, the change in the relative availability of these nutrients will also rise. Our results show that the change in the relative per capita availability of carbohydrates and sugar will fall while the relative per capita availability of protein, fat, cholesterol, vitamin A, and calcium will increase.

Implications and Conclusion

This article provides a careful examination of the linkages between consumer response to date labels, changes in food and agricultural markets, and ultimately per capita nutrient availability. Our research provides three contributions that shed new light on some understudied issues in the public policy debate concerning food waste[1]. First, we offer new results on the effectiveness of various date labels on consumers’ likelihood to discard food, and we are the first to do this across a full range of product categories. Second, our survey provides us with the data needed to quantify how a food waste mitigation strategy, namely changes in date labels, will affect markets in the food system. We do this by adapting a simulation model to assess the effect of a food waste reduction strategy on prices and quantities in food and agricultural markets. Third, because we see a possible link between food waste mitigation and dietary quality, we extend our framework to allow us to calculate the nutritional consequences of a reduction in food waste.

Overall, we find that the use of certain date labels has the capacity to reduce food waste relative to no date labels, but that such reductions in food waste will vary across food categories. Assuming that reductions in food waste will lead to a reduction in food purchases, we show how these disproportional changes will affect the purchases of key nutrients. Specifically, we show

how reductions in food waste will result in fewer overall calories purchased and reductions in purchases of various macro- and micronutrients, albeit reductions that vary in magnitude across the nutrients. We also use our simulated results and current nutrient consumption levels to report the changes in the relative per capita availability of nutrients. Our findings indicate that the relative per capita availability of carbohydrates and sugar will fall while the relative per capita availability of fats, protein and cholesterol will increase. Although this measure of per capita availability does not translate into a direct effect on consumption, we believe it highlights how food waste mitigation might impact nutrient consumption levels.

Our research highlights an interesting dimension that needs to be considered when evaluating policy proposals aimed to reduce food waste. Initiatives that could be used to combat food waste may have unintended consequences for food consumption and affect the types of foods (and nutrients) that are present in the household. In addition to examining the consequences of harmonizing date labels, our modeling framework can be used to study a wide range of food waste mitigation strategies in food and agricultural markets.

Endnotes

[1] One example is the bill titled "The Food Date Labeling Act" that was introduced in 2019 in the U.S. House of Representatives and Senate (H.R. 3981 and S. 2337). Additional details for the House version of this bill can be found at: https://www.congress.gov/bill/116th-congress/house-bill/3981/text

Table 1. Summary statistics for the survey data

Treatments	Extremely unlikely	Somewhat unlikely	Neither unlikely nor likely	Somewhat likely	Extremely likely	Total responses
			(share of respondents)			*(number of respondents)*
Control	0.402	0.262	0.078	0.145	0.112	579
UB+Green	0.570	0.204	0.069	0.071	0.086	59
UB+Blue	0.367	0.286	0.063	0.147	0.136	61
UB+Purple	0.245	0.258	0.112	0.180	0.204	55
BIUB+ Green	0.611	0.171	0.050	0.085	0.083	61
BIUB+Blue	0.383	0.239	0.074	0.167	0.137	60
BIUB+Purple	0.295	0.246	0.111	0.196	0.152	55
UB	0.376	0.276	0.093	0.138	0.117	54
BIUB	0.407	0.230	0.092	0.128	0.142	58
Best by	0.460	0.245	0.081	0.134	0.080	59
Sell by	0.480	0.220	0.067	0.151	0.082	57

Source: Authors' calculations based on data collected by authors.
Notes: UB denotes "Use by" and BIUB denotes "Best if Used by".

Table 2. Ordered logit model of likelihood to discard

Treatments/ Products	Label treatments only		Treatments plus items No interactions		Treatments plus items Interactions included (but not shown)	
	Estimate	*Standard error*	*Estimate*	*Standard error*	*Estimate*	*Standard error*
UB+Green	-0.936***	(0.099)	-1.193***	(0.106)	-1.127*	(0.486)
UB+Blue	0.0489	(0.093)	0.0235	(0.098)	0.494	(0.349)
UB+Purple	0.779***	(0.094)	1.049***	(0.100)	1.294***	(0.341)
BIUB+ Green	-0.868***	(0.104)	-1.074***	(0.111)	-0.475	(0.486)
BIUB+Blue	0.110	(0.092)	0.130	(0.097)	0.195	(0.385)
BIUB+Purple	0.837***	(0.095)	1.097***	(0.101)	1.525***	(0.359)
UB	0.1000	(0.097)	0.117	(0.103)	-0.0510	(0.397)
BIUB	0.00247	(0.098)	-0.00716	(0.104)	0.385	(0.397)
Best by	-0.311**	(0.097)	-0.374***	(0.102)	-0.0890	(0.373)
Sell by	-0.328***	(0.099)	-0.383***	(0.105)	0.0948	(0.401)
Bread			1.900***	(0.104)	2.038***	(0.147)
Butter			1.655***	(0.105)	1.751***	(0.149)
Chicken			4.239***	(0.107)	4.512***	(0.149)
Cookies			0.626***	(0.109)	0.704***	(0.155)
Eggs			2.678***	(0.104)	2.798***	(0.147)
Fruit			2.968***	(0.103)	3.220***	(0.145)
Ham			3.821***	(0.106)	4.068***	(0.149)
Jam			1.567***	(0.105)	1.610***	(0.150)
Juice			2.206***	(0.103)	2.373***	(0.146)
Milk			3.984***	(0.106)	4.147***	(0.148)
Nuts			0.396***	(0.111)	0.457**	(0.158)
Salad			3.208***	(0.104)	3.380***	(0.146)
Soup			2.090***	(0.105)	2.217***	(0.148)
Yogurt			3.473***	(0.105)	3.647***	(0.148)
Order=1	0.313*	(0.154)	0.377	(0.194)	0.378	(0.195)
Attention=1	-0.106	(0.286)	-0.136	(0.358)	-0.133	(0.360)
Observations	16565		16565		16565	
# of subjects	579		579		579	
Log likelihood	-20056.8		-17582.8		-17526.3	
χ^2	331.1		4251.6		4325.5	

Source: Authors' calculations based on survey data collected by authors.
Notes: UB denotes "Use by" and BIUB denotes "Best if Used by".

Table 3. Estimated margins on the likelihood to discard with "Best by" date label

	Somewhat likely		Extremely likely		Total likelihood to discard
Product	*Margin*	*Standard error*	*Margin*	*Standard error*	
Bread	-0.0176***	(0.005)	-0.0169***	(0.004)	-0.0345
Butter	-0.0175***	(0.005)	-0.0147***	(0.004)	-0.0322
Chicken	-0.0133***	(0.004)	-0.0401***	(0.011)	-0.0534
Cookies	-0.0130***	(0.003)	-0.0080***	(0.002)	-0.0210
Eggs	-0.0159***	(0.005)	-0.0251***	(0.006)	-0.0410
Fruit	-0.0151***	(0.004)	-0.0284***	(0.007)	-0.0435
Ham	-0.0143***	(0.004)	-0.0366***	(0.010)	-0.0509
Jam	-0.0174***	(0.005)	-0.0139***	(0.004)	-0.0313
Juice	-0.0172***	(0.005)	-0.0199***	(0.005)	-0.0371
Milk	-0.0141***	(0.004)	-0.0380***	(0.010)	-0.0521
Nuts	-0.0116***	(0.003)	-0.0070***	(0.002)	-0.0185
Salad	-0.0147***	(0.004)	-0.0309***	(0.008)	-0.0456
Soda	-0.0095***	(0.002)	-0.0054***	(0.001)	-0.0149
Soup	-0.0175***	(0.005)	-0.0187***	(0.005)	-0.0362
Yogurt	-0.0145***	(0.004)	-0.0335***	(0.009)	-0.0480

Source: Authors' calculations based on estimated coefficients on the "Best by" treatment from ordered logit model that controls for food products (without interaction terms for label treatments and food products).
Notes: Total likelihood to discard is the sum of margin estimates for the "Somewhat likely" and "Extremely likely to discard" responses.

Table 4. Parametrization of demand shocks by food category for the “Best by” treatment

Categories	*Estimated margins*	*Current food waste rates[a] (percent)*	*Shock parameter used in simulation model (percentage change)*
Cereal & bakery	-0.0278	19.0	-0.0053
Meat	-0.0522	22.0	-0.0114
Egg	-0.0410	21.0	-0.0086
Dairy	-0.0501	20.0	-0.0100
F&V	-0.0446	20.0	-0.0089
Other food	-0.0296	20.0	-0.0059
Non-alcohol beverage	-0.0260	20.0	-0.0052
FAFH	0	n/a	0
Alcohol	0	n/a	0

Source: The estimated margins for each food category are the simple average of total likelihood to discard for disaggregated food products in table 4. The waste rates are based on reported values for the United States from Buzby, Wells, and Hyman (2014).

Notes: F&V denotes fruits and vegetables; FAFH denotes food away from home.
The percentage change in food wasted for each food category from the “Best by” label change is calculated as the product of the estimated margin and waste rate for each food category.

Table 5. Average daily levels of caloric and nutrient intake by food group in the United States

Nutrient	*Cereal & bakery*	*Meat*	*Egg*	*Dairy*	*F&V*	*Other food*	*Nonalcoholic beverage*	*FAFH*	*Alcohol*	*Total*
Calories	355.27	207.35	73.08	201.08	156.97	476.33	125.32	224.11	860.37	2107.09
Protein	8.70	22.15	5.38	10.35	3.66	19.40	0.98	1.35	32.77	82.93
Carbohydrate	62.09	2.40	0.36	18.97	29.46	46.75	30.46	12.18	102.42	257.45
Sugar	14.78	0.38	0.25	17.11	12.97	14.29	26.77	1.49	46.39	114.68
Fiber	4.19	0.09	0	0.35	4.90	4.01	0.26	0.00	6.07	17.28
Fat	8.55	11.56	5.39	9.47	3.97	24.17	0.33	0.02	33.22	78.63
Cholesterol	9.73	75.30	154.66	31.3	2.77	76.47	0.29	0.28	111.06	277.07
Vitamin E	1.06	0.45	0.56	0.32	0.96	2.93	0.18	0.00	3.00	7.86
Vitamin A	104.71	23.38	70.49	156.71	125.90	128.88	10.36	0.24	210.35	664.05
Vitamin B1	0.55	0.16	0.02	0.09	0.13	0.34	0.07	0.02	0.61	1.69
Vitamin B2	0.43	0.17	0.19	0.43	0.11	0.34	0.22	0.09	0.74	2.16
Vitamin B6	0.43	0.38	0.06	0.11	0.31	0.36	0.09	0.18	0.77	2.11
Vitamin B12	0.90	1.33	0.35	1.18	0.07	0.88	0.09	0.07	1.85	5.35
Vitamin C	3.36	0.43	0	1.61	30.79	8.94	29.20	0.37	28.08	87.72
Vitamin D	0.47	1.01	0.87	2.32	0.06	0.60	0.21	0.00	1.39	5.19
Calcium	125.81	19.65	22.87	357.02	46.79	158.16	64.77	19.69	324.17	952.65
Magnesium	47.66	22.21	4.95	30.84	37.73	62.34	24.07	26.59	105.49	291.30
Iron	5.88	1.29	0.67	0.35	1.17	3.17	0.43	0.32	5.44	15.64
Sodium	531.26	604.52	132.23	231.77	242.11	1009.02	52.00	20.19	1467.80	3548.25
Potassium	198.73	314.84	58.78	353.67	522.43	508.68	302.40	148.01	1011.17	2762.71

Source: Authors' calculations based on National Health and Nutrition Examination Survey (2018).
Notes: Sample weights are used to calculate population totals.

Table 6. Impacts on food and farm markets from the response to the "Best by" treatment

Categories	*Quantity*	*Price*
	(percentage change)	
Food markets		
Cereal & bakery	-0.54	-0.03
Meat	-1.04	-0.37
Egg	-1.12	-0.30
Dairy	-0.90	-0.14
F&V	-0.86	-0.10
Other food	-0.57	-0.03
Nonalcoholic beverage	-0.55	-0.02
FAFH	-0.01	-0.02
Alcohol	0.14	-0.27
Agricultural markets		
Oilseeds	-0.75	-0.57
Food grains	-0.61	-0.21
Vegetable & melons	-1.05	-0.60
Fruits & tree nuts	-0.94	-0.57
Sugar cane & beets	-0.72	-0.55
Other crops	-0.87	-0.66
Cattle	-0.84	-0.52
Dairy	-0.70	-0.43
Poultry & eggs	-0.68	-0.42
Fish	-1.04	-2.61
Marketing inputs	-0.35	0.00

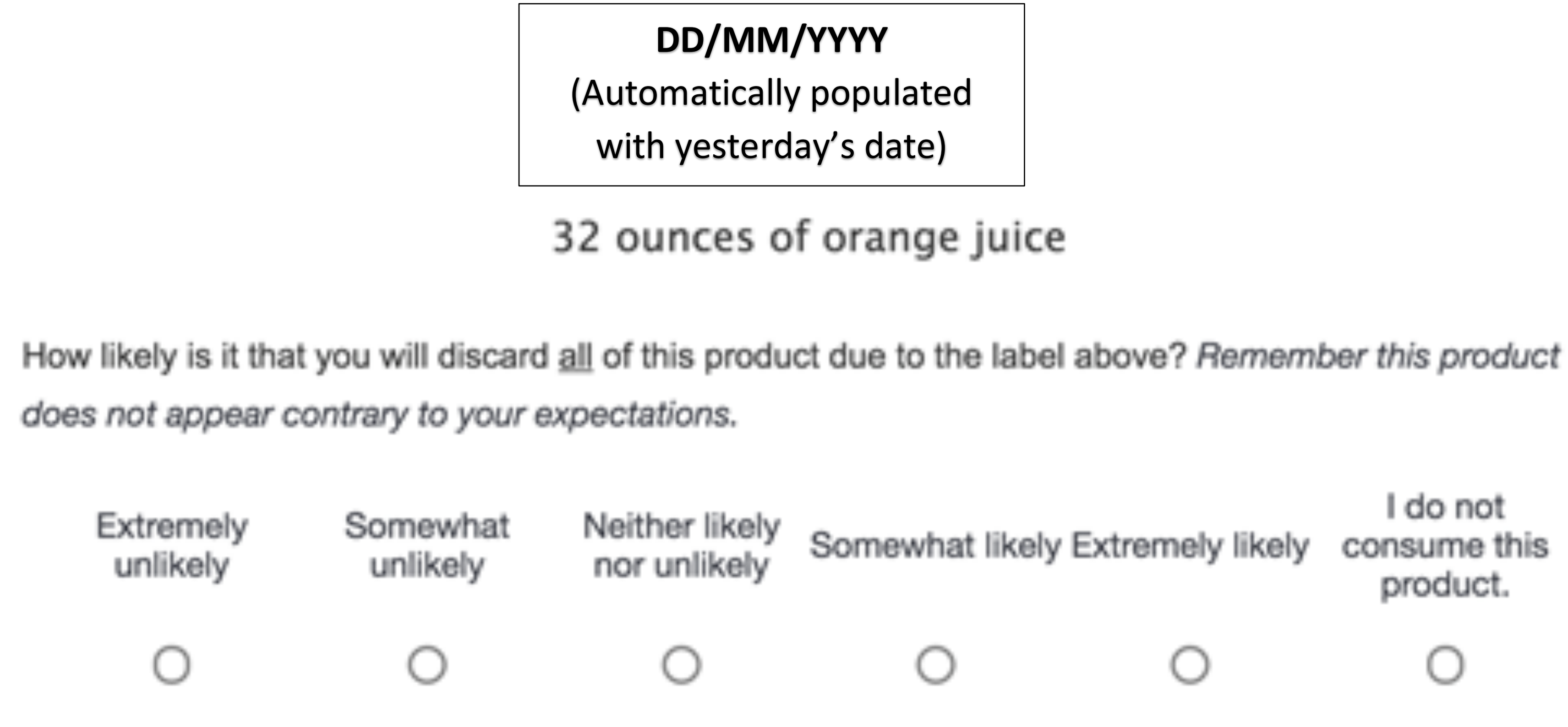
Source: Authors' calculations using the shock parameters for each food category in table 4 and the simulation model and model parameters outlined in equations 6–9.

Table 7. Annual impacts to nutrient and calorie purchases from the response to the "Best by" date label treatment

Changes in nutrients and energy	By food category									Total simulated change	Bench-mark change
	Cereal & bakery	Meat	Egg	Dairy	F&V	Other food	Non-alcoholic beverage	FAFH	Alcohol		
Calories	-708.1	-788.9	-269.3	-684	-519	-954.2	-231.8	12.4	57	-4085.9	-4085.9
Protein	-17.3	-84.3	-19.8	-35.2	-12.1	-38.8	-1.8	0.5	0.3	-208.5	-160.8
Carbohydrate	-123.8	-9.1	-1.3	-64.5	-97.4	-93.7	-56.3	1.5	3.1	-441.5	-499.2
Sugar	-29.5	-1.5	-0.9	-58.2	-42.9	-28.6	-49.5	0.7	0.4	-210.0	-222.4
Fiber	-8.4	-0.3	0	-1.2	-16.2	-8	-0.5	0.1	0	-34.5	-33.5
Fat	-17	-44	-19.9	-32.2	-13.1	-48.4	-0.6	0.5	0	-174.7	-152.5
Cholesterol	-19.4	-286.5	-570	-106.5	-9.2	-153.2	-0.5	1.6	0.1	-1143.6	-537.3
Vitamins											
E	-2.1	-1.7	-2.1	-1.1	-3.2	-5.9	-0.3	0	0	-16.4	-15.2
A	-208.7	-89	-259.8	-533.1	-416.2	-258.1	-19.2	3	0.1	-1781.0	-1287.7
B1	-1.1	-0.6	-0.1	-0.3	-0.4	-0.7	-0.1	0	0	-3.3	-3.3
B2	-0.9	-0.7	-0.7	-1.5	-0.4	-0.7	-0.4	0	0	-5.3	-4.2
B6	-0.8	-1.4	-0.2	-0.4	-1	-0.7	-0.2	0	0	-4.7	-4.1
B12	-1.8	-5.1	-1.3	-4	-0.2	-1.8	-0.2	0	0	-14.4	-10.4
C	-6.7	-1.6	0	-5.5	-101.8	-17.9	-54	0.4	0.1	-187.0	-170.1
D	-0.9	-3.8	-3.2	-7.9	-0.2	-1.2	-0.4	0	0	-17.6	-10.1
Calcium	-250.8	-74.8	-84.3	-1214.5	-154.7	-316.5	-119.8	4.7	5	-2205.7	-1847.3
Magnesium	-95	-84.5	-18.3	-104.9	-124.7	-124.8	-44.5	1.5	6.8	-588.4	-564.9
Iron	-11.7	-4.9	-2.5	-1.2	-3.9	-6.3	-0.8	0.1	0.1	-31.1	-30.3
Sodium	-1058.9	-2300	-487.3	-788.4	-800.4	-2020.2	-96.2	21.2	5.1	-7525.1	-6880.5
Potassium	-396.1	-1197.8	-216.6	-1203.1	-1727.2	-1018.2	-559.3	14.6	37.6	-6266.1	-5357.2

Source : Authors' calculations based on simulated quantity effects shown in table 7 and daily average energy and nutrient intakes reported in table 5.

Notes : F&V denotes fruits and vegetables and FAFH denotes food away from home. The benchmark change is the fixed change in nutrient consumption from an annual 4,085 calorie reduction based on the NHANES assuming no substitution between food products.



DD/MM/YYYY
(Automatically populated with yesterday's date)

32 ounces of orange juice

How likely is it that you will discard all of this product due to the label above? *Remember this product does not appear contrary to your expectations.*

Extremely unlikely | Somewhat unlikely | Neither likely nor unlikely | Somewhat likely | Extremely likely | I do not consume this product.

Figure 1. An example of the survey question used to elicit likelihood to discard a food product in the control (no date label)

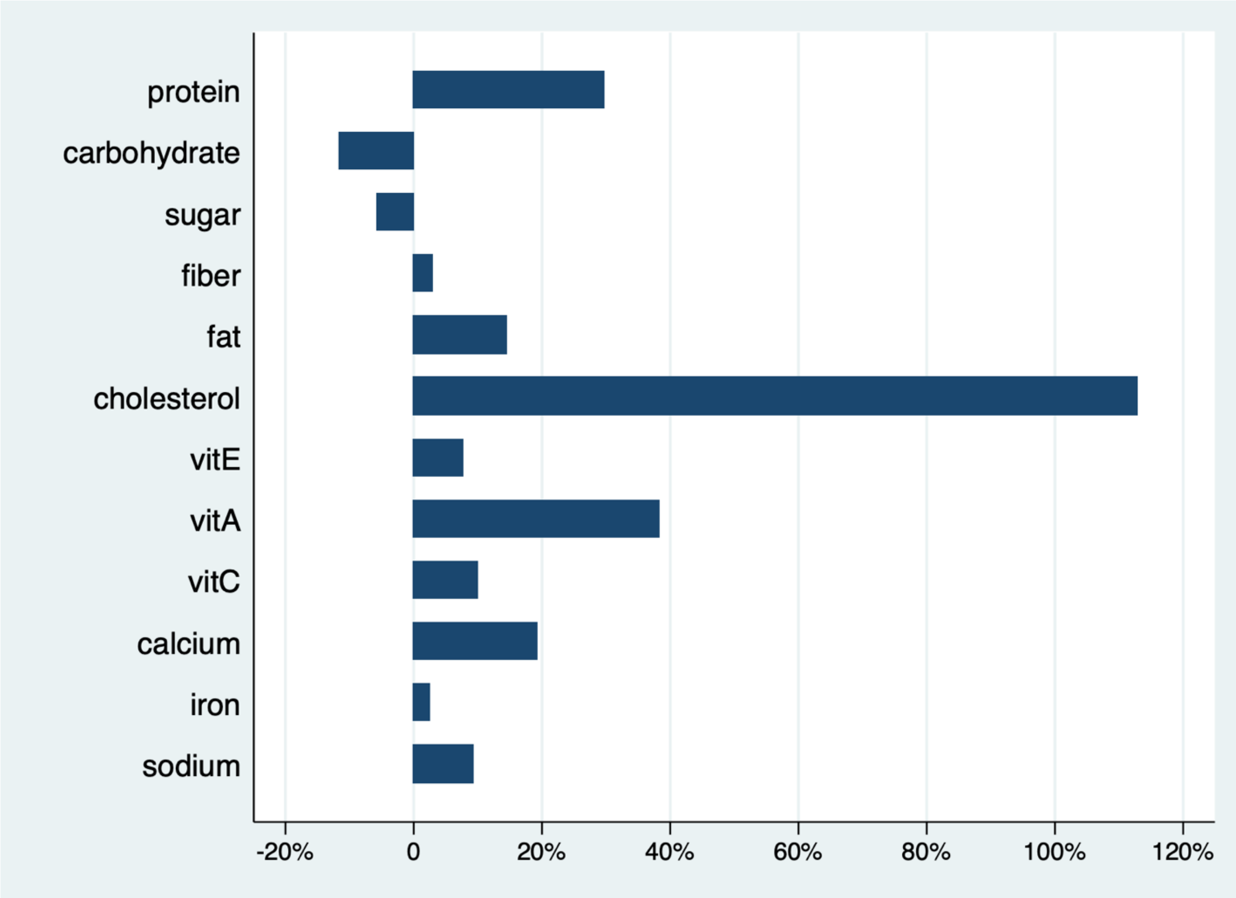


Figure 2. Percent change in the relative per capita availability of nutrients

Source: Authors' calculations based on total simulated change in nutrient consumption from the labeling treatment and the benchmark change shown in table 7.
Notes: These results show the change in per capita availability of nutrients (relative to a change that simply follows current consumption patterns) when subjects were exposed to the "Best by" date label.

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