



United States Department of Agriculture

Economic  
Research  
Service

Economic  
Research  
Report  
Number 179

December 2014

# Menu Labeling Imparts New Information About the Calorie Content of Restaurant Foods

Hayden Stewart, Jeffrey Hyman, and Diansheng Dong





United States Department of Agriculture

## Economic Research Service

[www.ers.usda.gov](http://www.ers.usda.gov)

### Access this report online:

[www.ers.usda.gov/publications/err-economic-research-report/err179](http://www.ers.usda.gov/publications/err-economic-research-report/err179)

### Download the charts contained in this report:

- Go to the report's index page [www.ers.usda.gov/publications/err-economic-research-report/err179](http://www.ers.usda.gov/publications/err-economic-research-report/err179)
- Click on the bulleted item "Download err179.zip"
- Open the chart you want, then save it to your computer

### Recommended citation format for this publication:

Stewart, Hayden. Jeffrey Hyman and Diansheng Dong. *Menu Labeling Imparts New Information About the Calorie Content of Restaurant Foods*, ERR-179, U.S. Department of Agriculture, Economic Research Service, December 2014.

Cover image: Shutterstock.

Use of commercial and trade names does not imply approval or constitute endorsement by USDA.

The U.S. Department of Agriculture (USDA) prohibits discrimination in all its programs and activities on the basis of race, color, national origin, age, disability, and, where applicable, sex, marital status, familial status, parental status, religion, sexual orientation, genetic information, political beliefs, reprisal, or because all or a part of an individual's income is derived from any public assistance program. (Not all prohibited bases apply to all programs.) Persons with disabilities who require alternative means for communication of program information (Braille, large print, audiotape, etc.) should contact USDA's TARGET Center at (202) 720-2600 (voice and TDD).

To file a complaint of discrimination write to USDA, Director, Office of Civil Rights, 1400 Independence Avenue, S.W., Washington, D.C. 20250-9410 or call (800) 795-3272 (voice) or (202) 720-6382 (TDD). USDA is an equal opportunity provider and employer.



**Economic  
Research  
Service**

Economic  
Research  
Report  
Number 179

December 2014

# Menu Labeling Imparts New Information About the Calorie Content of Restaurant Foods

Hayden Stewart, Jeffrey Hyman, and Diansheng Dong

## Abstract

Restaurant foods are typically higher in calories than meals consumed at home. Menu labeling regulations by the U.S. Food and Drug Administration aim to inform consumers about the calorie content of menu items. However, some consumers may already be making at least partially informed decisions. For example, as a rule of thumb, a consumer may be aware that deep-fried foods are higher in calories. He or she may also know to avoid side dishes like French fries and onion rings. Indeed, it has been argued that some consumers can already identify which foods best satisfy their needs and wants and gain little new information from menu labeling. In this study, following research in marketing science and behavioral economics, we assume that a representative consumer employs rules-of-thumb nutrition knowledge to judge the calorie content of restaurant foods when explicit information is unavailable. We then investigate whether rules of thumb accurately predict the calorie content of 361 meals sold by 2 major fast-food restaurants and 5,752 meals sold by 5 major full-service restaurants. Results show that some simple rules of thumb are fairly reliable predictors of actual calorie content. They and other information available at the point of sale also explain about half of the total variation in calories in restaurant foods. Nonetheless, we find that menu labeling still imparts substantial new information. In particular, it is likely that many Americans are already able to make crude choices between high- and low-calorie foods, based on their pre-existing understandings of nutrition. Menu labeling allows them to make finer adjustments in their food choices and behavior, if they wish to.

**Keywords:** Menu labeling, restaurant menu, calorie, food choices, obesity, nutrition information, menu board, Patient Protection and Affordable Care Act

## Acknowledgments

The authors thank Dean Jolliffe of the World Bank, Biing Hwan Lin of the U.S. Department of Agriculture/Economic Research Service, Professor Joshua Berning, University of Georgia, and Professor Brenna Ellison, University of Illinois for review comments including assistance with the econometric model. We also thank Andrew Stivers of the U.S. Food and Drug Administration for background information and review comments. Finally, we thank Priscilla Smith for editing and Curtia Taylor for design and layout, both in USDA/ERS.

## **Contents**

<b>Summary</b> .....	<b>iii</b>
<b>Introduction</b> .....	<b>1</b>
<b>The Debate Over Menu Labeling</b> .....	<b>3</b>
<b>Does Menu Labeling Affect Food Choices?</b> .....	<b>5</b>
<b>Theoretical Framework Behind the Study</b> .....	<b>7</b>
<b>Data Collected for the Study</b> .....	<b>9</b>
Rules of Thumb .....	11
Other Sources of Nutrition Information.....	13
<b>Regression Models</b> .....	<b>16</b>
<b>Results and Findings</b> .....	<b>18</b>
Marginal Effects.....	18
Goodness of Fit .....	18
What Consumers May and May Not Understand .....	20
The Consumer’s Level of Nutrition Knowledge .....	21
<b>Conclusions</b> .....	<b>23</b>
<b>References</b> .....	<b>24</b>
<b>Appendix tables</b> .....	<b>27</b>



Find the full report at [www.ers.usda.gov/publications/err-economic-research-report/err179](http://www.ers.usda.gov/publications/err-economic-research-report/err179)

# Menu Labeling Imparts New Information About the Calorie Content of Restaurant Foods

Hayden Stewart, Jeffrey Hyman, and Diansheng Dong

## What Is the Issue?

U.S. Food and Drug Administration regulations require chain restaurants to clearly and prominently display the calorie content of menu items. Major fast-food restaurants, for example, need to post the number of calories in burgers, sandwiches, and other foods on their menu boards; in full-service restaurants, calories are noted in the menus. Some localities around the United States previously had implemented their own regulations. In New York City, where menu labeling has been required since 2008, researchers found that about 28 percent of the customers at a fast-food eatery adjusted their order after noticing calorie information. In Philadelphia, where local menu labeling regulations also had been implemented, 34 percent of the customers at a full-service restaurant adjusted their order after noticing calorie information. Whether a particular consumer responds to menu labeling may furthermore vary with his or her pre-existing knowledge of nutrition. Behavioral economics postulates that, when restaurants do not provide explicit calorie information, consumers may use rules-of-thumb nutrition knowledge to judge the calorie content of meals. For example, a consumer may know that deep-fried foods are typically higher in calories, whereas meals containing fruits and vegetables are generally lower in calories. If such simple rules are effective for discriminating among restaurant meals, then some people already may be able to identify the foods that best satisfy their needs and wants without the help of menu labeling. In this study, we investigate the effectiveness of rules-of-thumb nutrition knowledge for judging the calorie content of restaurant meals, and the extent to which menu labeling imparts additional information.

## What Did the Study Find?

Prior to the passage of menu labeling laws, when restaurants were not required to provide explicit calorie data, Americans may have relied on their own knowledge of nutrition to guess the calorie content of foods. This may have worked to some extent since consumers can deduce the healthfulness of restaurant foods from some readily observable cues, as noted by the American Heart Association (AHA) and the National Heart, Lung and Blood Institute

ERS is a primary source of economic research and analysis from the U.S. Department of Agriculture, providing timely information on economic and policy issues related to agriculture, food, the environment, and rural America.

(NHLBI), among others. For example, as a rule of thumb, Americans should expect deep-fried foods to be higher in calories. If consumers want to lessen the amount of calories they consume, they also should seek out meals rich in fruits and vegetables, and avoid side dishes like French fries and onion rings.

This study confirms that consumers can discriminate fairly well between low- and high-calorie menu items using only rules of thumb. Results show that some simple rules of thumb are fairly reliable predictors of actual calorie content. They and other information available at the point of sale also explain about half of the total variation in calories in restaurant foods. Nonetheless, rules of thumb are blunt tools, and less effective for discriminating among foods that differ modestly in calorie content. For example, a consumer who knows some rules of thumb highlighted by the AHA and the NHLBI already should understand that a chicken sandwich meal at one fast-food restaurant contains fewer calories when ordered with a side dish of applesauce (800 calories) instead of French fries (1,190 calories). However, the same consumer may be unaware whether a sandwich featuring a deep-fried chicken fillet is more or less caloric than the same restaurant's signature hamburger, holding constant the side dish (720 calories with the applesauce, 1,110 with the fries). Similarly, when examining the menu at one full-service restaurant chain, this consumer may be unable to discriminate between a chicken breast served with bacon, cheese, and fried potato wedges (1,172 calories) and a cheeseburger served with fried potato wedges (1,238 calories).

Using rules of thumb can also lead to suboptimal choices because they are not always correct. For example, when dining at a fast-food chain restaurant, consumers should not consider meals less caloric, on average, just because they include fruits or vegetables. Indeed, many of the highest calorie burgers and sandwiches available at fast-food restaurants include lettuce and other vegetables. Similarly, when comparing the most indulgent, highest calorie meals available at a sit-down restaurant, consumers can disregard any rule of thumb about deep-fried foods being the more caloric. Deep-fried foods may actually be lower in calories than other highest calorie choices (such as a pasta dish).

Overall, consumers who have a basic knowledge of nutrition learn less new information from menu labeling than other consumers. However, prior to the labeling, even these consumers could make only crude choices among high- and low-calorie foods. Providing calorie information on menus should help all Americans to better assess the healthfulness of restaurant foods as well as the taste, cost, and convenience and make finer adjustments in their food choices and behavior, if they wish.

## **How Was the Study Conducted?**

A representative consumer was assumed to know some rules-of-thumb nutrition knowledge provided by the AHA and the NHLBI. We then collected detailed information on 361 meals sold by 2 fast-food chains and 5,752 meals sold by 6 sit-down restaurant chains. Finally, we conducted several statistical tests to measure our representative consumer's ability to discriminate among these meals using the rules of thumb. The more information he or she can figure out about the calories in the restaurant foods, the less new information menu labeling imparts, all else constant. Ordinary least squares and unconditional quantile regression models are estimated to gauge whether our representative consumer can understand variation in calories between restaurant meals in general as well as between meals that vary modestly in calorie content.

# Menu Labeling Imparts New Information About the Calorie Content of Restaurant Foods

Hayden Stewart, Jeffrey Hyman, and Diansheng Dong

## Introduction

Due to a menu-labeling provision of the 2010 Patient Protection and Affordable Care Act, consumers standing in line at fast-food chain restaurants will no longer have to guess the number of calories in their favorite foods. They will see the calorie content of various burgers and sandwiches printed on the menu board. The situation will be similar at sit-down chain restaurants. Patrons will see the calorie content of a steak meal printed on their handheld menus. Already, in the late 2000s, several State and local governments enacted menu labeling laws. The first was New York City in 2008. The Affordable Care Act and corresponding regulations issued by the U.S. Food and Drug Administration (FDA) will now require chain restaurants with 20 or more locations to post calorie information at all their U.S. eateries in a clear and conspicuous manner, along with a statement about an individual's daily caloric needs to help the public understand the significance of the calorie information.<sup>1</sup>

Prior to the listing of explicit calorie information on menus, Americans may have relied on their knowledge of nutrition to guess the calorie content of foods. According to the American Heart Association (AHA) and the National Heart, Lung and Blood Institute (NHLBI) of the National Institutes of Health, consumers can glean information about calories from some observable characteristics of menu items (AHA, 2013; NIH/NHLBI, 2013). As a rule of thumb, consumers should expect deep-fried foods to be higher in calories. They should also expect foods with cheese, mayonnaise, gravy, or a creamy or buttery topping to be higher in calories. Both organizations further believe that consumers can easily use such information. “You can eat heart-healthy,” according to the AHA, “if you know what to look for” (AHA, 2013).

The underlying premise of menu-labeling provisions in the 2010 law is that providing consumers with more accurate information will help them to make healthier choices. However, according to a growing body of research, only a portion of Americans choose lower calorie foods. Elbel et al. (2009) interviewed customers at a fast-food restaurant in New York City after the implementation of local menu-labeling requirements. Among customers who noticed the calorie information,

---

<sup>1</sup> In November 2014, FDA issued final regulations to carry out the 2010 law's labeling provisions. The regulations state that menus and menu boards should include both calorie information and the following statement: “2,000 calories a day is used for general nutrition advice, but calorie needs vary.” For more information on the final regulation, see FDA (2014).

about 28 percent report that it influenced their behavior.<sup>2</sup> In Philadelphia, Auchincloss et al. (2013) interviewed customers at a full-service restaurant also subject to local menu-labeling requirements. Among customers who noticed the calorie information at that restaurant, 34 percent report that it influenced their ordering decisions.<sup>3</sup> Whether a particular consumer responds to menu labeling may depend in part on his or her pre-existing knowledge of nutrition. Ellison et al. (2013) argue that some consumers already understand which foods are lower and higher in calories. For these consumers, “calorie labels provide little new information” (p. 8).

In this study, building on research in marketing science and behavioral economics, we investigate the extent to which rules-of-thumb nutrition knowledge can be used to judge the calorie content of restaurant meals and the extent to which menu labeling imparts additional information. First, we assume that a representative consumer gleans information about the calorie content of meals from some readily observable product characteristics. The AHA and the NHLBI identify the characteristics of restaurant foods likely associated with calorie content. Independent variables are created for each of these attributes. One variable, for example, identifies whether an entrée is deep fried or similarly prepared. Another identifies whether it includes cheese, mayonnaise, gravy, or a creamy or buttery topping. Finally, using ordinary least squares (OLS) and unconditional quantile regression (UQR) (Firpo et al., 2007 and 2009), we test the association between our independent variables and the calorie content of meals at fast-food and sit-down restaurants. The more information our representative consumer can glean from some simple rules of thumb about the calories in restaurant foods, the less new information he or she will learn from menu labeling, all else constant. We find that this consumer, who would otherwise rely on heuristics outlined by the AHA and the NHLBI, learns both old information and substantial new information.

---

<sup>2</sup> Elbel et al. (2013) report that 54 percent of consumers in their study noticed the calorie labels.

<sup>3</sup> Auchincloss et al. (2013) report that 76 percent of consumers in their study noticed the calorie labels.



## The Debate Over Menu Labeling

The Patient Protection and Affordable Care Act of 2010 represents the most significant overhaul of U.S. food-labeling laws since the implementation of the Nutrition Labeling and Education Act (NLEA) in the early 1990s. Under FDA regulations, authorized by the NLEA, food manufacturers must place a Nutrition Facts panel on most packaged products. Included on this panel are the size of a serving, the number of servings in a package, and calories per serving among other information. Kim et al. (2000) find that consumers who read the Nutrition Facts panel eat more fiber, less cholesterol, less sodium, and fewer calories from fat than their counterparts who don't read the panel. Though the growing problem of obesity in the United States did not abate over the 1990s and 2000s, despite implementation of the NLEA, Variyam and Cawley (2006) find that label users gained less weight than nonusers.<sup>4</sup> However, when eating out, consumers generally did not have such explicit nutrition information. The NLEA did not apply to restaurant foods.

Some restaurants did voluntarily provide explicit calorie data prior to the passage of menu-labeling laws. Many of these companies posted it online. However, according to Wootan et al. (2006), the data were not generally accessible onsite in restaurants. For example, in 2006, only 72 percent of McDonald's outlets in Washington, DC, provided instore nutrition information, and 59 percent provided it for a majority of items. Moreover, explicit nutrition information appeared on tray liners, in pamphlets, on posters, or on 1-page charts, but not on menu boards. Aside from McDonald's, Saelens et al. (2007) inspected 102 fast-food and 115 sit-down restaurants in Atlanta, GA. They found that only 6.9 percent of fast-food outlets placed nutrition information on menu boards and 5.2 percent of sit-down restaurants printed it on menus. Other research shows that, if nutrition information is not prominently displayed at the point of purchase, consumers are unlikely to use it (Roberto et al., 2009a).

Debate over mandatory menu labeling grew over the 1990s and 2000s as it became clear that eating out is associated with less healthful food choices (Variyam, 2005). Some believed that providing consumers with explicit nutrition information at the point of sale would help them to choose healthier food options and reduce unwanted weight gain. In a study supported by the Center for Science in the Public Interest (CSPI), for example, Backstrand et al. (1997) asked 256 dieticians to estimate the calories in 5 entrées sold by chain restaurants. The dieticians underestimated the calories in these foods by between 220 and 680 calories each. Since dieticians guessed inaccurately, Backstrand et al. (1997) conclude that "the average consumer has little chance of accurately assessing the healthfulness of meals served in restaurants" (p. 2). The AHA also endorsed menu labeling as "an important part of a comprehensive approach to addressing our nation's obesity epidemic..." (AHA, 2009). However, others opposed new regulations partly on the argument that most consumers can already identify more and less healthy meals, if they want to. The Center for Consumer Freedom (CCF) argued that "America has gotten to the point where we have warning labels on just about everything. We don't need government to tell us the difference between salad and a 12-piece bucket of chicken." (CCF, 2007).

On average, consumers supported menu labeling. National polls conducted before the passage of the 2010 Act found that support ranged between 67 percent and 83 percent (Roberto et al., 2009b). Now

---

<sup>4</sup> The result was statistically significant among only non-Hispanic, white women. However, according to Variyam and Cawley's (2006) calculations, the benefits to this subset of the population alone were sufficiently large to outweigh the total cost of the NLEA.

that the legislation is in effect, other research suggests that consumers' use of menu labels varies across demographic groups. Gregory et al. (2014) find that people who already have healthier diets and women, in particular, are more likely to use the information.

## Does Menu Labeling Affect Food Choices?

Many Americans care about identifying and choosing healthy foods, but not to the exclusion of taste, cost, or convenience, according to researchers. Glanz et al. (1998) asked 2,967 people to rate the level of importance they placed on the different characteristics of foods using a scale of 1 (not at all important) to 5 (very important). Respondents placed the most importance on taste (4.7) followed by cost (4.1), nutrition (3.9), convenience (3.8), and weight control (3.4), on average. Consistent with this result, when Jones (2010) studied how customers make choices at restaurants, many focus-group participants reported their intention to order tasty foods. These included one participant who likes to indulge at restaurants. From a menu with 11 items, she considered a T-bone steak and chicken alfredo pasta, even when told that 6 other items were lower in calories. However, because the steak had the least calories of the two dishes she liked, she would choose it over the pasta: “Both of these things I never make at home, and it would really feel like an indulgence for me. But even among my indulgences, it might impact which indulgence I take.” (p. 460)

In theory, menu labeling helps consumers who are weighing the taste, cost, healthfulness, and other attributes of different foods to identify the choice that best satisfies their needs and wants. Burton et al. (2006) identified several restaurant foods for which consumers tend to underestimate and overestimate calorie content. They then observed consumers’ choices among these foods with and without explicit calorie data. Menu labeling reduced the likelihood of purchasing an entrée if actual calories exceeded expectations. Purchase intentions remained constant or increased slightly if actual calories were consistent with expectations. “For example, if deli sandwiches are perceived as generally lower in calories than burger items, but are actually similar calorically, the evidence suggests that sandwich purchases would decrease more relative to burger purchases after menu labeling that shows their similar caloric content.” (Krieger and Saelens, 2013, p. 5).

In order for any new information to influence a consumer’s food choices at restaurants, it must also be salient in the consumer’s mind. According to Bordalo et al. (2012), consumers examine many characteristics of competing products when they choose among goods. However, if consumers are surprised by the price or quality of a product under consideration, they may focus their attention on that particular attribute. The consumer’s feelings about this one attribute can then have a disproportionate impact on the final choice among products. The researchers use this model of consumer behavior to explain many phenomena such as why many people switch from higher to lower grades of gasoline when gasoline prices rise. Bordalo et al.’s (2012) model of consumer behavior can also be applied to restaurant menu labeling. A consumer may be weighing the taste, cost, and healthfulness of two restaurant meals, and initially believe the foods are similar calorically. Menu labeling then reveals the true difference in calories. The magnitude of any surprises can be key. For example, a consumer might focus on each meal’s healthfulness after discovering a difference of several hundred calories. However, a modest discrepancy of 10 or 20 calories might not stand out in the same consumer’s mind and that consumer might instead focus on taste or cost.

In practice, according to a growing body of empirical research conducted in restaurants, consumers respond heterogeneously to menu labeling. Several studies, including Elbel et al. (2009), Pulos and Leng (2010), and Auchincloss et al. (2013), found that a fraction of people responded by ordering lower calorie foods. Others exhibited no response at all. Ellison et al. (2013) argued that this partly reflects differences in consumers’ knowledge of nutrition. Some Americans already may understand fairly well which foods are low and high in calories. The more a consumer understands about nutri-

tion, the less he or she will be surprised by menu labels and, in turn, the less likely he or she is to make different choices. Such consumer heterogeneity may further explain why researchers disagree about the size of the average change in calories ordered when consumers are exposed to calorie information. Roberto et al. (2010) found that participants in an experimental study consumed 177 fewer calories, on average, as a result of calorie information. Auchincloss et al. (2013) similarly found that consumers at a full-service restaurant ordered 155 fewer calories. By contrast, in Pulos and Leng (2010), consumers at 6 different full-service restaurants chose entrées with only 15 fewer calories. Bollinger et al. (2011) report that Starbucks' customers ordered 14 fewer calories per transaction. Elbel et al. (2009) found no evidence of a decrease in average calories ordered among the customers at a major fast-food chain. Different people were involved in the various studies.

## Theoretical Framework Behind the Study

When the quality of a food product is not explicitly revealed to consumers, marketing scientists believe that consumers may draw their own conclusions based on a small number of observable product characteristics. In particular, according to Olson and Jacoby (1972), consumers may focus on between four and seven product characteristics that they believe to predict true quality, and which they can confidently discern. For example, when evaluating meat at a supermarket, consumers may lack the confidence to use information about an animal's breed, even if it would help to predict quality. Instead, Acebron and Dopico (2000) find that consumers focus on color, freshness, visible fat, price, and presentation.

Behavioral economists similarly recognize that consumers use simple mental shortcuts to form judgments and make decisions since they do not understand the intricacies of nutrition science (Guthrie et al., 1999; Cash and Schroeter, 2010). Simple heuristics, such as rules of thumb, can be easily understood and applied in nearly every situation. ("Rule of thumb" is a method of estimating a value, based on common sense and experience, that is not intended to be scientifically accurate.) However, rules of thumb are not always correct and can lead to suboptimal choices. Thus, it is interesting to ask whether rules of thumb based on the observable attributes of meals are effective for judging calorie content at restaurants.

In this study, we mimic a representative consumer's situation in the absence of menu labeling. We assume that he or she makes judgments about the calorie content of restaurant meals based on observable product characteristics. These include a handful of characteristics that, according to the AHA and the NHLBI, do indicate a restaurant meal's calorie content. We begin by examining the calorie content of meals at some major chain restaurants. We then test the association between calorie content and the identified product characteristics. The more information our representative consumer can glean from these characteristics about the calories in restaurant foods, the less new information he or she will learn from menu labeling, all else constant. Table 1 provides definitions and mean values for the variables used in the study.

Table 1

**Definitions and means of variables used in the study**

		Fast-food restaurants	Full-service restaurants
CALORIES	Number of calories in the meal	726.25	1,087.37
HEALTHCLAIM	1 if a health claim appears on the menu next to the entrée; 0 otherwise	0	0.16
SMALLPORTION	1 if entrée represents a reduced-size portion; 0 otherwise	0.29	0.07
LARGEPORTION	1 if entrée represents an extra-size portion; 0 otherwise	0.1	0
DEEPPRIED	1 if deep-fried, batter-fried, country-fried, or similarly prepared; 0 otherwise	0.43	0.09
HEAVYSAUCE	1 if meal includes cheese, mayonnaise, gravy, or a creamy or buttery topping, unless menu specifies reduced-calorie versions; 0 otherwise	0.76	0.6
FRIES	1 if meal comes with french fries, onion rings, or similar extras; 0 otherwise	0.41	0.31
FATTYMEAT	1 if meal contains beef, bacon, pork chops, pepperoni, sausage, or similar meat products, unless menu specifies a lean cut; 0 otherwise	0.55	0.6
NOVEGGIES <sup>1</sup>	1 if meal includes neither fruits nor vegetables; 0 otherwise	0.12	0.08

<sup>1</sup> For the purposes of this study, we do not treat french fries or onion rings as vegetables. Thus, NOVEGGIES would equal one for a meal served with french fries and no other vegetables or fruit.

Note: Publicly available data were collected in spring 2012. We initially recorded the calories in standard menu items using the restaurants' websites. Stores in Montgomery County, MD were later visited to confirm that online information was accurate. We also created the variables SMALLPORTION, LARGEPORTION, and HEALTHCLAIM by observing restaurant menus. The American Heart Association (AHA) and the National Heart, Lung and Blood Institute (NHLBI) identify the characteristics of restaurant meals indicative of calorie content (AHA, 2013; NIH/NHLBI, 2013). Both organizations focus on the same key characteristics, all readily observable to customers. Based on this information, we created DEEPPRIED, HEAVYSAUCE, FRIES, FATTYMEAT, and NOVEGGIES. According to the information provided by the AHA and the NHLBI, as rules of thumb, we expect that values of 1 are associated with having more calories and values of 0 are associated with having fewer calories.

Source: USDA, Economic Research Service calculations based on publicly available data.

## Data Collected for the Study

In spring 2012, using restaurant companies' websites, we recorded information about the calorie content of standard menu items at a sample of fast-food and sit-down restaurants. The restaurants were then visited to confirm that online information was accurate. All data collected for the study are publicly available. Each sampled chain operates at least one restaurant in Montgomery County, MD, which implemented local labeling requirements in 2010.<sup>5</sup> The number of calories in meals at these restaurants is denoted CALORIES.

Meals from two fast-food restaurants were included in the study. We calculated the calories in 361 meals at these restaurants. Most meals included one entrée and one side dish.<sup>6</sup> We did not include calories from beverages, desserts, or other extra foods. The distribution of CALORIES for these two restaurants is shown in figure 1. Meals in the lower one-third of the distribution have 553 or fewer calories. Those in the middle tertile have 554 to 817 calories. Meals in the upper tertile contain 818 or more calories. The maximum value of CALORIES for our two fast-food restaurants is 1,710.

A separate sample of meals was collected from six casual dining, sit-down establishments. All of these chains offer dinner entrées and serve alcohol. The calories in 5,752 meals at these chains were recorded, including calories in entrées and in standard side dishes, but excluding those from beverages, desserts, and other extra foods.<sup>7</sup> Figure 2 presents the distribution of CALORIES for our six sit-down restaurants. Meals in the first tertile of the distribution have 900 or fewer calories. Meals in the middle tertile have 901 to 1,239 calories. In fact, the median meal (1,064 calories) without beverages or other extra foods contains about half of the daily energy requirements of a person on a 2,000-calorie reference diet, or about one-third of the energy requirements of an active, young adult male who needs 3,000 calories per day. Items in the upper tertile contain 1,240 or more calories. The maximum value of CALORIES for these six restaurants is 2,350.

Data collected for the study notably include a proportionally smaller number of fast-food meals than meals at full-service restaurants. We sampled only two fast-food restaurants for the study because each of these restaurants accounts for a proportionally greater share of their segment of the foodservice market than do any two of our full-service restaurants. Also, fast-food restaurants tend to offer a narrower range of menu choices than do full-service restaurants.

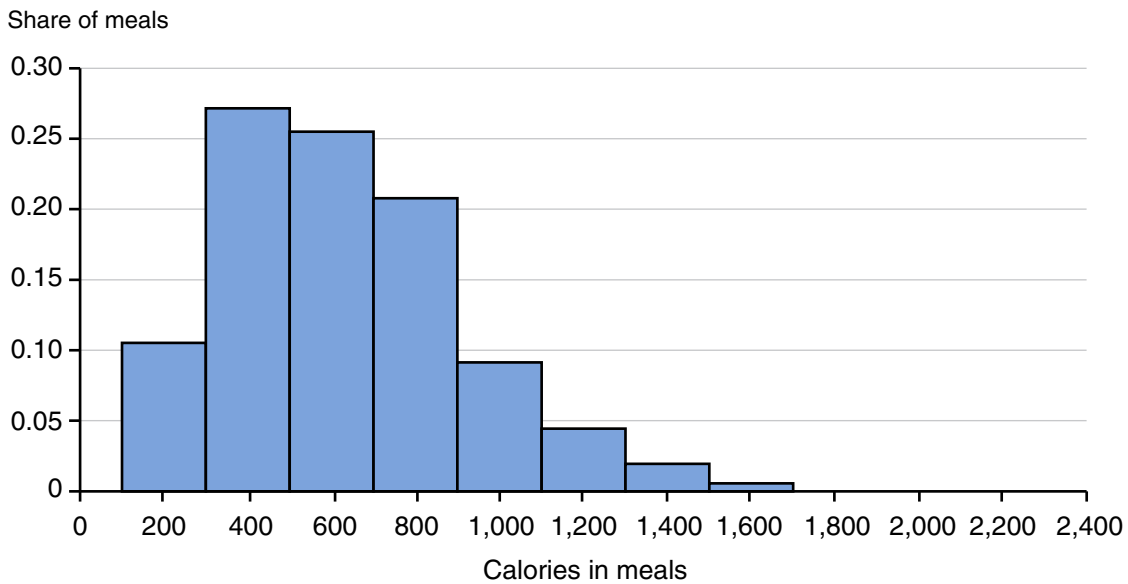
---

<sup>5</sup> We were able to obtain complete calorie information for all standard menu items since compliance with local labeling laws has been mandatory since January 1, 2011.

<sup>6</sup> Meals were generally defined by combining a selected entrée with one side dish. We paired one restaurant's cheeseburger, for example, with a medium fries. We also paired it with apple slices, a side salad, and a fruit and yogurt parfait. Each of these four pairings was defined as a separate meal. Selected entrées at the two fast-food restaurants included sandwiches, burgers, wraps, chicken pieces, and salads. Breakfast items were excluded. Only entrée salads were not paired with a side dish and assumed to represent a meal by themselves.

<sup>7</sup> Meals can include side dishes. For example, a steak entrée might come with a choice of two side dishes at no additional charge. Moreover, the restaurant could allow its customers to select among four possible side dishes, say, French fries, steamed vegetables, a baked potato, and rice. In this case, consumers could choose six different combinations of two side dishes. In this study, we treat each of these six possibilities as a separate meal, each of the six meals being composed of the steak and one of the possible combinations of side dishes. We do not consider side dishes for which customers have to pay extra money.

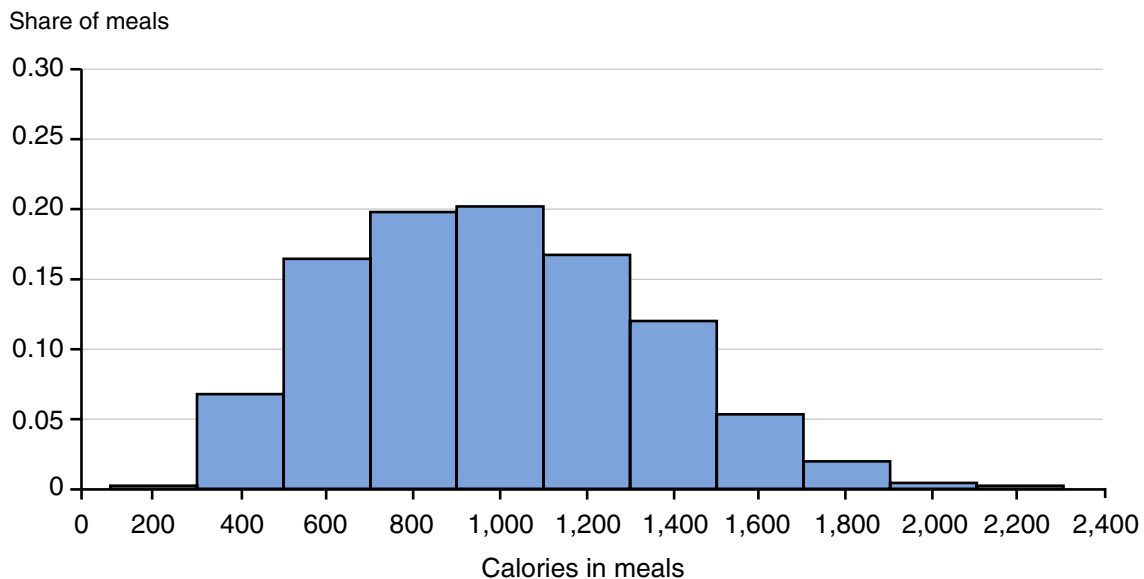
Figure 1  
**Distribution of calories in meals at fast-food restaurants**



Note: Data include the calories in 361 meals available at 2 fast-food restaurants in spring 2012. We initially recorded the calories in menu items using the restaurants' websites. Restaurants were later visited to confirm that online information was accurate. Meals were generally defined by combining a selected entrée with one side dish. We paired one restaurant's cheeseburger, for example, with a medium portion of fries. We then paired it with apple slices, a side salad, and a fruit and yogurt parfait. Each of these four pairings was defined as a separate meal. We do not account for any additional calories from beverages, desserts, or other extra foods.

Source: USDA, Economic Research Service calculations based on publicly available data.

Figure 2  
**Distribution of calories in meals at sit-down restaurants**



Note: Data include the calories in 5,752 meals available at 6 casual-dining, sit-down restaurants in spring 2012. We initially recorded the calories in menu items using the restaurants' websites. Restaurants were later visited to confirm that online information was accurate. Total calories account for those in entrées and in standard side dishes, but do not account for beverages, desserts, and other extra foods.

Source: USDA, Economic Research Service calculations based on publicly available data.



## Rules of Thumb

The AHA and the NHLBI identify the attributes of restaurant foods likely associated with calorie content. Both organizations focus on the same key characteristics, all readily observable to a restaurant's customers. Based on this information, we created five binary explanatory variables. Each equals 1 for foods that exhibit a particular product characteristic, and 0 (zero) otherwise. NOVEGGIES indicates that a meal includes neither vegetables nor fruits. Notably, we do not treat French fries or onion rings as vegetables for the purposes of this study. Thus, NOVEGGIES = 1 for a meal served with French fries and no other vegetables or fruit. FRIES = 1 if a meal comes with French fries or onion rings. DEEPPRIED indicates that an entrée has been deep fried, golden fried, or similarly prepared. HEAVYSAUCE indicates that menu items come with cheese or other condiments and toppings that are creamy or buttery, unless explicitly stated in the menu that reduced-calorie versions are used. FATTYMEAT = 1 if a meal contains beef, bacon, pork chops, pepperoni, sausage, or similar meat products, unless the menu specifies a lean cut. According to the information provided by the AHA and the NHLBI, as rules of thumb, we expect that values of 1 are associated with having more calories and values of 0 are associated with having fewer calories.

Finally, we create an additional variable, TOTALRULES, equal to the number of product attributes suggesting that a meal may be higher in calories. That is,  $TOTALRULES = FRIES + HEAVYSAUCE + FATTYMEAT + NOVEGGIES + DEEPPRIED$ . In our data, the maximum value of TOTALRULES = 4 for both our sit-down and fast-food eateries.

While we do not know the proportion of consumers who understand the information in table 1, other research suggests that Americans have some basic knowledge of nutrition no more complicated than our five rules of thumb. As described in Guthrie et al. (1999), the 1994 Diet Health Knowledge Survey (DHKS) asked consumers about their knowledge of and attitudes toward nutrition.<sup>8</sup> As a part of this survey, consumers were asked to identify which, in a series of paired foods, was higher in fat (hot dogs or ham, yogurt or sour cream, etc.) or higher in saturated fat (liver or T-bone steak, butter or margarine, etc.). The researchers found that almost 80 percent of consumers could correctly identify the higher fat food in five of six paired comparisons. About 60 percent were able to identify the higher saturated-fat food in three of four food pairs.

As a preliminary exercise, we test the association between our rules of thumb and the actual calorie content of selected restaurant meals. Shown in table 2 are the values of CALORIES and TOTALRULES for a small sample of meals. The data suggest that consumers, who know some rules of thumb highlighted by the AHA and NHLBI, can figure out that one fast-food chain's chicken sandwich meal contains fewer calories when ordered with applesauce (800 calories) instead of French fries (1,190 calories). However, such consumers may not know whether this sandwich is more or less caloric than the same restaurant's signature hamburger, holding constant the side dish (720 calories with the applesauce and 1,110 calories with the fries). The sandwich includes a deep-fried chicken fillet with lettuce, tomatoes, and mayonnaise, while the hamburger includes a grilled beef patty with tomatoes, lettuce, pickles, onions, and mayonnaise. TOTALRULES is the same for both entrées. Similarly, when dining at one full-service restaurant chain, this consumer may be unable to discriminate between a grilled chicken breast served with sautéed mushrooms, bacon, cheese, and fried potato wedges (1,172 calories) and a cheeseburger served with lettuce, tomatoes, onions,

---

<sup>8</sup> USDA's 1994-1996 Continuing Survey of Food Intakes by Individuals (CSFII) asked a nationally representative survey of individuals to report their food intake on 2 nonconsecutive days. The 1994 DHKS was a telephone followup to this survey. It included a sample of CSFII participants.

Table 2

**Calorie content of selected meals at two restaurants**

	CALORIES <sup>1</sup>	TOTALRULES <sup>2</sup>
<b>Meals at a selected fast-food restaurant</b>		
Deep-fried pieces of chicken (6 pieces) with applesauce	340	1
Salad with grilled chicken, croutons, and fat-free dressing	410	1
Hamburger sandwich (1/4 lb grilled beef patty) with applesauce	720	2
Chicken sandwich (deep-fried fillet) with applesauce	800	2
Hamburger sandwich (1/4 lb grilled beef patty) with medium french fries	1,110	3
Chicken sandwich (deep-fried fillet) with medium french fries	1,190	3
<b>Meals at a selected sit-down restaurant</b>		
Steak (8 oz prime rib) with chicken tortilla soup and mixed vegetables	726	1
Steak (9 oz sirloin) with grilled shrimp, asparagus, and mixed vegetables	777	1
Steak (8 oz prime rib) with chicken tortilla soup and sweet potato fries	1,075	2
Steak (9 oz sirloin) with grilled shrimp, asparagus, and sweet potato fries	1,126	2
Grilled chicken breast served with bacon, cheese, and fried potato wedges	1,172	3
Cheeseburger served with fried potato wedges	1,238	3

<sup>1</sup>CALORIES does not account for any additional calories from beverages, desserts, or other extra foods.

<sup>2</sup>Using information supplied by the American Heart Association and the National Heart, Lung, and Blood Institute, we identified the characteristics of restaurant meals that may be associated with the calorie content. These characteristics are detailed in table 1. TOTALRULES equals the total number of product characteristics according to which a meal may be high in calories.

Lb = pound

Oz = ounce

Note: Publicly available data were collected in spring 2012. We initially recorded the calories in standard menu items using the restaurants' websites. Stores were later visited to confirm that online information was accurate.

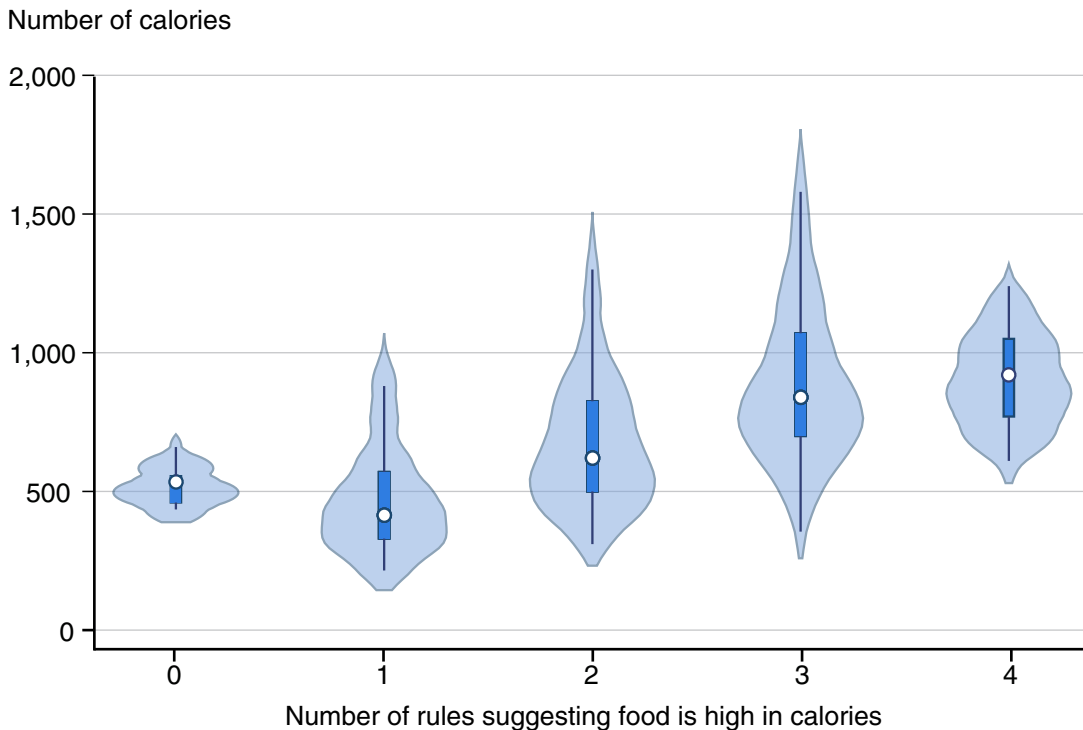
Source: USDA, Economic Research Service calculations based on publicly available data.

pickles, and fried potato wedges (1,238 calories). Not only is TOTALRULES the same for each meal, but the values of DEEPFRIED, HEAVYSAUCE, FRIES, FATTYMEAT, and NOVEGGIES are also identical. Consumers need a more nuanced knowledge of nutrition than our rules of thumb to discriminate between these meals.

To further gauge the association between TOTALRULES and CALORIES for all meals, not just for the 12 meals examined in table 2, violin plots are created (figs. 3 and 4). As described in Hintze and Nelson (1998), violin plots are similar to box plots. They display the center and spread of the data. In addition, they reveal the distribution of the data, with its valleys, peaks, and bumps. For example, shown in the left-most plot in figure 4 is the distribution of CALORIES for 591 full-service restaurant meals for which TOTALRULES = 0. We expect these meals to represent the lowest calorie choices at these restaurants. In fact, when consumers select among these 591 meals, they receive a dish with 900 or fewer calories with a probability of 87 percent (513 out of 591). By contrast, as shown in the fourth plot from the left in figure 4, among meals for which TOTALRULES = 3, we find that 76 percent (738 out of 969) contain 1,200 or more calories. Nonetheless, figure 3 and figure 4 also suggest that heuristics are a blunt tool. CALORIES still varies widely among meals sharing the same values for TOTALRULES.

Figure 3

### Rules of thumb and calorie content of fast-food meals, violin plot



Note: To discriminate between lower and higher calorie meals, when explicit calorie information is not provided, a consumer may use rules of thumb (a method of estimating a value, based on common sense and experience). In this study, we create five binary variables to account for some key characteristics of restaurant meals. These include DEEPPFRIED, HEAVYSAUCE, FRIES, FATTYMEAT, and NOVEGGIES. Full definitions are provided in table 1. As rules of thumb, we expect that values of 1 are associated with having more calories and values of 0 are associated with having fewer calories. Finally, we created an additional variable, TOTALRULES, which equals the sum of DEEPPFRIED, HEAVYSAUCE, FRIES, FATTYMEAT, and NOVEGGIES. In other words, TOTALRULES equals the number of product attributes according to which a meal may be high in calories. The first violin plot above includes meals for which TOTALRULES = 0. The second column includes meals for which TOTALRULES = 1. And, finally, the fifth column includes meals for which TOTALRULES = 4, the maximum value of the variable.

Source: USDA, Economic Research Service calculations based on publicly available data.

## Other Sources of Nutrition Information

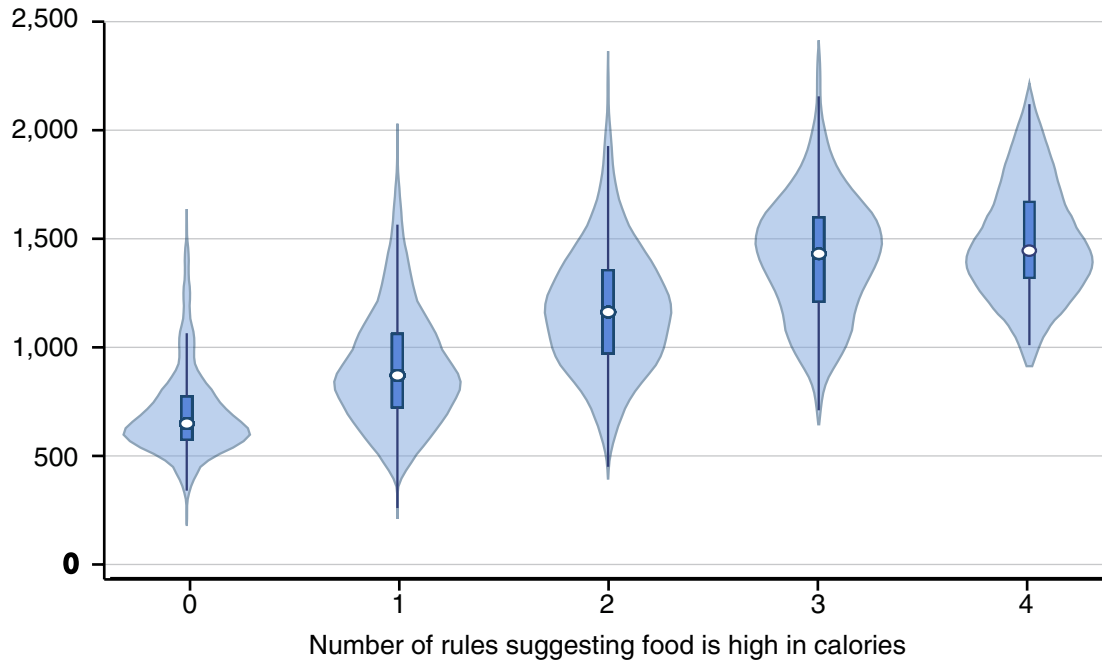
While most restaurants traditionally have not posted explicit nutrition data at the point of sale, they have provided limited information about the healthfulness of their menu items in other ways. Placing nutrition claims next to selected entrées has been one of these practices. Claims have included statements, such as “low calorie” or “low fat,” or consisted of logos like the AHA’s “Heart Check” mark. The 6 sit-down restaurants in this study all placed statements next to selected foods claiming that a particular food contained or could be prepared to contain less than a certain number of calories, such as 550 or 600.<sup>9</sup> We created the binary variable, HEALTHCLAIM, to account for these cases. This variable = 1 for menu items associated with a health claim and 0 otherwise.

<sup>9</sup> This is aside from numeric calorie labels, which were not available on otherwise similar menus provided by the restaurants under study in communities without local menu-labeling laws in 2012.

Figure 4

**Rules of thumb and calorie content of sit-down restaurant meals, violin plot**

Number of calories



Note: To discriminate between lower and higher calorie meals, when explicit calorie information is not provided, a consumer may use rules of thumb (a method of estimating a value, based on common sense and experience). In this study, we create five binary variables to account for some key characteristics of restaurant meals. These include DEEPFRIED, HEAVY SAUCE, FRIES, FATTYMEAT, and NOVEGGIES. Full definitions are provided in table 1. As rules of thumb, we expect that values of 1 are associated with having more calories and values of 0 are associated with having fewer calories. Finally, we created an additional variable, TOTALRULES, which equals the sum of DEEPFRIED, HEAVY SAUCE, FRIES, FATTYMEAT, and NOVEGGIES. In other words, TOTALRULES equals the number of product attributes according to which a meal may be high in calories. The first violin plot above includes meals for which TOTALRULES = 0. The second column includes meals for which TOTALRULES = 1. And, finally, the fifth column includes meals for which TOTALRULES = 4, the maximum value of the variable.

Source: USDA, Economic Research Service calculations based on publicly available data.

Finding the right size meal at a restaurant is also important to calorie control. Not only do Young and Nestle (2003, 2007) find that restaurant meals commonly exceed standard serving sizes,<sup>10</sup> but restaurants have been offering larger portion sizes over time. One notable example is Burger King’s introduction of a Triple Whopper sandwich in 2005. This entrée contains 1,140 calories and weighs 16 ounces (oz) including the meat, bun, vegetables, and other ingredients. By contrast, the traditional, single-patty Whopper sandwich contains 670 calories and weighs 10 oz. According to Young and Nestle (2003), fast-food restaurants now market some foods in portion sizes two to five times larger than their original size. However, many restaurants still help consumers to identify and order smaller portion sizes, if they want. Both of the fast-food restaurants in this study offer smaller sized sandwiches and burgers weighing 5.3 oz or less. Customers can also buy 4 or 6 pieces of deep-fried chicken instead of the 10- or 20-piece sizes. Similarly, some of the sit-down restaurants under study

<sup>10</sup> The Nutrition Facts panel reports serving sizes. These quantities are based on the reference amount customarily consumed per eating occasion (RACC) as reported in the 1970s and 1980s by Americans participating in food consumption surveys conducted by the U.S. Department of Agriculture.

sell a 6-oz “petite” steak instead of a 10- or 14-oz steak. Some also offer half racks of ribs instead of full racks. The variable SMALLPORTION = 1 for meals featuring a small-sized entrée and 0 for other meals. LARGEPORTION = 1 for meals featuring extra-sized entrées.

## Regression Models

To mimic our representative consumer's situation in the absence of menu-labeling laws, when calorie information is not explicitly reported, we regress CALORIES on our explanatory variables. A real-life consumer would need to know the values of our model's parameters to predict the number of calories in the meals. As discussed below, we do not necessarily expect consumers to know these values. However, if the rules of thumb highlighted by the AHA and NHLBI are effective for discriminating between lower and higher calorie choices, then consumers who know this information may still be less surprised by explicit calorie data. Thus, we focus on the marginal effects of DEEPFRIED, HEAVYSAUCE, FRIES, FATTYMEAT, and NOVEGGIES. Our goal is to determine whether the variables have a consistent and statistically significant association with CALORIES. If so, these product characteristics could form the basis of rules of thumb that, in turn, could reliably identify low- from high-calorie menu choices. We also examine the goodness-of-fit statistic,  $R^2$ .

An ordinary least squares (OLS) regression of CALORIES on our explanatory variables produces an estimate of the model,  $CALORIES = X\beta + \varepsilon$ , where  $\varepsilon$  is a stochastic residual with mean 0 and constant variance,  $\beta$  contains the unknown parameters, and  $X$  includes a constant, DEEPFRIED, HEAVYSAUCE, FRIES, FATTYMEAT, NOVEGGIES, SMALLPORTION, LARGEPORTION, and HEALTHCLAIM. For a model without higher order polynomial terms, as is well known,  $\beta$  equals the marginal effect of  $X$  on the population-average value of CALORIES, all else constant. Thus, we can ask questions like "How much higher in calories is a deep-fried food, on average, holding constant other attributes of the food?"

However, since OLS parameters measure the average association between CALORIES and each of the five product characteristics under study, OLS results do not measure these associations at particular points on the distribution of CALORIES. The marginal effects of DEEPFRIED, HEAVYSAUCE, FRIES, FATTYMEAT, and NOVEGGIES are not necessarily the same at all points. Also, the collective explanatory power of the variables, as measured by  $R^2$ , may vary across the distribution of CALORIES. Indeed, as shown in table 2, heuristics appear to be blunt tools capable of separating low- and high-calorie menu items, but unable to more finely discriminate between items that differ modestly in calorie content. To measure the association between our explanatory variables and CALORIES at specified points within the middle, lower, and upper tails of the distribution of CALORIES, we use Firpo et al.'s (2007, 2009) unconditional quantile regression (UQR) method in addition to OLS. This method has been recently applied in obesity research, among other areas. Jolliffe (2011) uses UQR to investigate the relationship between income and body mass index (BMI). He finds that income increases the BMIs of underweight Americans and decreases those of obese Americans.

Estimating an UQR model involves transforming one's dependent variable. The newly transformed variable is called the recentered influence function (RIF). In this study, CALORIES must be transformed. As detailed in Firpo et al. (2007, 2009), the formula is:

$$RIF(\text{calories}; q_\tau) = q_\tau + (\tau - I\{\text{calories} \leq q_\tau\})/f_{CALORIES}(q_\tau)$$

where  $q_\tau$  is the value of CALORIES at the  $\tau$ th quantile of the distribution,  $f_{CALORIES}(q_\tau)$  denotes the value of that distribution evaluated at  $q_\tau$ , and the indicator function  $I\{\text{calories} \leq q_\tau\}$  equals 1 if CALORIES is less than or equal to  $q_\tau$  and 0 otherwise. The variable RIF can next be regressed on

X to estimate the model,  $RIF = \alpha X + v$  where  $v$  is a stochastic residual with mean zero and constant variance, and  $\alpha$  contains the parameters to be estimated.<sup>11</sup> For a model without higher order polynomial terms,  $\alpha$  equals the marginal effect of  $X$  on the value of CALORIES at the  $\tau^{\text{th}}$  quantile of the distribution, all else constant. Thus, we can ask questions like “What is the association between calorie content and deep frying at the 10th, 30th, 60th, and 90th percentiles of CALORIES, all else constant?”

---

<sup>11</sup> Firpo et al. (2009) label this specification of their model RIF-OLS. We used a Stata ado file provided by Nicole Fortin at <http://faculty.arts.ubc.ca/nfortin/datahead.html>.

## Results and Findings

OLS and UQR models were estimated for fast-food and sit-down restaurants (tables 3 and 4). Below, we examine results for each type of restaurant. We then consider the amount of information that consumers may be able to glean about the calorie content of the meals, given their level of nutrition knowledge. Finally, we consider other specifications of our model that embody alternative assumptions about consumers and ask whether our key results are significantly changed.

### Marginal Effects

Estimation results show that DEEPPRIED, HEAVYSAUCE, FRIES, FATTYMEAT, and NOVEGGIES are all associated with CALORIES and may likewise form the basis of rules of thumb that, in turn, could be used to somewhat reliably decipher low- from high-calorie menu choices. In the first columns of tables 3 and 4, OLS parameter estimates are mostly significant and reveal positive associations between CALORIES and each product characteristic. For example, ordering a meal with French fries or onion rings increases the calories in a fast-food meal by 327 and the calories in a sit-down restaurant meal by 269, on average.

However, rules of thumb do not always work as expected. Consumers at fast-food restaurants should not automatically assume that meals with fruits or vegetables are less caloric. The OLS parameter estimate on NOVEGGIES is negative (see table 3). To be sure, most of the higher calorie burgers and sandwiches offered by our two fast-food chains come with lettuce and other vegetables.

Our results also confirm that rules of thumb are much less effective for discriminating among meals that differ modestly in calorie content. Only FRIES is statistically significant at the 60th and 90th percentiles of CALORIES for fast-food meals (see table 3). All other rules of thumb lack power for choosing among the highest calorie meals at that type of restaurant.

Similarly, when choosing among the highest calorie choices at a sit-down restaurant, deep fried foods may actually be relatively lower in calories than the other highest calorie choices. The marginal effect of DEEPPRIED is negative at the 90th percentile of CALORIES (see table 4). Notably, after further investigation, we found that this result was not robust. The coefficient was statistically insignificant if we excluded meals sold by any one of three chain restaurants from the data set. Nonetheless, when choosing among the highest calorie meals at a sit-down restaurant, consumers can still disregard the rule of thumb about deep-fried foods being even more caloric.

### Goodness of Fit

Goodness-of-fit statistics reveal that our five rules of thumb along with SMALLPORTION, LARGEPORTION, and HEALTHCLAIM explain half or more of the overall variation in CALORIES. As shown in the first columns of tables 3 and 4,  $R^2$  is 0.76 in our OLS model for fast-food meals and 0.5 in our OLS model for sit-down restaurant meals. While our model's predictive power is substantial, it still leaves much of the variation in CALORIES unexplained. Moreover, according to our UQR results,  $R^2$  tends to be lower near the tails of the distribution of CALORIES than around its center. For meals at fast-food restaurants, it is 0.21 at the 10th percentile (see table 3). For sit-down restaurants, it is 0.18 at the 10th percentile and 0.14 at the 90th percentile (see table 4).



Table 3

**Estimation results for calories in fast-food meals**

	OLS	UQR (10th centile)	UQR (30th centile)	UQR (60th centile)	UQR (90th centile)
Constant	501.63*** (25.69)	253.85*** (62.41)	317.39*** (55.08)	611.79*** (50.56)	853.62*** (65.13)
DEEPPRIED	84.66** (21.84)	69.82 (57.04)	147.00*** (46.16)	61.10 (47.08)	63.49 (73.02)
HEAVYSAUCE	59.10** (19.52)	103.91** (43.55)	61.84* (35.99)	34.42 (34.91)	10.92 (58.96)
FRIES	327.41*** (16.97)	154.08*** (26.72)	311.11*** (26.58)	340.59*** (35.10)	437.69*** (82.50)
FATTYMEAT	63.58*** (22.50)	34.63 (61.00)	126.67*** (47.49)	54.81 (47.51)	26.71 (59.21)
NOVEGGIES	-66.05** (26.44)	68.69*** (29.85)	42.68 (35.92)	-15.92 (53.51)	-308.70*** (96.38)
SMALLPORTION	-219.61*** (17.04)	-211.99*** (40.47)	-282.59*** (31.66)	-299.98** (31.17)	-149.96*** (42.09)
LARGEPORTION	470.18*** (25.82)	19.34*** (62.41)	101.75*** (33.60)	375.12** (37.22)	1,350.62*** (65.62)
R <sup>2</sup>	0.76	0.21	0.41	0.47	0.47

## Hit-and-miss analysis

All combinations of 2 meals: 79.3 percent correctly predicted

Combinations of meals with 200(+) calorie difference: 91.4 percent correctly predicted

OLS = Ordinary least squares regression

UQR = Unconditional quantile regression

R<sup>2</sup> = Proportion of the variation in the dependent variable that is explained by the independent variables

Hit-and-miss analysis = A measure of the predictive accuracy of the model calculated using OLS results to estimate the number of calories in each meal. A selected meal's predicted calorie content was then compared against that of the other meals. This process was repeated until all possible combinations of two different meals had been compared. Our model correctly predicted whether a selected meal was higher, lower, or equal in calories to another selected meal for 79.3 percent of all pairwise comparisons. Moreover, if we restricted our hit-and-miss analysis to only combinations of 2 meals with an actual difference of 200 or more calories, then the percentage correctly predicted increased to 91.4 percent.

Note: Standard errors are in parentheses. Statistically significant at the \*\*\*1-percent, \*\*5-percent, and \*10-percent levels.

Source: USDA, Economic Research Service calculations based on publicly available data.

Table 4

**Estimation results for calories in sit-down restaurant meals**

	OLS	UQR (10th centile)	UQR (30th centile)	UQR (60th centile)	UQR (90th centile)
Constant	718.25*** (7.33)	370.86*** (15.84)	425.13*** (11.86)	721.19*** (10.07)	1,258.58*** (11.68)
DEEPPRIED	131.53*** (11.94)	186.18*** (11.03)	305.07*** (16.69)	129.83*** (21.83)	-69.42*** (21.70)
HEAVYSAUCE	145.45*** (6.83)	85.24*** (10.84)	160.35*** (10.08)	192.07*** (11.62)	140.66*** (13.63)
FRIES	269.07*** (7.30)	170.92*** (7.78)	297.05*** (9.73)	284.92*** (12.43)	317.31*** (19.81)
FATTYMEAT	339.81*** (6.93)	256.71*** (11.36)	395.18*** (11.11)	433.03*** (11.58)	232.66*** (14.25)
NOVEGGIES	236.85*** (13.02)	157.87*** (12.38)	230.02*** (16.98)	261.18*** (24.46)	242.75*** (39.24)
HEALTHCLAIM	-70.10*** (9.82)	-39.29** (18.27)	-4.20 (17.29)	-106.13*** (16.25)	-84.90*** (15.91)
SMALLPORTION	-341.63*** (12.83)	-183.23*** (23.30)	-364.23*** (22.36)	-464.81*** (17.76)	-283.75*** (14.90)
R <sup>2</sup>	0.50	0.18	0.36	0.34	0.14

## Hit-and-miss analysis

All combinations of 2 meals: 71.7 percent correctly predicted

Combinations of meals with 200(+) calorie difference: 80.4 percent correctly predicted

OLS = Ordinary least squares regression

UQR = Unconditional quantile regression

R<sup>2</sup> = Proportion of the variation in the dependent variable that is explained by the independent variables

Hit-and-miss analysis = A measure of the predictive accuracy of the model calculated using OLS results to estimate the number of calories in each meal. A selected meal's predicted calorie content was then compared against that of the other meals. This process was repeated until all possible combinations of two different meals had been compared. Our model correctly predicted whether a selected meal was higher, lower, or equal in calories to another selected meal for 71.7 percent of all pairwise comparisons. Moreover, if we restricted our hit-and-miss analysis to only combinations of 2 meals with an actual difference of 200 or more calories, then the percentage correctly predicted increased to 80.4 percent.

Note: Standard errors are in parentheses. Statistically significant at the \*\*\*1-percent, \*\*5-percent, and \*10-percent levels.

Source: USDA, Economic Research Service calculations based on publicly available data.

## What Consumers May and May Not Understand

Product characteristics identified by the AHA and NHLBI as being indicative of the calorie content of restaurant foods—DEEPPRIED, HEAVYSAUCE, FRIES, FATTYMEAT, and NOVEGGIES—are significantly associated with CALORIES for the most part. As such, they may underlie rules of thumb that, in turn, identify low- from high-calorie menu items to some extent. To gauge our representative consumer's ability to distinguish between higher and lower calorie menu items, we further test the discriminatory power of our model in the spirit of a hit-and-miss analysis. Specifically, we used our OLS results to predict the number of calories in each of our 361 fast-food meals. One meal was then selected. We compared its predicted calorie content against the predicted calorie content

of each of the other 360 meals. The same process was next repeated for another fast-food meal until all possible combinations of two different fast-food meals had been compared. In total, our model correctly identified whether a selected meal was higher, lower, or equal in calories to another selected meal for 79 percent of all pairwise comparisons. Moreover, among comparisons with an actual difference in calories of 200 or more between the 2 meals, the percentage correctly predicted is 91 percent. For meals at sit-down restaurants, these shares were 72 percent and 80 percent, respectively.

It appears that consumers with some basic knowledge of nutrition can discriminate fairly well between low- and high-calorie restaurant meals, especially if the foods contain substantially different numbers of calories. However, inherent in our regression models are some assumptions about our representative consumer. Implicitly, when multiple rules are “broken,” it is assumed that a consumer compounds calorie estimates. For example, when judging an item at a sit-down restaurant that is both deep fried and served with French fries, our representative consumer thinks to add 131 calories for the entrée being deep fried and another 269 calories for the side dish of French fries (400 extra calories in total). This clearly requires our consumer to have a pretty good idea of the relationship between each rule of thumb and the calorie content of the meals (i.e., he or she must know our model coefficients). However, real-life consumers who know the information outlined by the AHA and the NHLBI still may underestimate the size of the coefficients in our model. For example, they may believe that deep frying adds only 50 calories and ordering a side of French fries increases total calories by only 100, all else constant. If so, as argued by organizations like the Center for Science in the Public Interest, consumers would tend to underestimate the total amount of calories in restaurant meals. Nonetheless, as argued by organizations like the Center for Consumer Freedom, they could still guess fairly well whether a menu item is higher or lower in calories than other menu items, especially when the foods have substantially different numbers of calories.

## The Consumer’s Level of Nutrition Knowledge

To gain additional insights on our representative consumer’s ability to judge the calorie content of restaurant meals, if he or she has a less or more nuanced knowledge of nutrition, we examine four alternative specifications of the model. In the first of these alternative specifications, our representative consumer understands that DEEPPRIED, HEAVYSAUCE, FRIES, FATTYMEAT, and NOVEGGIES are all associated with an item being more caloric. However, he or she does not know that ordering a side dish of French fries increases the total number of calories in a meal more than does adding a slice of cheese, all else constant. FRIES and the four other rules are assumed to be equally important. Thus, our consumer simply counts the total number of product characteristics according to which a meal may be higher in calories. A model embodying this assumption is estimated by regressing CALORIES on a constant term, TOTALRULES, SMALLPORTION, LARGEPORTION, and HEALTHCLAIM. The results are shown in appendix tables 1 and 2. When comparing two meals with an actual calorie difference of 200 or more, our representative consumer can still identify the higher calorie choice 84 percent of the time at fast-food restaurants and 73 percent of the time at sit-down restaurants. These results are slightly less than estimates reported above for fast-food restaurants in table 3 (91 percent of the same pairwise comparisons) and sit-down restaurants in table 4 (80 percent of the same pairwise comparisons).

In a second alternative specification of the model, our representative consumer is also unaware of two of the five rules. He or she does not know the caloric implications of choosing a fatty meat, nor does our consumer know to seek out meals with fruits and vegetables. To estimate a model

embodying these assumptions, we dropped FATTYMEAT and NOVEGGIES from the analysis. We then created the new variable, TOTALRULES2, which equals the sum of FRIES, HEAVYSAUCE, and DEEPFRIED. Finally, we replaced TOTALRULES with TOTALRULES2 in the above regression model. Estimation results are shown in appendix tables 3 and 4. We find that, when comparing two meals with an actual calorie difference of 200 calories or more, our representative consumer can identify the higher calorie choice 81 percent of the time at fast-food restaurants, but only 59 percent of the time at sit-down restaurants.

Next, we considered two alternative specifications of the model in which our representative consumer has a more nuanced understanding of nutrition than captured by the explanatory variables in table 1. In the first of these two models, we added the variable BACON to our model for fast-food restaurants. This extra variable = 1 for burger and sandwich meals with added bacon, such as a bacon cheeseburger, and 0 for other meals. Results are shown in appendix table 5. Adding this variable to our model had little or no impact on our results.

Finally, in a specification of the model inspired by Chandon and Wansink's (2007) "health halo" hypothesis, we accounted for the possibility that consumers may believe the meals offered by one restaurant to be generally healthier than the meals offered by the other restaurants. In our model for sit-down restaurants, we added binary indicator variables for five of the six chains under study. Results are shown in appendix table 6. Adding these variables to our model had little or no impact on our results.

Overall, having considered several alternative specifications of the model, it appears that consumers who understand the information outlined by the AHA and the NHLBI can discriminate fairly well between lower and higher choices. Nonetheless, rules of thumb are blunt tools, and menu labeling likewise imparts much additional information. Moreover, consumers who do not know the information outlined by the AHA and the NHLBI are likely to understand less about the calorie content of restaurant foods on their own, and they will gain relatively more new information when provided with explicit calorie information.

## Conclusions

Menu-labeling laws require restaurant chains to post calorie information in a clear and conspicuous manner at the point of sale. This should enable consumers to better identify the meals that best satisfy their needs and wants. However, according to a growing body of research, many consumers do not adjust their food choices. Ellison et al. (2013) hypothesize that some of these consumers can already use their pre-existing understandings of nutrition to identify lower and higher calorie choices and, as such, gain little new information from menu labeling. Our findings extend this hypothesis. Behavioral economists and marketing scientists believe that consumers infer a product's quality based on some observable characteristics. The AHA and the NHLBI further identify the observable characteristics of restaurant foods likely associated with calorie content. These associations may underlie rules of thumb that consumers can use for discriminating among restaurant foods. In this study, we test the efficacy of such simple heuristics. Results confirm that some consumers may be able to identify lower calorie from higher choices. For such consumers, some of the new information now being provided through menu-labeling laws is in fact "old" information.

However, according to our study results, menu labeling is likely to improve all Americans' abilities to weigh the taste, cost, and healthfulness of restaurant foods. It imparts additional information over general rules of thumb in at least a few ways. Heuristics are less effective for discriminating between foods that differ only modestly in calorie content. Moreover, when using rules of thumb, consumers may still underestimate the total calorie content of restaurant meals. Menu labeling will reveal the exact difference in calories between meals, even small differences, and include a statement about how those differences relate to an individual's daily energy requirements. Overall, judging by these findings and the results of previous studies, many Americans may already be making crude choices between high- and low-calorie foods, based on their pre-existing understandings of nutrition. Menu labeling allows them to make finer adjustments in their food choices and behavior, if they choose to do so.

That many consumers continue to order the same foods when exposed to calorie information does not imply that menu labeling fails to teach influential new information. A growing body of research investigates whether consumers order lower calorie foods at restaurants. Some do. Others appear unresponsive. One possible explanation is that, when more knowledgeable consumers compare two restaurant meals, they are only modestly surprised by the differences in calories. If so, according to Bordalo et al.'s (2012) theory of consumer choice, these discoveries may be insufficiently large to motivate a change in food choices. Of course, consumers could respond to menu labeling in other important ways. For example, understanding how the foods they purchase at restaurants fit within their daily caloric and other nutritional needs may motivate consumers to compensate by eating less at home or exercising more.<sup>12</sup> Following an approach similar to Variyam and Cawley's (2006) study of Americans' body mass index before and after implementation of NLEA, future research could attempt to identify the effects of menu labeling on weight gain over time.

---

<sup>12</sup> There is some empirical support for this possibility. Roberto et al. (2010) find that placing a recommended daily caloric requirement label next to explicit calorie information did not impact calories consumed at a restaurant. However, it did encourage consumers to reduce their calorie intake over the course of the entire day, including foods consumed after leaving the restaurant.

## References

- Acebron, L., and D. Dopico. 2000. "The Importance of Intrinsic and Extrinsic Cues to Expected and Experienced Quality: An Empirical Application for Beef," *Food and Quality Preference* 11(May 2000): 229-38.
- Auchincloss, A., G. Mallya, B. Leonberg, A. Ricchezza, K. Glanz, and D. Schwarz. 2013. "Customer Responses to Mandatory Menu Labeling at Full-Service Restaurants," *American Journal of Preventive Medicine* 45(December 2013):710-19
- American Heart Association. 2013. *Dining Out*. [http://www.heart.org/HEARTORG/GettingHealthy/NutritionCenter/DiningOut/Dining-Out\\_UCM\\_304183\\_SubHomePage.jsp](http://www.heart.org/HEARTORG/GettingHealthy/NutritionCenter/DiningOut/Dining-Out_UCM_304183_SubHomePage.jsp) (accessed April 2013).
- American Heart Association. 2009. *Policy Position Statement on Menu Labeling* (June 2009) [http://www.heart.org/idc/groups/heart-public/@wcm/@adv/documents/downloadable/ucm\\_301652.pdf](http://www.heart.org/idc/groups/heart-public/@wcm/@adv/documents/downloadable/ucm_301652.pdf) (accessed April 2013).
- Backstrand J., M. Wootan, L. Young, and J. Hurley. 1997. *Fat Chance*. Center for Science in the Public Interest, Washington, DC, 1997. <http://portionteller.com/pdf/cspistudy97.pdf>
- Bollinger, B., P. Leslie, and A. Sorensen. 2011. "Calorie posting in chain restaurants," *American Economic Journal: Economic Policy* 3(February 2011): 91-128.
- Bordalo, P., N. Gennaioli, and A. Shleifer. 2013. "Salience and Consumer Choice," *Journal of Political Economy* 121(October 2013): 803-43.
- Burton, S., E. Creyer, J. Kees, and K. Huggins. "Attacking the Obesity Epidemic: The Potential Benefits of Providing Nutrition Information in Restaurants." *American Journal of Public Health* 96(September 2006): 1669–1675.
- Cash, S., and C. Schroeter. "Behavioral Economics: A New Heavyweight in Washington?" *Choices* 25(2010, 3rd quarter).
- Center for Consumer Freedom. 2007. *Fat Menus Don't Guarantee Skinny Customers*. <http://www.consumerfreedom.com/2007/06/3367-fat-menus-dont-guarantee-skinny-customers> (accessed November 2013).
- Chandon, P., and B. Wansink. 2007. "The Biasing Health Halos of Fast-Food Restaurant Health Claims: Lower Calorie Estimates and Higher Side-Dish Consumption Intentions," *Journal of Consumer Research* 34(October 2007): 301-14.
- Elbel, B., R. Kersh, V. Brescoll, and L. Dixon. 2009. "Calorie Labeling and Food Choices: A First Look at the Effects on Low-Income People in New York City." *Health Affairs* 28(October 2009): w1110-w1121.
- Ellison, B., J. Lusk, and D. Davis. 2013. "Looking at the Label and Beyond: The Effects of Calorie Labels, Health Consciousness, and Demographics on Caloric Intake in Restaurants," *International Journal of Behavioral Nutrition and Physical Activity* 10 (February 2013).

- Firpo, S., N. Fortin, and T. Lemieux. 2007. *Unconditional Quantile Regressions*, Working Paper No. 339, National Bureau of Economic Research, Cambridge, MA, 2007.
- Firpo, S., N. Fortin, and T. Lemieux. 2009. “Unconditional Quantile Regressions,” *Econometrica* 77(May 2009): 953-73.
- Glanz, K., M. Basil, E. Maibach, J. Goldberg, and D. Snyder. 1998. “Why Americans Eat What They Do: Taste, Nutrition, Cost, Convenience, and Weight Control Concerns as Influences on Food Consumption,” *Journal of the American Dietetic Association* 98(October 1998): 1118-26.
- Gregory, C., I. Rahkovsky, and T. Anekwe. 2014. *Consumers’ Use of Nutrition Information When Eating Out*. USDA, Economic Research Service, EIB-127. <http://www.ers.usda.gov/publications/eib-economic-information-bulletin/eib127.aspx> (June 2014)
- Guthrie J., B. Derby, and A. Levy. 1999. “What People Know and Don’t Know About Nutrition,” *American’s Eating Habits: Changes and Consequences*. USDA, Economic Research Service, AIB-750 [http://www.ers.usda.gov/media/91066/aib750m\\_1\\_.pdf](http://www.ers.usda.gov/media/91066/aib750m_1_.pdf) (May 1999)
- Hintze, J. and R. Nelson. 1998. “Violin Plots: A Box Plot-Density Trace Synergism,” *The American Statistician* 52 (May 1998): 181-84.
- Jolliffe, D. 2011. “Overweight and Poor? On the Relationship Between Income and the Body Mass Index,” *Economics and Human Biology* 9(2011): 342-55.
- Jones, C. 2010. “Encouraging Healthy Eating at Restaurants: More Themes Uncovered Through Focus Group Research,” *Services Marketing Quarterly* 31(2010): 448-65.
- Kim, S., R. Nayga, and O. Capps, Jr. 2000. “The Effect of Food Label Use on Nutrient Intakes: An Endogenous Switching Regression Analysis,” *Journal of Agricultural and Resource Economics* 25(July 2000): 215-231.
- Krieger, J., and B. Saelens. 2013. *Impact of Menu Labeling on Consumer Behavior: A 2008-2012 Update*. Minneapolis, MN: Robert Wood Johnson Foundation, Healthy Eating Research: 2013. <http://healthyeatingresearch.org> (accessed January 2014).
- National Institutes of Health, National Heart, Lung, and Blood Institute. 1998. “General Tips for Healthy Dining Out,” *Guidelines on Overweight and Obesity: Electronic Textbook*, [http://www.nhlbi.nih.gov/guidelines/obesity/e\\_txtbk/appndx/6a3a.htm](http://www.nhlbi.nih.gov/guidelines/obesity/e_txtbk/appndx/6a3a.htm) (accessed April 2013).
- Olson, J., and J. Jacoby. 1972. “Cue Utilization in the Quality Perception Process,” *Proceedings of the Third Annual Conference of the Association for Consumer Research*. Iowa City, IA: Association for Consumer Research, 1972: 167-79.
- Pulos, E., and K. Leng. 2010. “Evaluation of a Voluntary Menu-Labeling Program in Full-Service Restaurants,” *American Journal of Public Health* 100(June 2010): 1035-39.
- Roberto, C., H. Agnew, and K. Brownell. 2009a. “An Observational Study of Consumers’ Accessing of Nutrition Information in Chain Restaurants,” *American Journal of Public Health* 99(May 2009): 820-21.

- Roberto C., M. Schwartz, and K. Brownell. 2009b. "Rationale and evidence for menu-labeling legislation," *American Journal of Preventive Medicine* 37(December 2009): 546-51.
- Roberto, C., P. Larsen, H. Agnew, J. Baik, and K. Brownell. 2010. "Evaluating the Impact of Menu Labeling on Food Choices and Intake," *American Journal of Public Health* 100(February 2010): 312-18.
- Saelens, B., K. Glanz, J. Sallis, and L. Frank. 2007. "Nutrition Environment Measures in Restaurants (NEMS-R) Development and Evaluation," *American Journal of Preventive Medicine* 32(April 2007): 273-81.
- U.S. Food and Drug Administration. 2014. *Menu and Vending Machine Labeling Requirements*, <http://www.fda.gov/Food/IngredientsPackagingLabeling/LabelingNutrition/ucm217762.htm>
- Variyam, J. 2005. *Nutrition Labeling in the Food-Away-From-Home Sector: An Economic Assessment*. USDA, Economic Research Service, ERR-4. April 2005. Available at <http://www.ers.usda.gov/publications/err-economic-research-report/err4.aspx>
- Variyam, J., and J. Cawley. 2006. *Nutrition Labels and Obesity*, Working Paper No. 11956, National Bureau of Economic Research, Cambridge, MA.
- Wootan, M., M. Osborn, and C. Malloy. 2006. "Availability of Point-of-Purchase Nutrition Information at a Fast-Food Restaurant," *Preventive Medicine* 43(December 2006): 458-59.
- Young, L., and M. Nestle. 2003. "Expanding portion sizes in the US marketplace: Implications for nutrition counseling," *Journal of the American Dietetic Association* 103(February 2003): 231-34.
- Young, L., and M. Nestle. 2007. "Portion Sizes and Obesity: Responses of Fast-Food Companies," *Journal of Public Health* 28(February 2007): 238-48.



## Appendix tables

Appendix table 1

### Estimation results for calories in fast-food meals, first alternative model

	OLS	UQR (10th centile)	UQR (30th centile)	UQR (60th centile)	UQR (90th centile)
Constant	409.71*** (25.46)	216.70*** (48.62)	228.78*** (46.92)	478.09*** (42.45)	756.21*** (47.21)
TOTALRULES	145.46*** (10.19)	104.21*** (18.80)	173.86*** (15.90)	152.77*** (16.73)	174.79*** (41.32)
SMALLPORTION	-205.17*** (19.84)	-209.34*** (41.20)	-259.18*** (34.20)	-276.92*** (31.29)	-133.04** (37.17)
LARGEPORTION	465.11*** (30.30)	11.51 (18.41)	96.83*** (27.07)	375.78*** (30.73)	1,390.31*** (174.48)
R <sup>2</sup>	0.66	0.20	0.36	0.39	0.42

#### Hit-and-miss analysis

All combinations of 2 meals: 71.0 percent correctly predicted

Combinations of meals with 200(+) calorie difference: 83.9 percent correctly predicted

OLS = Ordinary least squares regression

UQR = Unconditional quantile regression

R<sup>2</sup> = Proportion of the variation in the dependent variable that is explained by the independent variables

Hit-and-miss analysis = A measure of the predictive accuracy of the model calculated using OLS results to estimate the number of calories in each meal. A selected meal's predicted calorie content was then compared against that of the other meals. This process was repeated until all possible combinations of two different meals had been compared. Our model correctly predicted whether a selected meal was higher, lower, or equal in calories to another selected meal for 71.0 percent of all pairwise comparisons. Moreover, if we restricted our hit-and-miss analysis to only combinations of 2 meals with an actual difference of 200 or more calories, then the percentage correctly predicted increased to 83.9 percent.

Note: Standard errors are in parentheses. Statistically significant at the \*\*\*1-percent, \*\*5-percent, and \*10-percent levels.

Source: USDA, Economic Research Service calculations based on publicly available data.

Appendix table 2

**Estimation results for calories in sit-down restaurant meals, first alternative model**

	OLS	UQR (10th centile)	UQR (30th centile)	UQR (60th centile)	UQR (90th centile)
Constant	710.51*** (7.39)	367.78*** (15.57)	421.91*** (11.89)	722.81*** (10.01)	1,235.07*** (12.03)
TOTALRULES	244.56*** (3.73)	172.03*** (6.70)	282.14*** (4.93)	292.01*** (5.06)	213.38*** (9.60)
HEALTHCLAIM	-68.46*** (9.46)	-45.15*** (15.93)	-23.13 (15.23)	-99.76*** (15.15)	-74.17*** (15.24)
SMALLPORTION	-295.53*** (12.96)	-138.67*** (23.50)	-301.67*** (22.13)	-402.04*** (17.20)	-276.15*** (12.92)
R <sup>2</sup>	0.46	0.16	0.33	0.31	0.12

## Hit-and-miss analysis

All combinations of 2 meals: 64.5 percent correctly predicted

Combinations of meals with 200(+) calorie difference: 73.4 percent correctly predicted

OLS = Ordinary least squares regression

UQR = Unconditional quantile regression

R<sup>2</sup> = Proportion of the variation in the dependent variable that is explained by the independent variables

Hit-and-miss analysis = A measure of the predictive accuracy of the model calculated using OLS results to estimate the number of calories in each meal. A selected meal's predicted calorie content was then compared against that of the other meals. This process was repeated until all possible combinations of two different meals had been compared. Our model correctly predicted whether a selected meal was higher, lower, or equal in calories to another selected meal for 64.5 percent of all pairwise comparisons. Moreover, if we restricted our hit-and-miss analysis to only combinations of 2 meals with an actual difference of 200 or more calories, then the percentage correctly predicted increased to 73.4 percent.

Note: Standard errors are in parentheses. Statistically significant at the \*\*\*1-percent, \*\*5-percent, and \*10-percent levels.

Source: USDA, Economic Research Service calculations based on publicly available data.

Appendix table 3

**Estimation results for calories in fast-food meals, second alternative model**

	OLS	UQR (10th centile)	UQR (30th centile)	UQR (60th centile)	UQR (90th centile)
Constant	466.87*** (23.45)	263.43*** (39.83)	320.97*** (43.12)	552.05*** (40.35)	1,378.85*** (10.78)
TOTALRULES2	166.45*** (12.62)	115.67*** (20.62)	184.14*** (18.36)	166.18*** (20.53)	206.19*** (12.09)
SMALLPORTION	-201.31*** (20.39)	-206.61** (41.49)	-254.69 (36.68)	-272.93*** (31.89)	-54.14*** (15.28)
LARGEPORTION	521.34*** (31.01)	51.50*** (17.73)	162.83*** (24.98)	434.11*** (27.57)	-201.15*** (10.46)
R <sup>2</sup>	0.64	0.18	0.31	0.37	0.42

## Hit-and-miss analysis

All combinations of 2 meals: 68.0 percent correctly predicted

Combinations of meals with 200(+) calorie difference: 80.6 percent correctly predicted

OLS = Ordinary least squares regression

UQR = Unconditional quantile regression

R<sup>2</sup> = Proportion of the variation in the dependent variable that is explained by the independent variables

Hit-and-miss analysis = A measure of the predictive accuracy of the model calculated using OLS results to estimate the number of calories in each meal. A selected meal's predicted calorie content was then compared against that of the other meals. This process was repeated until all possible combinations of two different meals had been compared. Our model correctly predicted whether a selected meal was higher, lower, or equal in calories to another selected meal for 68.0 percent of all pairwise comparisons. Moreover, if we restricted our hit-and-miss analysis to only combinations of 2 meals with an actual difference of 200 or more calories, then the percentage correctly predicted increased to 80.6 percent.

Note: Standard errors are in parentheses. Statistically significant at the \*\*\*1-percent, \*\*5-percent, and \*10-percent levels.

Source: USDA, Economic Research Service calculations based on publicly available data.

Appendix table 4

**Estimation results for calories in sit-down restaurant meals, second alternative model**

	OLS	UQR (10th centile)	UQR (30th centile)	UQR (60th centile)	UQR (90th centile)
Constant	896.27*** (7.68)	502.31*** (12.37)	626.95*** (11.76)	955.09*** (10.94)	1,378.85*** (10.78)
TOTALRULES2	216.61*** (5.85)	148.75*** (7.68)	258.61*** (7.43)	248.00*** (8.19)	206.19*** (12.09)
HEALTHCLAIM	-54.22*** (11.44)	-36.73** (17.56)	-2.85 (16.74)	-87.11*** (16.20)	-54.14*** (15.28)
SMALLPORTION	-210.19*** (15.34)	-78.76*** (23.68)	-202.95*** (22.75)	-300.47*** (17.20)	-201.15*** (10.46)
R <sup>2</sup>	0.24	0.08	0.17	0.16	0.07

## Hit-and-miss analysis

All combinations of 2 meals: 53.2 percent correctly predicted

Combinations of meals with 200(+) calorie difference: 58.7 percent correctly predicted

OLS = Ordinary least squares regression

UQR = Unconditional quantile regression

R<sup>2</sup> = Proportion of the variation in the dependent variable that is explained by the independent variables

Hit-and-miss analysis = A measure of the predictive accuracy of the model calculated using OLS results to estimate the number of calories in each meal. A selected meal's predicted calorie content was then compared against that of the other meals. This process was repeated until all possible combinations of two different meals had been compared. Our model correctly predicted whether a selected meal was higher, lower, or equal in calories to another selected meal for 53.2 percent of all pairwise comparisons. Moreover, if we restricted our hit-and-miss analysis to only combinations of 2 meals with an actual difference of 200 or more calories, then the percentage correctly predicted increased to 58.7 percent.

Note: Standard errors are in parentheses. Statistically significant at the \*\*\*1-percent, \*\*5-percent, and \*10-percent levels.

Source: USDA, Economic Research Service calculations based on publicly available data.

Appendix table 5

**Estimation results for calories in fast-food meals, third alternative model**

	OLS	UQR (10th centile)	UQR (30th centile)	UQR (60th centile)	UQR (90th centile)
Constant	498.3*** (26.1)	254.86*** (65.23)	316.33*** (57.48)	617.04*** (52.13)	857.14*** (66.14)
DEEPPRIED	87.4*** (22.17)	68.99 (59.47)	147.87*** (48.64)	56.8 (48.53)	77 (62.11)
HEAVYSAUCE	61.56*** (19.82)	103.16** (44.05)	62.63* (36.85)	30.55 (35.66)	23.09 (61.11)
FRIES	325.86*** (17.12)	154.55*** (27.05)	310.62*** (26.98)	343.03*** (35.41)	430.02*** (83.4)
FATTYMEAT	71.33*** (24.85)	32.28 (69.72)	129.14*** (55.86)	42.61 (54.72)	65.02 (67.97)
BACON	-16.55*** (22.48)	5.02 (40.47)	-5.27 (44.4)	26.06 (49.64)	-81.88 (90.29)
NOVEGGIES	-61.14** (27.27)	67.2*** (32.23)	44.24 (38.17)	-23.65 (55.33)	-284.41*** (99.05)
SMALLPORTION	-221.17*** (17.19)	-211.51*** (40.82)	-283.09*** (32.17)	-297.52** (31.8)	-157.69*** (42.2)
LARGEPORTION	467.2*** (26.16)	20.24*** (23.99)	100.8*** (34.99)	379.82** (38.48)	1335.56*** (172.13)
R <sup>2</sup>	0.76	0.21	0.41	0.47	0.47

## Hit-and-miss analysis

All combinations of 2 meals: 80.3 percent correctly predicted

Combinations of meals with 200(+) calorie difference: 92.2 percent correctly predicted

OLS = Ordinary least squares regression

UQR = Unconditional quantile regression

R<sup>2</sup> = Proportion of the variation in the dependent variable that is explained by the independent variables

Hit-and-miss analysis = A measure of the predictive accuracy of the model calculated using OLS results to estimate the number of calories in each meal. A selected meal's predicted calorie content was then compared against that of the other meals. This process was repeated until all possible combinations of two different meals had been compared. Our model correctly predicted whether a selected meal was higher, lower, or equal in calories to another selected meal for 80.3 percent of all pairwise comparisons. Moreover, if we restricted our hit-and-miss analysis to only combinations of 2 meals with an actual difference of 200 or more calories, then the percentage correctly predicted increased to 92.2 percent.

Note: Standard errors are in parentheses. Statistically significant at the \*\*\*1-percent, \*\*5-percent, and \*10-percent levels.

Source: USDA, Economic Research Service calculations based on publicly available data.

Appendix table 6

**Estimation results for calories in sit-down restaurant meals, fourth alternative model**

	OLS	UQR (10th centile)	UQR (30th centile)	UQR (60th centile)	UQR (90th centile)
Constant	792.84*** (29.55)	288.62*** (57.06)	461.65*** (46.61)	905.08*** (56.62)	1,334.01*** (70.56)
DEEPPRIED	131.95*** (11.72)	188.02*** (11.14)	305.97*** (16.89)	129.66*** (21.45)	-68.51*** (20.52)
HEAVYSAUCE	155.44*** (6.79)	92.87*** (11.09)	174.29*** (10.78)	198.03*** (11.44)	154.02*** (13.65)
FRIES	268.21*** (7.44)	175.31*** (8.47)	305.39*** (10.23)	280.73*** (12.56)	306.31*** (19.95)
FATTYMEAT	316.56*** (7.93)	233.15*** (11.28)	356.49*** (12.19)	427.88*** (13.79)	199.75*** (18.22)
NOVEGGIES	186.49*** (13.84)	138.25*** (16.44)	173.63*** (19.55)	198.25*** (25.51)	200.69*** (40.74)
HEALTHCLAIM	-144.23*** (9.82)	-88.88*** (22.13)	-119.02*** (23.02)	-176.20*** (22.91)	-129.73*** (21.54)
SMALLPORTION	-342.77*** (23.24)	-183.79*** (23.24)	-364.34*** (22.90)	-461.52*** (18.66)	-294.46*** (16.19)
CHAIN2	4.25 (38.41)	43.52 (70.86)	-10.92 (60.75)	-74.54 (73.76)	22.48 (94.13)
CHAIN3	-34.43 (29.72)	127.14** (56.75)	38.02 (46.51)	-178.30*** (56.86)	-25.72 (71.89)
CHAIN4	59.32* (33.19)	162.81** (65.54)	158.42*** (54.21)	-43.73 (61.77)	5.72 (74.13)
CHAIN5	-108.62*** (29.31)	66.59 (55.96)	-77.03* (45.88)	-217.26*** (56.09)	-113.08 (71.23)
CHAIN6	32.47** (30.58)	122.81** (56.33)	56.60 (47.96)	-71.39 (59.35)	84.97 (77.24)
R <sup>2</sup>	0.52	0.18	0.37	0.35	0.15

## Hit-and-miss analysis

All combinations of 2 meals: 74.4 percent correctly predicted

Combinations of meals with 200(+) calorie difference: 83.1 percent correctly predicted

OLS = Ordinary least squares regression

UQR = Unconditional quantile regression

R<sup>2</sup> = Proportion of the variation in the dependent variable that is explained by the independent variables

Hit-and-miss analysis = A measure of the predictive accuracy of the model calculated using OLS results to estimate the number of calories in each meal. A selected meal's predicted calorie content was then compared against that of the other meals. This process was repeated until all possible combinations of two different meals had been compared. Our model correctly predicted whether a selected meal was higher, lower, or equal in calories to another selected meal for 74.4 percent of all pairwise comparisons. Moreover, if we restricted our hit & miss analysis to only combinations of 2 meals with an actual difference of 200 or more calories, then the percentage correctly predicted increased to 83.1 percent.

Note: Standard errors are in parentheses. Statistically significant at the \*\*\*1-percent, \*\*5-percent, and \*10-percent levels.

Source: USDA, Economic Research Service calculations based on publicly available data.