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Simulated Models Suggest That Price per Calorie Is the Dominant Price Metric That Low-Income Individuals Use for Food Decision Making[1–3]

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Abstract

Background: The price of food has long been considered one of the major factors that affects food choices. However, the price metric (e.g., the price of food per calorie or the price of food per gram) that individuals predominantly use when making food choices is unclear. Understanding which price metric is used is especially important for studying individuals with severe budget constraints because food price then becomes even more important in food choice.

Objective: We assessed which price metric is used by low-income individuals in deciding what to eat.

Methods: With the use of data from NHANES and the USDA Food and Nutrient Database for Dietary Studies, we created an agent-based model that simulated an environment representing the US population, wherein individuals were modeled as agents with a specific weight, age, and income. In our model, agents made dietary food choices while meeting their budget limits with the use of 1 of 3 different metrics for decision making: energy cost (price per calorie), unit price (price per gram), and serving price (price per serving). The food consumption patterns generated by our model were compared to 3 independent data sets.

Results: The food choice behaviors observed in 2 of the data sets were found to be closest to the simulated dietary patterns generated by the price per calorie metric. The behaviors observed in the third data set were equidistant from the patterns generated by price per calorie and price per serving metrics, whereas results generated by the price per gram metric were further away.

Conclusions: Our simulations suggest that dietary food choice based on price per calorie best matches actual consumption patterns and may therefore be the most salient price metric for low-income populations. *J Nutr* 2016;146:2304–11.

Keywords: food decision making, food price, price metric, low income, simulation

Introduction

Poor diet quality is a major contributor to morbidity and mortality globally, accounting for 11.3 million deaths and 241.4 million disability-adjusted life years in the world in 2013 (1). In the United States, although there have been small improvements in diet quality over the last 10 y, the average diet quality is quite poor, and disparities exist by socioeconomic status. Food is perceived to be abundant in the United States, and overconsumption of food is the major cause of the US obesity epidemic (2). However, many populations do not have easy access to healthier items such as fruits and vegetables; lower-quality diets generally cost less per calorie than higher-quality diets (3). Understanding the process that people use in deciding what they eat is important because it can help us to identify strategies that may help to improve diet quality choices.

Price, taste, and convenience have been consistently cited as the top features that people consider when deciding what types of food to eat (4). Food price has received attention recently as both a potential explanation for the generally poor diet quality in the US population as well as the disparities in diet quality (5, 6). Researchers have noted that time trends of aggregate food price indicate that the price per kilogram of fruits and vegetables has increased substantially, whereas those of sweets and oils has

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remained stable (7). Furthermore, some researchers have argued that there is an economic incentive for populations with restricted budgets to consume calorically dense foods and that this may offer an explanation for the documented inverse relation between income and obesity risk (8). However, this argument is predicated on the assumption that people evaluate the price of food according to price per calorie (PPC)[8]. Drewnowski and Specter (8) and Drewnowski (9) demonstrated that when food groups are evaluated according to PPC, the more energy-dense foods are cheaper per calorie. However, it is unclear whether consumers evaluate the relative cost of food according to their cost per calorie or to other cost metrics. Researchers have argued that consumers are more likely to consider the cost per volume, weight, or serving when making food decisions (10). The answer to which foods are most expensive depends on which of these price metrics are used (9, 10). This issue becomes especially important for understanding decision making among individuals with restricted budgets, in which food price becomes the leading factor for food decision making (11). It is additionally important when considering manipulating the price of food as a way of incentivizing healthier diets.

Researchers have previously used simulation models to study whether is it possible to make food choices that meet dietary guidelines on a restricted budget. Computational approaches, typically based on linear programming, have been used to build such models (12). The use of linear programming-based models has been limited to testing the feasibility of following recommended diet guidelines in regard to their cost or to finding ways to improve the nutritional quality of food aid (12–18). To our knowledge, no studies have used simulation models to evaluate the effects of the price metric used by individuals with a restricted food budget on food choice or to determine the price metric that leads to dietary patterns that most closely match observational data. Given the importance of the price metric on intervention design and food policy, we believe such a simulation study would be a useful addition to the existing literature.

We used agent-based modeling (ABM) for our simulation approach because it can model individualized decision-making processes and has the ability to generate patterns of behavior through an emergent, button-up process (19). In our simulated environment, individuals (agents) chose their food based on 1 of 3 price metrics: PPC ($/100 kcal), price per gram (PPG) ($/100 g), and price per serving (PPS) ($/serving), whereas all other factors (e.g., taste) remained unchanged. Serving refers to the serving sizes of different food items (e.g., fruits and vegetables or soups and fluid milk) as indicated by FDA reference amounts customarily consumed (20). We used the food price data as reported in another work (9). We refer to these 3 metrics as PPC, PPG, and PPS, respectively. We used PPX to generically represent any one of these metrics. These metrics form the bases of the 3-food selection criteria that have been widely used in studies of price impact on dietary intake (9, 10). The food consumption patterns generated by each metric were compared against 3 independent data sources to determine the food choice approach that best matched the consumption patterns observed in US populations.

[8] Abbreviations used: ABM, agent-based modeling; AIC, Akaike information criterion; BLS, Bureau of Labor Statistics; EI, energy intake; FAFH, food away from home; HEI, healthy eating index; ICP, International Comparison Program; PPC, price per calorie; PPG, price per gram; PPS, price per serving; RSS, residual sum of squares; SAD, sum of absolute differences.

Methods

Study population and design. ABM defines a set of agents, in our case representing individuals, and a set of attributes for the agents. Agents are able to perform a set of actions within a simulated environment. Our ABM simulated the food consumption patterns of the adult US population for the year 2001. We used 2001 because the PPC, PPG, and PPS of the 9 major food groups were available for this particular year from previously published work (9). The simulated individuals in our model were representative of the US population of adults >20 y old in terms of age, sex, income, and dietary intake.

Databases. We used several databases to assign the parameter values of the agents in our ABM. The Bureau of Labor Statistics (BLS) and US census data were used to assign the demographic, income, and food budget parameters of each agent (21, 22). NHANES data sets were used to determine the diet compositions (23), and the USDA Food and Nutrient Database for Dietary Studies (24) was used to obtain food price values. Healthy eating index (HEI) data for NHANES participants (25) and the 2005 International Comparison Program (ICP) data set (26) were used to compare of our simulated results to actual data. Details about the procedure for obtaining data from these databases and employing them are provided in the following sections.

Demographics. We assigned age, sex, and income to our population of agents based on data from the US Census Bureau and BLS. Age and sex were assigned with the probability equal to the distribution based on 2001 US Census data (21). The income for each agent was based on the distribution of income in the United States according to the BLS data set for 2001 (22). Annual after-tax income from this data set was used for our study. We used quintile data for the after-tax income of the total US population from this data set. Each agent was assigned to one of the quintiles with a probability of 20%. The agent's income was randomly generated with the use of the mean and SD for that quintile of income.

After initializing the whole population, we continued our simulations only on those agents with the lowest 13% of income in the population because our research question was particularly concerned with how lower-income populations make dietary decisions. The choice of 13% was a result of using the lowest 2 code values indicating income ranges in the NHANES data set (23). We performed additional analyses for other thresholds (**Supplemental Methods**, **Supplemental Figures 1–3**).

Food budget. To assign each agent a daily food budget, we used data from BLS to find the mean and distribution of the proportion of annual income spent on food. Because the data on the price of food (described in the "Food Price" section) assumes that all food is prepared at home, we needed to find the daily food expenditure as if all food were prepared at home. BLS provides an estimate for food expenditures at home and food away from home (FAFH); in 2001, FAFH was 42.2% of total food expenditure. To find the daily expenditure as if all food were prepared at home, we excluded the cost of any nonfood item from the FAFH portion of daily food expenditure. By the nonfood portion, we mean any expense other than the retail price of the consumed food, including labor, tips, and any extra tax in restaurants. According to USDA reports (11, 27), restaurant prices were 168.4% higher than retail food prices in 2001. Accordingly, 63% [168.4/(100 + 168.4)] of FAFH was spent on nonfood items. The food expenditure value was then updated by subtracting this nonfood expense so that an agent's food budget became equivalent to its calculated diet cost. Both income and food expenditures were divided by 365 to give the daily food expenditure, which we call the food budget.

Diet composition. Assigning diet composition was a multistep process. Briefly, our goal was to assign each agent an energy intake (EI) amount based on their age and sex and a diet composition based on the percentage of energy from the 9 major food categories described by the USDA and identifiable in the NHANES data set (24). Specifically, each agent was randomly assigned a total daily EI according to NHANES data for the mean EI for each age category (20–39, 40–59, and 60–74 y) and sex with the use of the mean and SD of these 6 distributions (2 sexes within 3 age groups) as reported by Ford and Dietz (28). Agents' total EI did not change with the budget constraints introduced later in our simulation. This is because, in our model, it was assumed that total food intake is determined by energy and not nutrient requirements (14); it was also assumed that diet quality is affected before diet quantity in food-insufficient households (29). Hence, the daily EI was not reduced for agents with low budgets.

After assigning the total EI for each agent, the percentage of EI from each major food category was initialized based on NHANES mean values. We assigned the mean composition of the diet according to the USDA's 9 primary food groups for 2001 (24): *1*) milk and milk products; *2*) meat, poultry, and fish; *3*) eggs; *4*) dry beans, legumes, nuts, and seeds; *5*) grain products; *6*) fruits; *7*) vegetables; *8*) fats, oils, and salad dressings; and *9*) sugars, sweets, and beverages. We refer to these groups as milk, meat, eggs, beans, grains, fruits, vegetables, fats, and sugars, respectively. The mean proportion of total energy from each of these 9 food categories was derived from NHANES 2001–2002 data with the use of USDA food codes in the NHANES 2001–2002 dietary food recall data set (23) to identify food groups. The resulting mean diet composition for adults had the following percentages of daily caloric EI: 10.7% milk, 18.6% meat, 1.9% eggs, 3.1% beans, 33.4% grains, 4.8% fruits, 7.8% vegetables, 3.0% fats, and 16.6% sugars. Within the ABM, the initial diet of each agent was represented by this tuple (list of percentages). Changes in the diet (described in the "Food Decision-Making" section) were represented by changes in the values of the tuple, with the restriction that the sum of percentages remained equal to 1 (100%).

Food price. The mean PPC, PPG, and PPS of each of these 9 food categories was derived from previously published work (9). These data were originally calculated with the use of the USDA Food and Nutrient Database for Dietary Studies version 1.0 (24) and the Center for Nutrition Policy and Promotion food prices database (30) and were related to 2001. Mean and SD values for the unit prices of food were used to randomly generate food prices at the beginning of our simulation. Serving size (in grams) and energy density (kilocalories per 100 g) of various foods were also obtained from the same reference.

Food decision making. Agents in our model chose their food such that their diet was as close as possible to the mean diet. However, we did not allow the cost to exceed their food budget limit. This assumption was based on socio- and ethnologic observations that have shown that low-income populations maintain their identity and self-respect by retaining familiar dietary patterns instead of purchasing the cheapest source of nutrients to achieve a healthy diet (14, 31). The process that agents followed in choosing their diet is shown in **Figure 1**. In this process, agents started with their mean diet and calculated the cost based on their own daily energy intake. If the cost for following the current diet was higher than their daily food budget limit, agents updated the energy proportion values by decreasing the caloric intake from a food category that had a higher price per *X*, where *X* designates the food metric chosen for an ABM scenario, and balancing this decreased caloric intake by increasing the intake from a food category that had a lower price per *X*. Although the net caloric intake remained the same, the net cost of the diet decreased because of the differential pricing of the 2 food categories. The 2 food categories were chosen with probabilities proportional to the values of the mean diet such that a higher value in the mean diet resulted in a higher probability of being chosen as an increasing category and lower probability of being chosen as a decreasing category. Details about this process, along with technical aspects of implementation, are provided in Supplemental Methods and Supplemental Figure 1. Each ABM scenario (PPC, PPG, and PPS) was run separately so that we could compare the results across the 3 price metrics.

With the use of the mean diet for determining the probabilities of choosing the increasing and decreasing food categories, we allowed the model to indirectly include all of the factors that can affect food decision making of individuals, such as taste and convenience; i.e., we took the mean diet as the expressed preferences of the population, thus accounting for taste, convenience, health, and other preferences. We assumed that a higher proportion of energy coming from a specific food category in the mean diet demonstrated a higher preference for consumption of that food category. Hence, the mean diet foods with the largest percentages of daily caloric intake had the highest probabilities of becoming an increasing food category, whereas those with the lowest percentages of daily intake had the highest probabilities of becoming a decreasing food category.

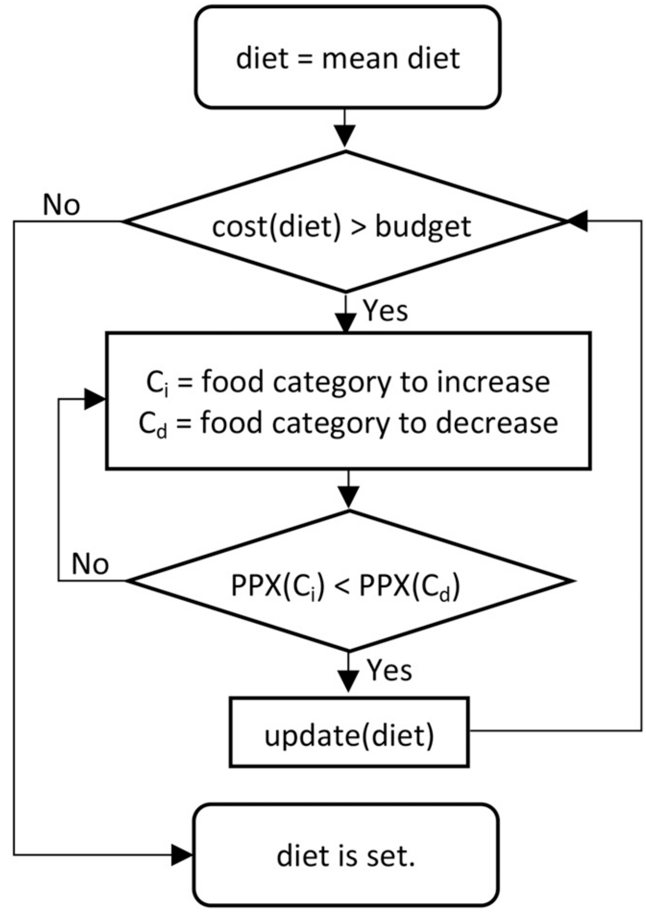

FIGURE 1 Flowchart of the food decision–making process that an agent uses to determine their diet (the portion of EI from each of the 9 major USDA food categories). An agent goes through this process every day for a period of 30 d in every simulation run. Agents use 1 of 3 price metrics in each run. These 3 metrics are shown by PPX, which refers to PPC, PPG, or PPS. EI, energy intake; PPC, price per calorie; PPG, price per gram; PPS, price per serving.

To ensure that unrealistic diet patterns were not generated by our model, we set minimum and maximum proportions of energy for each food category with the use of the 10th and 90th percentiles from the NHANES data set. These percentile values were calculated with the use of the same process used to determine the mean diet.

Each simulation was performed over a 1-mo period, during which we assumed that there were no changes in food prices and agent body weights. The results reported are based on the mean food consumption over this time period. Models were run 100 times. Each simulation lasted 30 s. The agents' population size was set to 201 million, which was equal to the number of adults aged >20 y in the United States as of April 2000 (21). Our ABM was implemented in the NetLogo environment (32).

Comparison of simulation results with data. We compared the results obtained from the 3 price-metric scenarios of our ABM to several data sets to see which of the scenarios generated dietary patterns that were closest to those observed in the data. First, we compared the simulated percentages to total EI for each food category to NHANES data. Total family income (variable INDFMINC) from the NHANES 2001–2002 data set was used to determine individuals in the lowest 13% bracket, who were of interest in our study. It should be noted that we used BLS data (22) to initialize the income and food budget levels of our agents rather than NHANES because the latter did include food budget data.

We then compared the mean HEI of simulated individuals in our model to the HEI from the NHANES 2001–2002 population, as calculated and reported by the USDA (25). Specifically, we used the sequence identifications of NHANES 2001–2002 participants with incomes in the lowest 13% of the income distribution to extract the individual HEI component scores of the same individuals from the USDA HEI data set. We used the reported scores for 5 categories of food rather than the aggregated HEI score because the rest of the categories in the original data set did not match our 9 food categories. The ranges for these scores were between 0 and 10. The individuals who followed the recommended USDA food guide pyramid servings per day received the maximum score for the HEI component, and those who consumed less than the minimum recommended amount received the minimum score. People with dietary intakes within the recommended and minimum recommended levels received proportional scores (33).

We used income elasticity for food subcategories for the third comparison of our simulation results. The original data were collected through the ICP 2005 data set (26), and the elasticity values have been reported by the USDA (34). The ICP data related to 2005; it has been shown previously that the value of the income elasticity of demand for various goods does not change notably over time (35). In our simulations, we recorded the food consumptions of the simulated population with baseline settings. The income level of agents was then increased by 1%, and the new food consumption levels were recorded. Income elasticity was calculated with the use of these 2 sets of values.

Statistical analyses. All analyses were conducted with the use of Stata version 14.0 (StataCorp LP). Sampling weights, sampling units, and strata were set according to NHANES analytic guidelines (22). We used 3 techniques to compare the results obtained from each of the 3 price metrics: *1*) sum of absolute differences (SAD) between simulated results and actual data, *2*) residual sum of squares (RSS) divided by the number of data points, and *3*) Akaike information criterion (AIC), where AIC = $n \ln(\mathrm{RSS}/n) + 2k$, in which n is the number of samples used to evaluate the results (i.e., the number of simulations) and k is the number of food groups.

Results

Three sets of results are presented in this section. **Figure 2** displays the percentage of total diet EI from 9 food categories that was simulated with the use of the 3 price-metric ABM scenarios. These results were compared to the calculated percentages from NHANES data. The NHANES values show the mean percentage of total EI from each category of food for adults in the lower 13% income group. The SAD between

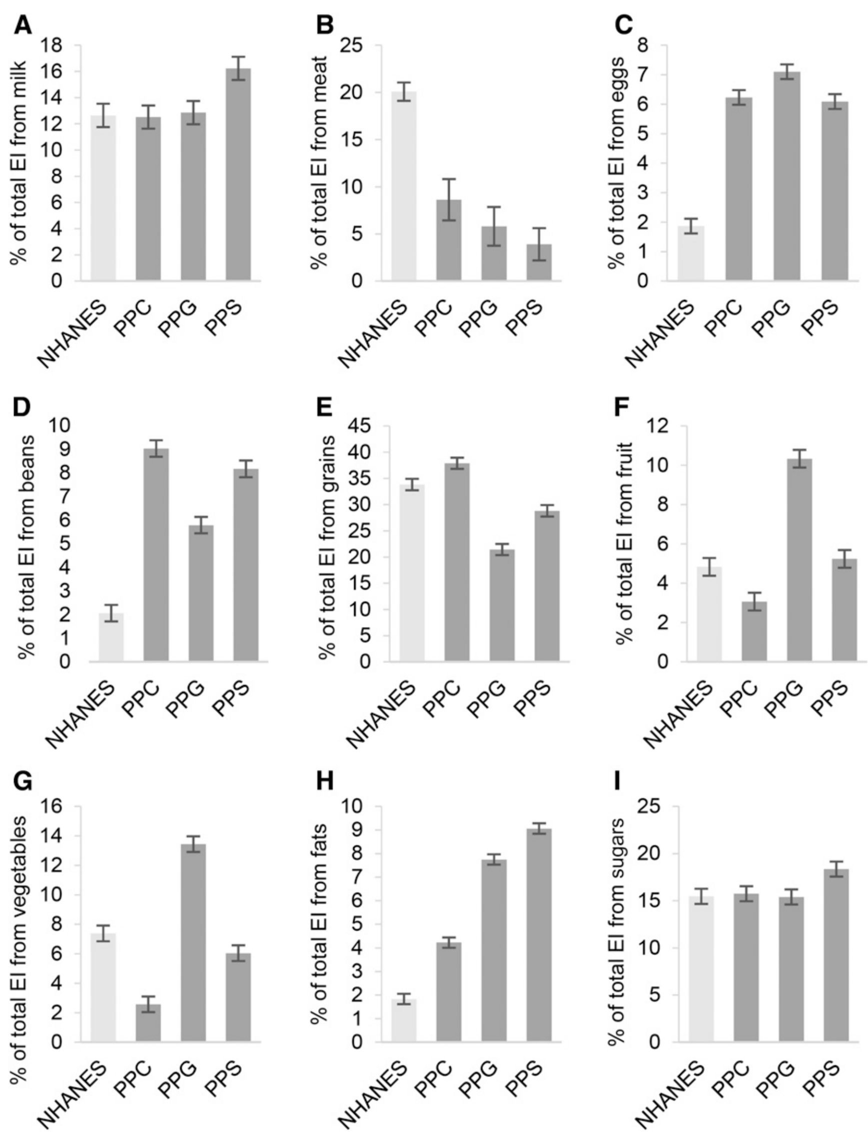

FIGURE 2 Percentage of total dietary energy from the 9 major USDA food categories [milk (A), meat (B), eggs (C), beans (D), grains (E), fruits (F), vegetables (G), fats (H), and sugars (I)] for adults in the lowest 13% income bracket calculated from NHANES 2001–2002 and simulated results with the use of 3 price-metric scenarios. The ABM results used the following criteria for decision making: PPC, PPG, and PPS. Values are means ± 95% CIs, and there were 100 simulations. Each chart refers to one of the food categories indicated on the vertical axis. ABM, agent-based modeling; EI, energy intake; PPC, price per calorie; PPG, price per gram; PPS, price per serving.

TABLE 1 Comparison of simulated results obtained from 3 price-metric scenarios and actual data for the 3 experiments reported in this article[1]

Experiment	SAD	RSS/k^2	AIC[3]
Total EI, %			
PPC	36.24	27.51	−111.07
PPG	53.40	55.67	−40.58
PPS	46.98	46.41	−58.76
HEI			
PPC	8.93	4.52	−714.68
PPG	12.84	8.15	−620.88
PPS	8.77	4.96	−467.27
Income elasticity of demand			
PPC	0.73	0.07	−291.71
PPG	1.29	0.17	−232.76
PPS	2.83	0.78	−282.46

[1] Smaller values are closer to actual data. AIC, Akaike information criterion; EI, energy intake; HEI, healthy eating index; PPC, price per calorie; PPG, price per gram; PPS, price per serving; RSS, residual sum of squares; SAD, sum of absolute differences.
[2] k = 9 in the first experiment, 5 in the second, and 4 in the third.
[3] AIC = $n \ln(\mathrm{RSS}/n) + 2k$, n = 100 in all cases.

simulated values and NHANES for all 9 food categories, RSS (divided by the number of data points k), and AIC are shown in **Table 1** for each of the 3 scenarios. Results based on PPC showed smaller differences from the actual data based on each of the 3 measures. For meat, eggs, grains, fats, and sugars, the PPC predictions were closest to the actual intakes of NHANES respondents. For beans, PPG results were closest. For dairy, fruits, and vegetables, PPS results were closest to NHANES data. In the fruits and sugars categories, the PPC results were still close to the NHANES data because the 95% CIs overlapped with the NHANES data.

In our second set of results, we used the simulated intakes to calculate the HEI food component scores for the population and compared these scores to the HEI food component scores of the NHANES population. These results are shown in **Figure 3**. Overall, the PPC and PPS price-metric scenarios performed similarly (Table 1), with the sum of 5 absolute differences for the 3 methods being equal to 8.9 for PPC, 12.8 for PPG, and 8.8 for PPS. For 3 of the 5 HEI component scores (dairy, meat, and grains), the PPC scenario predicted intakes that generated HEI scores closest to the actual HEI scores of the NHANES participants. PPS values were closest to the actual HEI scores for the fruits and vegetables categories. RSS and AIC values also showed a similar pattern.

In our third analysis, we compared income elasticities obtained from our model to data from the ICP (**Figure 4**). Based on the ICP data, grains and fats are inferior goods because they have negative values for income elasticity, meaning that as people have more income they decrease the consumption of these foods. Dairy and fruit products are normal goods, with positive income elasticity values. All 3 simulated price-metric scenarios generated negative values for the income elasticity of fat, which was in the same direction as the ICP data. SAD, RSS, and AIC values showed that the PPC scenario generated the closest patterns to the actual data (Table 1). The 95% CI for the PPC scenario predicted income elasticity for fruits that overlapped the 95% CI for ICP. Once again, in 3 of 4 cases, PPC led to more realistic results than the other 2 scenarios.

Discussion

Among the 3 price-metric scenarios in our ABM simulations, the PPC metric produced results that were most similar to data on dietary habits. In addition, the PPC metric produced results most consistent with data on the sensitivity of dietary composition to changes in income. These results are consistent with the ideas put forward by Drewnowski and Specter (8). Although all 3 price metric scenarios generated results that were relatively close to the data, the PPC metric generally outperformed the PPG and PPS metrics.

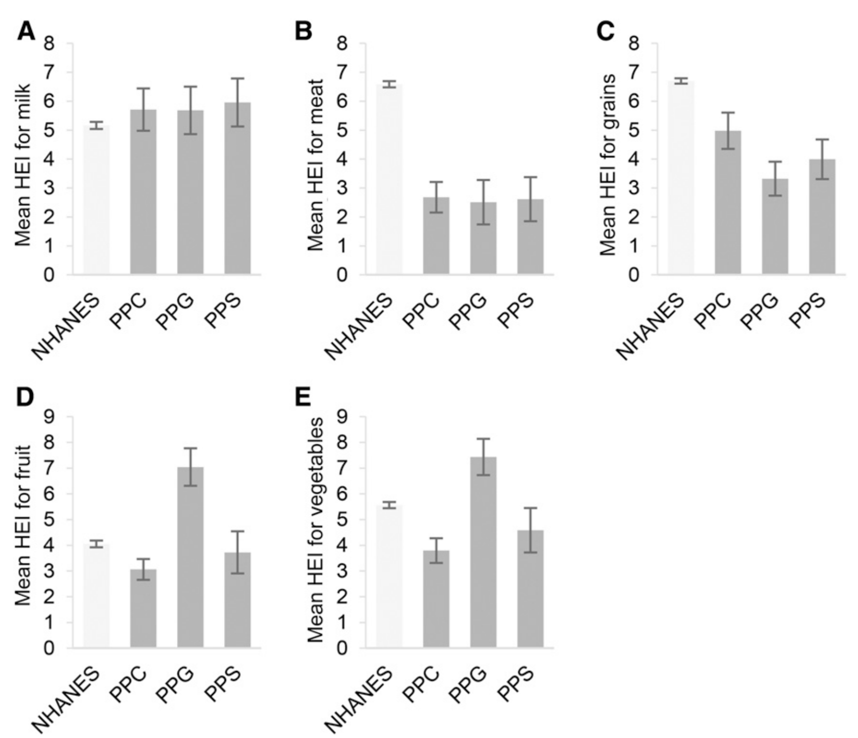

FIGURE 3 Mean HEI score of simulated individuals compared to NHANES 2001–2002 low-income adults for 5 food categories: milk (A), meat (B), grains (C), fruits (D), and vegetables (E). Values are means ± 95% CIs, and there were 100 simulations. HEI, healthy eating index; PPC, price per calorie; PPG, price per gram; PPS, price per serving.

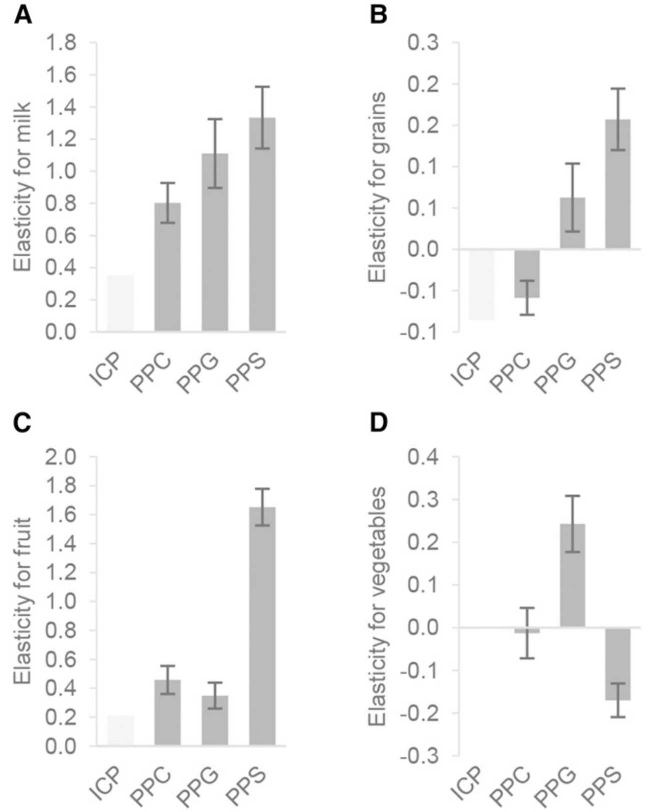

FIGURE 4 Income elasticity of demand for 4 food categories: milk (A), grains (B), fruits (C), and vegetables (D). The values relate to the low-income adult US population as calculated from the ICP data set (reported by the USDA) and compared to the results from our ABM simulations based on the 3 different food decision–making scenarios (PPC, PPG, and PPS). The value for ICP in panel D is −0.001. Values are means ± 95% CIs, and there were 100 simulations. CIs were not available for ICP data. ABM, agent-based modeling; ICP, International Comparison Program; PPC, price per calorie; PPG, price per gram; PPS, price per serving.

The following discussion may explain some of the dietary patterns that were observed in the ABM results. We found that agents that used PPC for decision making had a higher consumption of grains. This may be because, based on our food price data (9), the grains category had the lowest PPC. Hence, under PPC decision-making rules, increasing grain consumption was the most cost-effective way of maintaining dietary EI while lowering the total food budget for the agents representing the lowest 13% income group (Figure 2E). Similarly, because fruits had the lowest PPG, the PPG scenario led to the highest consumption of fruits (Figure 2F). Likewise, because fats had the lowest PPS, the PPS scenario led to a high consumption of fats (Figure 2H).

Another noteworthy result in our findings is that, for grains, only the PPC scenario led to negative values for income elasticity (Figure 4B). We believe this was because grains have the lowest PPC among the 9 food groups. When an agent in our ABM had more money to spend on food, the least expensive food group had the highest probability of being replaced by more costly foods.

Our simulation addresses several criticisms and difficulties that have arisen in the literature on the cost of healthier foods relative to less healthy foods. Two primary critiques have been levied against the assertion that healthy foods cost more. The first relates directly to the purpose of our article. It has been argued effectively by Carlson and Frazão (36) that we do not know whether people evaluate the cost of food based on PPC, PPG, or PPS and that the answer of whether healthy food costs more differs depending on which metric is used. For instance, Carlson and Frazão (10) reported that, based on NHANES and Center for Nutrition Policy and Promotion data sets, for all metrics except for PPC, healthy foods actually cost less than less healthy foods. With the use of similar data sets, Davis and Carlson (37) also reported that no statistical support exists for high energy-dense food being cheaper than low energy-dense food. If people do use one of these other price metrics, it would be difficult to argue that there is an economic incentive to consume junk food; instead, other factors would be needed to explain the disparity in healthy diets that has been observed between high- and low-income populations. Our work sought to address the question of which metric is being used, and we have developed simulation models that incorporate these metrics for food choice. Our comparison of model results to several large data sets supports the assertion that low-income populations evaluate food cost with the use of the PPC metric.

Second, in response to earlier findings that energy density was negatively correlated with cost per calorie and that there may be an economic incentive for low-income populations to consume energy-dense foods, Lipsky (38) asserted that the finding was likely an artifact and that a negative correlation between energy cost and energy density will always be found because of having calories in the numerator and denominator ($/kcal and kcal/g). Others have used a variety of arguments to counter this assertion and have found that the negative correlation could not be reproduced with randomly generated numbers (39, 40). These challenges were avoided in our work by letting the food consumption patterns emerge through individualized decision-making agents. In other words, our results were not obtained with the use of an analytical method, and we did not study existing food consumption patterns to form our conclusions as did Drewnowski and Specter (8), Davis and Carlson (37), and Schroeter et al. (41). Instead, we used a bottom-up approach to generate those patterns with the use of agents that followed a price metric and that adjusted dietary composition through a set of simple rules. Although our model cannot be used for addressing questions related to the negative correlation between food price and energy density, it does suggest that actual consumption patterns are consistent with the PPC price metric for food decision making. By extension, foods that are relatively cheap per calorie will be the preferred foods for low-income individuals.

The limitations of this study are worth noting. In this work, we assumed there was a single dominant price metric used by low-income populations; a combination of the 3 price metrics may be more realistic. The data used in this work relate to 2001. Although this did not affect our methodology (i.e., comparing agent-based simulations with data), more recent data may be different from the 2001 data because of changes in dietary price metrics. However, we would expect these differences to be small because the relative prices of different types of foods did not change substantially over this time period. For instance, according to BLS annual consumer price index data sets, the relatively more expensive food groups in 2001 (42) remained relatively more expensive than other food groups in 2016 (43). The mean annual inflation rate ranged from the lowest value of 2.9% for fats and oils to the 2 highest values of 3.6% for grain products and 5% for eggs. Eggs contributed only 1.9% of daily caloric intake, and the remainder of the food groups had differences in the inflation rate of ≤0.7%/y (44). Our model cannot be used to assess decision making among people who spend more than the mean diet cost; in addition, it should not be generalized to higher-income populations. This is not a severe limitation because our study is on low-income individuals, for whom price becomes the key factor of dietary behaviors and for whom the strong relation between poverty and both malnutrition and obesity are most relevant (45).

In conclusion, our findings suggest that low-income populations choose foods based on their PPC. These findings may have important public health and policy implications. Specifically, the relatively high PPC of healthy foods may be a substantial barrier to eating these foods for low-income populations regardless of their PPG or PPS. The results of our study indicate that researchers, agencies, and policy makers should consider ways of manipulating PPCs when considering ways of discouraging low-quality diets and encouraging high-quality diets.

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References

1. Forouzanfar MH, Alexander L, Anderson HR, Bachman VF, Biryukov S, Brauer M, Burnett R, Casey D, Coates MM, Cohen A. Global, regional, and national comparative risk assessment of 79 behavioural, environmental and occupational, and metabolic risks or clusters of risks in 188 countries, 1990–2013: a systematic analysis for the Global Burden of Disease Study 2013. Lancet 2015;386:2287–323.
2. Ogden CL, Carroll MD, Kit BK, Flegal KM. Prevalence of childhood and adult obesity in the United States, 2011–2012. JAMA 2014; 311:806–14.
3. Darmon N, Drewnowski A. Contribution of food prices and diet cost to socioeconomic disparities in diet quality and health: a systematic review and analysis. Nutr Rev 2015;73:643–60.
4. Glanz K, Basil M, Maibach E, Goldberg J, Snyder D. Why Americans eat what they do: taste, nutrition, cost, convenience, and weight control concerns as influences on food consumption. J Am Diet Assoc 1998;98: 1118–26.
5. Bleich SN, Jones-Smith J, Wolfson JA, Zhu X, Story M. The complex relationship between diet and health. Health Aff (Millwood) 2015;34:1813–20.
6. Rao M, Afshin A, Singh G, Mozaffarian D. Do healthier foods and diet patterns cost more than less healthy options? A systematic review and meta-analysis. BMJ Open 2013;3.
7. Popkin BM. Agricultural policies, food and public health. EMBO Rep 2011;12:11–8.
8. Drewnowski A, Specter S. Poverty and obesity: the role of energy density and energy costs. Am J Clin Nutr 2004;79:6–16.
9. Drewnowski A. The cost of US foods as related to their nutritive value. Am J Clin Nutr 2010;92:1181–8.
10. Carlson A, Frazão E. Are healthy foods really more expensive? It depends on how you measure the price. Washington (DC): USDA; 2012.
11. Dykstra H, Davey A, Fisher JO, Polonsky H, Sherman S, Abel ML, Dale LC, Foster GD, Bauer KW. Breakfast-skipping and selecting low-nutritional-quality foods for breakfast are common among low-income urban children, regardless of food security status. J Nutr 2016;146: 630–6.
12. Masset G, Monsivais P, Maillot M, Darmon N, Drewnowski A. Diet optimization methods can help translate dietary guidelines into a cancer prevention food plan. J Nutr 2009;139:1541–8.
13. Darmon N, Ferguson E, Briend A. Linear and nonlinear programming to optimize the nutrient density of a population's diet: an example based on diets of preschool children in rural Malawi. Am J Clin Nutr 2002;75:245–53.
14. Darmon N, Ferguson EL, Briend A. A cost constraint alone has adverse effects on food selection and nutrient density: an analysis of human diets by linear programming. J Nutr 2002;132:3764–71.
15. Dibari F, Diop EHI, Collins S, Seal A. Low-cost, ready-to-use therapeutic foods can be designed using locally available commodities with the aid of linear programming. J Nutr 2012;142:955–61.
16. Hlaing LM, Fahmida U, Htet MK, Utomo B, Firmansyah A, Ferguson EL. Local food-based complementary feeding recommendations developed by the linear programming approach to improve the intake of problem nutrients among 12–23-month-old Myanmar children. Br J Nutr 2016;116(Suppl 1):S16-26.
17. Maillot M, Drewnowski A. Energy allowances for solid fats and added sugars in nutritionally adequate U.S. diets estimated at 17–33% by a linear programming model. J Nutr 2011;141:333–40.
18. Monsivais P, Aggarwal A, Drewnowski A. Are socioeconomic disparities in diet quality explained by diet cost? J Epidemiol Community Health 2012;66:530–5.
19. Hammond RA. Complex systems modeling for obesity research. Prev Chronic Dis 2009;6:A97.
20. FDA. Electronic code of federal regulations, sec. 101.9: nutrition labeling of food [Internet]. [cited 2016 Aug 10]. Available from: https://www.accessdata.fda.gov/scripts/cdrh/cfdocs/cfcfr/CFRSearch.cfm?fr=101.9.
21. Meyer J. Age: 2000 [Internet]. [cited 2016 Jun 1]. Available from: http://1.usa.gov/1Ur5O2V.
22. US Department of Labor. Quintiles of income before taxes, Consumer Expenditure Survey, 2001 [Internet]. [cited 2016 Jun 1]. Available from: http://1.usa.gov/258Whl8.
23. CDC. NHANES 2001–2002 [Internet]. [cited 2016 Jun 1]. Available from: http://1.usa.gov/23hXuTI.
24. USDA. Food and nutrient database for dietary studies, v1.0 [Internet]. [cited 2016 Jun 1]. Available from: http://www.ars.usda.gov/News/docs.htm?docid=12068.
25. USDA. Healthy eating index 2001–2002 data [Internet]. [cited 2016 May 1]. Available from: http://1.usa.gov/1UHq7IL http://1.usa.gov/1UHq7IL.
26. World Bank. The 2005 International Comparison Program database [Internet]. [cited 2016 Jun 1]. Available from: http://bit.ly/1T0ILvi.
27. USDA. Relative prices of food at three stages of the system [Internet]. [cited 2016 Jun 1]. Available from: http://1.usa.gov/1eztJVr.
28. Ford ES, Dietz WH. Trends in energy intake among adults in the United States: findings from NHANES. Am J Clin Nutr 2013;97:848–53.
29. Basiotis PP. Validity of the self reported food sufficiency status item in the US Department of Agriculture's Food Consumption Surveys. In: Haldeman V, editor. Proceedings for the 38th Annual Conference of the American Council on Consumer Interest; 1992 Mar 25–28; Toronto. p. 262–70.
30. Carlson A, Lino M, Juan W, Marcoe K, Bente L, Hiza HA, Guenther PM, Leibtag ES. Development of the CNPP prices database [Internet]. [cited 2016 June 1]. Available from: http://1.usa.gov/1R9eRQL.
31. Dowler E. Poverty, food and nutrition. In: Strelitz J, Lister R, editors. Why money matters: family income, poverty and children's lives. London: Save the Children, 2008:p. 34–43.
32. Center for Connected Learning and Computer-BasedModeling. NetLogo [Internet]. [cited 2016 May 1]. Available from: https://ccl.northwestern.edu.
33. Bowman SA, Gerrior MLSA, Basiotis PP. The healthy eating index, 1994–96. Fam Econ Rev 1998;11:2.
34. Seale JL, Regmi A. Modeling international consumption patterns. Rev Income Wealth 2006;52:603–24.
35. Perloff JM. Microeconomics: theory and applications with calculus. Upper Saddle (NJ): Pearson Education; 2014.
36. Carlson A, Frazão E. Food costs, diet quality and energy balance in the United States. Physiol Behav 2014;134:20–31.
37. Davis GC, Carlson A. The inverse relationship between food price and energy density: is it spurious? Public Health Nutr 2015;18:1091–7.
38. Lipsky LM. Are energy-dense foods really cheaper? Reexamining the relation between food price and energy density. Am J Clin Nutr 2009;90: 1397–401.
39. Drewnowski A. Reply to LM Lipsky et al. Am J Clin Nutr 2011;93: 868–9.

40. Darmon N, Maillot M. In foods, energy is cheap where it is abundant and expensive where it is scarce: this is a fact, not an artifact. Am J Clin Nutr 2010;91:1068–9.

41. Schroeter C, Lusk J, Tyner W. Determining the impact of food price and income changes on body weight. J Health Econ 2008; 27:45–68.

42. US Bureau of Labor Statistics. 2001 Consumer price index for all urban consumers: U.S. city average, by expenditure category and commodity and service group [Internet]. [cited 2016 Jun 1]. Available from: http://www.bls.gov/cpi/cpid01av.pdf.

43. US Bureau of Labor Statistics. CPI detailed report—data for May 2016 [Internet]. [cited 2016 Jul 10]. Available from: http://www.bls.gov/cpi/cpid1605.pdf.

44. USDA. Methodology behind the quarterly food-at-home price database [Internet]. [cited 2016 Jul 1]. Available from: http://www.ers.usda.gov/media/142331/tb1926_1_.pdf.

45. Tanumihardjo SA, Anderson C, Kaufer-Horwitz M, Bode L, Emenaker NJ, Haqq AM, Satia JA, Silver HJ, Stadler DD. Poverty, obesity, and malnutrition: an international perspective recognizing the paradox. J Am Diet Assoc 2007;107:1966–72.