Informational Policy Improves Consumers' Choice for Healthier Food

Norman Lo and Anoshua Chaudhuri

Department of Economics, San Francisco State University

March 24, 2016

Abstract:

As reported by Centers for Disease Control and Prevention (CDC) in 2010, more than 78 million US adults and about 12.5 million children and adolescents were obese. Up until 2010, the US had the highest rate of childhood obesity among 30 industrialized nations. This paper explores consumer use and understanding of nutrition labels; as well as the impact of food labeling on dietary habits. Our theoretical model is an extension of the innovative weight management framework introduced by Lakdawalla and Philipson (2009). The model illustrates that imperfect information about food quality promotes body weight gain during the economic expansion. We also analyze the impact of mandated nutrition labeling on body weight across different education attainment groups. The estimated impacts of nutrition label on BMI and risk of obesity is much higher for the higher education attainment group, which provides evidence on how informational policy could help consumers make healthier food choice and improve on balance diet.

Key words: nutrition labelling; health information; dynamic weight management model

JEL classification: I12

1. Introduction:

The prevalence of overweight and obesity has increased rapidly in the United States. As reported by the Centers for Disease Control and Prevention (CDC), more than one-third of U.S. adults were obese in 2011-2012. Obese and overweight could lead to many related conditions including heart disease, stroke, type-2 diabetes, and certain type of cancer, which generate large additional direct and indirect health care expenses. The CDC estimated an annual medical cost of obesity in the U.S. was $147 billion in 2008 and the annual medical costs for people who are obese were, on average, $1,429 higher than those of normal weight. Some studies suggest that these costs will continue to increase with the increasing prevalence of obesity in the U.S., especially severe obesity, which is projected to continue to rise. Regulators, aiming to combat the obesity epidemic, require an understanding of food consumption choices made by different types of consumers, effectiveness of food labeling policies, and the costs for both the private and public sectors. A clear inference is difficult to make because the empirical relationship between food labeling and consumer body weight are complicated and not easy to quantify based on the available data. In this paper, we aim to explain the effect of nutrition labeling of food on consumer dietary habits as one of the way to address the obesity epidemic in the U.S.

1.1 Brief overview of the food market in the U.S.

During World War I, farmers worked hard to produce record crops and livestock. As prices fell, farmers tried to produce even move to pay their debts, taxes, and living expenses. In the early 1930, prices dropped so low that many farmers went bankrupt and lost their farms. In 1933, the first farm bill, known as the Agriculture Adjustment Act (AAA), was passed by Congress. It was designed to help U.S. farmers to overcome the economic hardship after WWI and during the Great Depression. The law set limits on the size of the crops and livestock farmers could produce to eliminate surplus and increased food prices. The farmers who agreed to limit production were paid a subsidy by the government. By 1938, Congress passed a new Agricultural Adjustment Act, also known as the "New Deal", with a built-in requirement to update it every five years.

One popular idea is that American farm subsidies contributed significantly to the rising rates of obesity and reducing these subsidies would help solve the problem. However, evidence indicates that farm subsidies have had very modest effect on the prices of farm commodities and the cost of food at retail.[1] Instead, the price support system and farm subsidies actually promoted agricultural innovations and technological change, which caused expansion in supply of food and lowered the cost of calories. In 1960, the bulk of food preparation was done by families that cooked their own food and ate it at home. The revolution in the mass preparation of food changed the dynamics of the food industry. Technological innovations, such as vacuum packaging, improved preservatives, artificial flavors, and microwaves, have enabled food manufacturers to cook food centrally and ship it to consumers for rapid consumption. Prices for agricultural commodities fell substantially in real terms, using the U.S. GDP deflator, by 54 percent for livestock products, 72 percent for field crops, 28 percent for vegetables, and 23 percent for fruits and nuts between 1950 and 2002.[2] These price changes had significant impacts on the cost of producing processed food and the prices paid by consumers for food,

---

[1] J. Alston, D. Sumner, S. Vosti, Farm Subsidies and Obesity in the United States: National Evidence and International Comparisons, Food Policy 33.6 (2008): 470-479

[2] Alston, J. M., Beddow, J. M., & Pardey, P. G. (2009). Agricultural research, productivity, and food prices in the long run. *Science*, *325*(5945), 1209-1210.

especially for carbonated soft drinks.[3] By law of demand, the lower prices of food encourage food consumption, better technology encouraged food consumption away from home and ultimately contributed to obesity.

1.2 Reduced energy output

Technological innovation not only improves production efficiency and lowers production cost; it also shifts market jobs from strenuous physical work to sedentary occupation. Historically, workers were paid to exercise through manual labor. As demand for on-the-job exercise has become less common, many workers today must pay to exercise, mainly in terms of foregone leisure. Lakdawalla and Philipson (2007) presents evidence which suggest that occupation has a real effect in the determination of weight for male workers.[4] A male worker who spends 18 years in the most fitness-demanding occupation has BMI 3.5 full units lighter than a person in the least physically demanding occupation.

The nationwide drop in leisure-time physical activity, especially among young women, may also be responsible for the upward trend in obesity rates. According to "The American Journal of Medicine"[5], researchers from Stanford University discovered that the number of US adult men who reported no physical activity jumped from 11.4% in 1994 to 43.5% in 2010. For women, the number increased from 19.1% in 1994 to 51.7% in 2010. The average BMI has increased across the board, with notable rise found among young women age 18-39, during the period. Stanford University School of Medicine identified a significant association between the level of leisure-time physical activity and increases in both BMI and waist circumference.

1.3 Role of nutritional labelling

In real-world situations, consumers choose foods within the context of a total diet in order to obtain greater expected utility from their food. Part of that utility is derived from consuming food to maintain or improve health status.[6] Consumers have different risk preference to determine different bundles of foods. If their perceptions of risks associated with foods are incorrect, consumers either take more risks than they would like or pay more than they should for the optimal level of food consumption.

On the other hand, food producers supply food quality if it is profitable for them or if they are required to do so. The marginal cost is likely to increase for an additional unit of food quality produced. In general, the market for food quality is characterized by a rising supply curve and a falling demand curve.[7] Under perfect market conditions, the market demand and supply reflects a level of risk which is acceptable and provides the optimum level of food safety.

---

[3] Trend in food and Nutrient Intakes by Adults: NFCS 1977-78, CSFII 1989-91, and CSFII 1994-95

[4] Lakdawalla, Darius, and Tomas Philipson. "Labor supply and weight." *Journal of Human Resources* 42, no. 1 (2007): 85-116.

[5] http://dx.doi.org/10.1016/j.amjmed.2014.05.026), are published online in advance of The American Journal of Medicine, Volume 127/Issue 8 (August 2014) published by Elsevier

[6] Van Ravenswaay, E.O. "Valuing Food Safety and Nutrition: The Research Needs." Value Food Safety and Nutrition. J.A. Caswell, ed., pp. 3-26. Boulder CO: Westview Press, 1995.

[7] Henson, S., and B. Traill. "Demand for Food Safety, Market Imperfections, and the Role of Government." Food Policy 18(1993):152-62.

Suppose we assume that all market participants are fully informed about the nature of the product, where both producers and consumers are price takers and that market prices fully reflect all the costs accepted and benefits enjoyed by the society. The market price will transmit all necessary information, so that a variety of products with different associated quality will be offered for sale at a variety of prices.[8] However, the market for food quality is not perfect. In most cases, the most significant imperfections are that sellers are better informed about quality attributes than consumers. The misperceptions of the risks and hazards of consuming particular foods hurt not only consumers' pocketbook, but also their health.

The Nutrition Labeling and Education Act of 1990 (NLEA), which went into effect in 1994, is mandatory in the form of a standardized nutrition information panel that presents data on the macro- and micronutrients found in a food. The mandatory disclosures make it practicable for consumers to judge food quality before purchasing. The informational policy influences market for quality in different ways, which include product design, advertising, consumer confidence in food quality, and consumer education.[9] In this paper, we examine the impact of the informational policy Nutrition Labeling and Education Act on changing consumer's levels of understanding about food quality attributes and how that may have altered their consumption behavior.

2. Literature Reviews:

2.1 The US food consumption behavior and food policy

A direct way to study food consumption behavior is to derive the price elasticity of demand for food. Andreyeva et al., (2010)[10] provides a systematic literature review on the price elasticity of demand for major food categories. The study finds the mean price elasticity estimates ranging from 0.27 to 0.81 (absolute values), with the highest price elasticities for food away from home, soft drinks, juice, meats, and fruit, whereas the most inelastic demand for eggs. From a public health perspective, more elastic demand for food is encouraging if change in demand is a priority since price changes might have the greatest impact on consumer food choices, nutrition, and health.

Other studies examine the price responsiveness between different demographic groups. For instance, Park et al., (1996)[11] analyzes the own-price and income elasticities of twelve food commodity groups according to household poverty status using the 1987-88 Nationwide Food Consumption Survey (NFCS). The results indicate own-price elasticities were similar between the income groups for most commodities, but income elasticities were consistently higher for the lower income group. Raper et al., (2002)[12] analyzes the price responsiveness of nine aggregate expenditure categories with the diary portion of the 1992 Consumer Expenditure Survey (CES). Similar results were found in the study. The

---

[8] Caswell, Julie A., and Eliza M. Mojduszka. "Using informational labeling to influence the market for quality in food products." *American Journal of Agricultural Economics* (1996): 1248-1253.

[9] Caswell, J.A., and D.I. Padberg. "Toward a More Comprehensive Theory of Food Labels." Amer. J. Agr. Econ. 74(May 1992):460-68

[10] Andreyeva, T., Long, M. W., & Brownell, K. D. (2010). The impact of food prices on consumption: a systematic review of research on the price elasticity of demand for food. *American journal of public health*, *100*(2), 216.

[11] Park JL, Holcomb RB, Raper KC, Capps O Jr., A Demand Systems Analysis of Food Commodities by US Households Segmented by Income, Am J Agric Econ. 1996;78(2):290-300

[12] Raper KC, Wanzala MN, Nayga RM Jr., Food Expenditures and Household Demographic Composition in the US: A Demand Systems Approach, Appl Econ. 2002; 34(8):981-992

paper raise questions about the effectiveness of the food stamp program. Since there are minimal restrictions on type of food items purchased with food stamps, households are not required to use food stamps for the purchase of relatively healthier foods instead of typically less healthy convenience foods.

2.2 Obesity epidemic attributes from the farm policies

Many studies tried to link the US "obesity epidemic" with the farm subsidies. One idea is that American farm subsidies made fattening foods relatively cheap and abundant, which contribute significantly to obesity. Alston et al., (2008)[13] examined the magnitude of the impact of farm subsidies on the total availability and prices of farm commodities. The result suggests that farm subsidies have had very modest and mixed effects on ingredients in more-fattening foods. The small commodity price impacts also imply very small effects on costs of food at retail. Since food consumption is relatively unresponsive to market price change, food consumption patterns should not be affected by the small food price changes. The paper concludes that the magnitude of the farm subsidies effects must be small on most farm commodity prices and even smaller effect on consumption.

Other studies try to link the U.S. farm policies for sweetener crops and the consumption and composition of sweeteners in the US diet. Beghin and Jensen (2008)[14] examines the effect of farm policies on the price of corn-based sweeteners. In the 1970s, the high fructose corn syrup (HFCS) price fell rapidly and remained relatively low for the following 30 years. The HFCS became an inexpensive substitute for sugar in food from 1970 and gained popularity with food processors as a sweetener. The study illustrates that public policy have affected sweetener availability and use in two major ways, namely investment in agricultural research and development (R&D) and farm price policies. No evidence was found that agricultural policies influence the consumption of sugar and other sweetener. The link between US sweetener consumption and farm policy is weak because HFCS has become a very specialized input in the beverage and other manufactured food industries. Also, the total value of the product is relatively small, suggesting that farm policy had very minimum influence on the composition of food products containing sweeteners.

2.3 Obesity epidemic attributed to sweetened beverages

In the literature of obesity epidemic, sweetened beverages are viewed by many as a major contributor to obesity and related health problems. According to the National Health and Nutrition Examination Survey III (NHANES III, 1988-1994 and the NHANES 1999-2004[15], per-capita daily caloric contribution from sugar-sweetened beverages and 100% fruit juice increased from 242 kcal/day in 1988-1994 to 270 kcal/day in 1999-2004. Carman (1982)[16] shows that high fructose corn syrup (HFCS) had a substantial raw material cost advantage compare to sugar cane and sugar beet. The advantage for HFCS widens when refining and milling costs are included. The study suggests the possible cost

---

[13] J. Alston, D. Sumner, S. Vosti, Farm Subsidies and Obesity in the United States: National Evidence and International Comparisons, Food Policy 33.6 (2008): 470-479

[14] J. Beghin and H. Jensen, Farm Policies and Added Sugars in US Diets, Food Policy 33.6 (2008): 480-488)

[15] The NHANES is an ongoing series of nationwide surveys and clinical examinations conducted by the National Center for Health Statistics. A multistage, clustered, probability sampling strategy was used to select households and individuals to provide national estimates representative of the civilian noninstitutionalized US population.

[16] H. Carman, A Trend Projection of High Fructose Corn Syrup Substitution for Sugar, Amercian Journal of Agricultural Economics 64.4 (1982): 625-633

saving to manufacturers and price reductions to consumers not only promote substitution of HFCS for sugar, it also makes sweetened food products more accessible.

Blair and Sobal (2004)[17] demonstrates that the increase in U.S. obesity parallels increase in the amount of food available per capita in U.S. retail outlets between the years of 1983 and 2000. Among the USDA food category, the change in HFCS supply is the greatest between 1983 and 2000, which adding approximately 171kcal per capita per day to the food supply.[18] The paper also points out that high level of fructose in the diet may contribute to increased obesity through its metabolic pathway since fructose does not trigger the appetite suppression or weight maintenance effects of insulin and leptin. Increased adiposity promotes the metabolic syndrome leading to diabetes, high blood pressure, and high blood lipids.

Many studies found clear associations of soft drink intake with increased energy intake and body weight. Wang et al. (2008)[19] suggests that reducing intake of empty calories by limiting sugar-sweetener beverage consumption is the key to promote healthy eating and prevent excess weight gain. Vartanian et al., (2007)[20] also concludes that soft drinks only offer energy with little accompanying nutrition, displace other nutrient sources, and are linked to several key health conditions such as diabetes. Therefore, reduction in soft drink consumption is recommended.

There are already some public policies restricting sweetened beverage consumption in the school environment. In some areas in the U.S., soda tax or soft drink tax, which is a tax or surcharge on soft drink, is applied and aim to discourage unhealthy diets and offset the economic costs of obesity. However, Chouinard et al., (2005)[21] examines the impact of fat tax (taxes on fatty foods) on high caloric food consumption and found that it has relatively little effect on the quantity of fat products consumed of any group. On the other hand, Yen et al., (2004)[22] suggests that nutrition educational programs and advertising campaigns about sugar and dairy product intakes can be effective in curtailing soft drink consumption and promote healthier diets. Tax policy can affect sweetened beverage consumption in short-run, but education and information policy may have a bigger role to promote healthy and balanced diets in the long-run.

2.4 Food Accessibility and Availability

Over the past 3 decades, fast-food retails sales in the United States have soared 900% from $16.1 billion in 1975 to 153.1 billion in 2004. In 1967, fast-food accounted for 14.3% of total away-from-home food expenditures, and by 1999 it reached 35.5%.[23] People are also shifting food consumption away from home, which is shown on Fig. 1. With almost half of the US food spending going toward food eaten away from home, fast-food consumption has become an important contributor to the rise

---

[17] Blair, Dorothy, and Jeffery Sobal. "Luxus consumption: Wasting food resources through overeating." *Agriculture and Human Values* 23.1 (2006): 63-74.
[18] The food availability data is measured by using the US Food Supply Data per capita (USFSD) (ERS,2003). USFSD are collected every year for each food item in a consistent manner that takes into consideration changes in food supply and consumption practices.
[19] Wang, Y. Claire, Sara N. Bleich, and Steven L. Gortmaker. "Increasing caloric contribution from sugar-sweetened beverages and 100% fruit juices among US children and adolescents, 1988–2004." *Pediatrics* 121.6 (2008): e1604-e1614.
[20] Vartanian LR, Schwartz MB, Brownell KD., Effects of Soft Drink Consumption on Nutrition and Health: A Systematic Review and Meta-Analysis, AM J Public Health, 2007;97(4):667-675
[21] Chouinard, H. H., Davis, D. E., LaFrance, J. T., & Perloff, J. M. (2005). The effects of a fat tax on dairy products. *Department of Agricultural & Resource Economics, UCB*.
[22] Yen ST, Lin BH, Smallwood DM, Andrews M., Demand for Non-alcoholic Beverages: The Case of Low-income Households, Agribusiness. 2004;20(3): 309-321
[23] Reported by the U.S. Department of Agriculture/Economic Research Service

in the prevalence of obesity in children and adolescents. The major different between fast-food and other types of food-away-from home is that fast-food restaurant provides immediate service, a consistent and popular product, standardized menu, and consistent quality. Consumers can minimize their time need be spent obtaining product information. But the key advantage of fast food is that they are generally in easily reached, nearby locations. Consider the portion sizes and the corresponding caloric content of the foods served at fast-food restaurants, people start realizing the contribution of fast-food consumption on weight gain and obesity.

General speaking rapid growth of fast-food industry reduces time cost for consuming the food and makes food consumption more convenience and accessible. Jekanowski et al., (2001)[24] examines the impact of convenience and accessibility on demand for food-away-from home. The results strongly suggest the growth in fast-food consumption is attributable to an increasing supply of convenience. An increase in the number of fast food outlets in a market directly increases quantity consumed by decreasing the cost of obtaining a fast food meal. Furthermore, Austin et al., (2005)[25] points out that the fast-food industry markets heavily to children and adolescents, who make up a significant part of the industry's consumer base. Evidences show that fast-food restaurants were statistically significantly clustered in areas within a short walking distance from schools. As a result, poor-quality food environments (high calories, fat, added sugars, sugar-sweetened drinks, and fewer fruits and vegetables) were exposed to children within their school neighborhoods.

On average in the United States, there has been a reduction in time costs of food preparation of about 20 minutes per capita per day from 1965 to 1995. The prevalence of fast-food has been a significant contribution to the reduction of time cost. Cutler et al., (2003)[26] emphasizes the change in time costs of food preparation lower total price of food consumption and rise food consumption. The increased food consumption may harm health by gaining weight if a consumer has self-control problems. If the health cost of overconsuming is greater than the welfare gain from lower costs of food preparation, people are worse off. In fact, this condition requires perfect information, which consumers are usually lacking of the information in making a food consumption decision, especially before the nutrition labelling was mandated.

2.5 Nutrition Labeling and Information Policy

In the nutrition labels literatures, researchers study consumer use and understanding of nutrition labels, as well as the impact of labelling on dietary habits. In short, nutrition labeling reduces the imperfect information and prevents firms from taking advantage concerning product characteristics and selling poor quality commodities. Caswell and Mojduszka (2014)[27] discuss the use of informational labeling to influence the quality of food product. The study suggests that the mandatory nutrition labeling provide incentive to food producer to provide quality food and better consumers' food purchasing patterns. In the more recent studies, Restrepo (2014)[28] finds that menu labeling has a significant impacts on health behaviors at point-of-purchase in chain restaurants.

---

[24] Jekanowski MD, Binkley JK, Eales J, Convenience, Accessibility, and the Demand for Fast Food, J Agric Resour Econ.2001;26(1):58-74

[25] J. Alston, D. Sumner, S. Vosti, Farm Subsidies and Obesity in the United States: National Evidence and International Comparisons, Food Policy 33.6 (2008): 470-479

[26] Cutler, D., Glaeser, E., & Shapiro, J. (2003). *Why have Americans become more obese?* (No. w9446). National Bureau of Economic Research.

[27] Caswell, Julie A., and Eliza M. Mojduszka. "Using informational labeling to influence the market for quality in food products." *American Journal of Agricultural Economics* (1996): 1248-1253.

[28] Restrepo, Brandon. "Calorie labeling in chain restaurants and body weight: evidence from New York." (2014).

Campos et al., (2011)[29] provides a systematic review on nutrition labels on pre-packaged foods. The results suggest that nutrition labels are a cost effective population level intervention and perceived as a highly credible source of information that many consumers use nutrition labels to guide their selection of food products. The evidence also shows that the use of nutrition labels is consistently linking with healthier diets. However, the nutrition labels are lower use among children, adolescents and older adults who are obese. The effectiveness of nutrition labels would depend on consumer understanding and appropriate use of labeling information.

2.6 Empirical Evidence

From the CES[30] data collected from the Bureau of Label Statistic, we noticed some changes in consumption behavior for certain type of foods after the implementation of nutrition labels on packaged food in 1994. For instance, the total food expenditure spent on sugars and sweeteners had dropped for all education levels and all age groups after the year of 1994 (Fig. 3 and Fig. 4). Many factors could affect consumption habits, such as size of the package, level of income, or price of sugars and sweeteners. Therefore, there is no obvious evidence to show that people were spending less on sugars and sweeteners based on the additional nutrition information labels on packaged foods.

Kim et al., (2000)[31] provides supportive evidences to our theoretical model. Kim et al examines the impact of consumers' use of food labels on nutrient intake. As mentioned in earlier sections, the label use decision is based on individual self-selection. Consumers with higher education or those who are more concerned about a healthy diet are more likely to use nutrition label on packaged foods, whereas low income family or people who put more importance on taste of the foods may not care to use the information provided on packaging labels. This self-selection bias implies that the unobserved variables may influence both the label use decision and nutrient intake. This econometric issue is called endogeneity, which will result in inconsistent estimates of the effect of label use on nutrient intake.

The study controls for the heterogeneity in the label use decision by employing the endogenous switching regression techniques. The model consists of nutrient intake equations for label users and non-label users and an equation for the label use decision. The label use decision is modeled by a set of standard dependent variables and nutrient intakes are estimated separately for each group conditional on label use. In this model, an individual's utility is assumed to be a function of the consumption of food, nonfood, and health. The expected utility of label use is compared to the utility of nonuse.

The paper uses survey data from the USDA's 1994-96 CSFII[32] and DHKS[33]. Both surveys contain data on nutrient intake by individuals and detailed information about the individual's socioeconomic background, health and diet related information, and questions on label usage. The dependent variables include the binary variable of label use for the label use decision model and average daily percentage of calories from total fat, average daily percentage of calories from saturated fat, average

---

[29] Campos, Sarah, Juliana Doxey, and David Hammond. "Nutrition labels on pre-packaged foods: a systematic review." *Public health nutrition* 14.08 (2011): 1496-1506.

[30] Consumer Expenditure Survey contain expenditure data organized by various demographic characteristics.

[31] Kim, S. Y., Nayga Jr, R. M., & Capps Jr, O. (2000). The effect of food label use on nutrient intakes: an endogenous switching regression analysis. *Journal of Agricultural and resource Economics*, 215-231.

[32] Continuing Survey of Food Intake by Individuals is a nationwide food consumption survey since 1930's, which provides continuous information on the food and nutrient intakes of the U.S. population.

[33] Diet and Health Knowledge Survey is a nationwide telephone survey designed to collect data on individuals' attitudes and knowledge about nutrition and nutrient intakes.

daily cholesterol intake, average daily fiber intake, and average daily sodium intake for nutrient intake estimation. Explanatory variables consist of personal or household demographics, demographic factors, and knowledge about linkage between diet and health problem.

The effect of food label use was analyzed with the benchmark recommendations of the Dietary Guidelines[34] for Americans for each nutrient intake. The dietary guidelines were published cooperatively by the USDA and the U.S. Department of Health and Human Services. The result shows about 0.15% of consumers meet the guideline of 30% or less calories from total fat before use of the nutrition label compare to 2.31% after they read nutrition labels. Label use increases the percentage of consumers meeting the dietary guideline of calories from saturated fat from 0.29% to 8.82%. Similar results are also captured on cholesterol intakes and fiber intake with the exception of sodium intakes. In general, the result indicates that nutritional label use improves the intakes by consumers of selected nutrients. These findings illustrate the importance of nutrition label use in promoting nutrient intake and healthy diets.

3. Theoretical Analysis:

3.1 Dynamic Weight Management Model

Dynamic Weight Management Model was first presented by Lakdawalla and Philipson (2009)[35]. The model starts with an individual's current period utility function, which depends on perceived food consumption, αF, other consumption, C, and his current weight. Food consumption is perceived because nutrition information is not fully revealed or the individual is lacking of nutrition knowledge. Utility rises in perceived food consumption and other consumption, but is non-monotonic in weight. Intuitively, food consumption and alternative consumption are not substitutes, which means (U_{FC}) greater or equal to 0. Finally, the utility function U is expected to be continuous, strictly concave, differentiable, and bounded.

$$\mathrm{U}(\alpha \mathrm{F}, \mathrm{C}, \mathrm{W}), \text{where } 0 < \alpha \leq 1$$

The individual has an "ideal weight", W_O. This "ideal weight" is preferred by this individual under any circumstances. In another words, this individual prefers to gain weight when her weight is below W_O, but prefers to lose weight when above it. The model considers an individual's weight, W_t, is the state variable in a dynamic problem. Weight depreciates over time, which we can interpret this depreciation as metabolic cost of living to the next period. It can be accumulated by food consumption, F, or reduced by exercising, S. Therefore, the transition equation can be written as a function of next period's weight, W_{t+1}, depends on current weight, food consumption, and physical activities. Furthermore, the transition function g is expected to be continuous and concave.

[34] The guidelines recommend a) choose a diet that provides no more than 30% of calories from fat, b) reduce saturated fat to less than 10% of calories, c) the daily value of diet for cholesterol is 300 milligrams or less, d) the daily value of diet for sodium is 2,400 milligrams or less, and e) the daily value of diet for dietary fiber is 25 grams or more.

[35] Lakdawalla D, Philipson T., The Growth of Obesity and Technological Change, Economics and Human Biology, Economics & Human Biology 7.3 (2009): 283-293

$$W_{t+1} = (1-\delta) * W_t + g(F, S)$$

The individual is given a budget constraint. The total income of the individual, Y, will be spends on food consumption and consumption on other goods, C. P is the price of food so the total consumption on food is p*αF. The imperfect information factor is represented by α. The interpretation of α comes from the fact that people do not fully understand the nutrition content of the food they consume. By our restriction on α, consumers only underestimate the nutrition value for food purchased. In this case, the individual would consume more than what is actually needed.

$$\mathrm{p} * \alpha \mathrm{F} + \mathrm{C} \leq \mathrm{Y}$$

When α is equal to 1, the individual has full understanding of the food product purchased. For simplicity, we consider the individual will spend all the income on food consumption and others with no saving. We also assume that no other source of income except for working income.

The value function V for this individual is given by,

$$\mathrm{V}(W_t) = Max_{f,c,W_{t+1}}[U(\alpha F, C, W) + \beta V(W_{t+1})]$$

$$\text{Subject to budget constraint:} \quad \mathrm{p} * \alpha \mathrm{F} + \mathrm{C} \leq \mathrm{Y}$$

$$\text{Weight constraint: } W_{t+1} = (1-\delta) * W_t + g(F, S)$$

The value function is expected to be continuous, strictly concave, and differentiable. The model interprets agricultural innovation on the supply side as a reduction in p and sedentary technological change on the demand side as a reduction in S.

$$\alpha * U_F(\alpha F, Y - p * \alpha F, W_t) + \beta V'(W_{t+1}) * g_F = \alpha * p * U_C(\alpha F, Y - p * \alpha F, W)$$

The first order condition implies marginal utility of consumption must be equal to the overall marginal utility of food, which equals the marginal utility of eating plus the marginal value of the weight change induced by eating.

$$\mathrm{V}'(W_t) = U_{W_t}(\alpha F, Y - P * \alpha F, W_t) + \beta V'(W_{t+1}) * (1-\delta)$$

The envelope condition implies that the long-run marginal value of additional weight is equal to the marginal utility of weight in the current period plus the discounted future marginal utility of weight. This model of weight yields a unique and stable steady-state in food and weight, as long as the marginal utility of food is falling in weight.

$$V'\big(W_t + g(F,S)\big) = \frac{\alpha * [P * U_C - U_F]}{g_F}$$

The left-hand side is the marginal benefit of weight tomorrow and the right-hand side is the marginal cost of spending resources on weight gain. This optimality condition illustrates the optimal food policy falls in current weight W. When W rises, V' falls as a result of concavity and ($pU_C - U_F$) rises because increases in weight lower the marginal utility of food. As a result, the marginal utility of weight tomorrow falls below its cost. In order to reach equilibrium, the individual will eat less. Therefore, the optimal food policy can be demonstrated as below,

$$\Phi(W; S, p, Y);\ \frac{d\Phi}{dW} < 0$$

The steady-state food consumption is defined implicitly according to $g(F(S,W_t), S) = \delta W_t$, which F increases in W and S.

$$F(S, W);\ \frac{dF}{dW} > 0$$

A steady-state equilibrium (W*, F*) exists when the steady-state food consumption curve intersects the optimal food policy. This equilibrium condition is illustrated in Fig. 2.

3.2 Contribution of Imperfect Information

Other steady-state determinants of weight have been discussed in Lakdawalla and Philipson (2009). For the purpose of this study, we mainly focus our discussion on the effect of imperfect information on food consumption choice and application of informational policy. As discussed in the previous section, the rational individual decides how much to consume at the optimal condition with respect to food price, income, weight, and physical activity in order to maximizing utility in long-run. However, it is only true if information is fully revealed for food consumption choice and everyone has full knowledge in using this information. The perfect information condition can be achieved when α is equal to 1. When α is less than 1, the model suggests that there is existence of missing nutrition information or the individual is lacking of nutrition knowledge. As a result, the rational individual would consume more than what is needed to maintain the ideal weight and end up gaining unnecessary weight.

According to Campos et al., (2011), consumers tend to look more closely at nutrients they wish to avoid, such as fat, energy content, protein, cholesterol, carbohydrates, and types of fat. By using the nutrition labels, consumers can reduce the imperfect nutrition information (α) and avoid related consequence from overconsuming. Several studies have reported an association between label use and lower fat consumption. Neuhouser et al., (1999)[36] finds that labels on packaged foods can be helpful for persons wishing to lower their fat intake. Also, the study demonstrates the strong

---

[36] Neuhouser, M. L., Kristal, A. R., & Patterson, R. E. (1999). Use of food nutrition labels is associated with lower fat intake. *Journal of the American Dietetic Association*, *99*(1), 45-53.

relationships between health beliefs and nutrition label use, which suggests that people interested in health would read the information on food labels to make food purchasing decisions.

Nayga (1999)[37] examines the effect of use of nutritional labels on consumers' choice for healthier food products. Healthier foods are more valued by consumers who are more likely to choose a healthier alternative of a food product, namely whites, females, and nutritional label users. On the other hand, consumers who are less likely to choose a healthier food product, includes blacks, younger individuals, those who put more importance on taste when food shopping, and those who less frequently use nutrition labels, may subject themselves to unnecessary health risks. The study suggests public health education programs should be targeted toward these consumers. Nutrition labels provide information for consumers who care about their consumption choice, but it also requires nutrition knowledge to facilitate a healthier food consumption choice.

4. Data

4.1 Data Source

The data used in this analysis were drawn from the 1991, 1993, 1995, 1998 National Health Interview Survey (NHIS), which is one of the oldest national health survey since July 1957. The survey covers the civilian noninstitutionalized population of the United States. The NHIS data are obtained through personal interviews with household members. Each week a probability sample of households is interviewed by personnel of the US Bureau of the Census to obtain information on the health and other characteristics of each household member. The sample for our study was adults between the age of 17 and 99 year old. We excluded respondents who had incomplete data on height, weight, gender, income, education attainment, or ethnicity. The final unweighted sample size was 57,302 for 4 years combined.

The reason for drawing samples from these four years because the surveys had a specific question asking how often the interviewee read the nutrition label on a pre-packaged food when purchasing the food for the first time. For the purpose of our analysis, this information is essential for us to identify the effect of imperfect information on individual choice for maintaining an ideal body weight (measured by body mass index, BMI).

Table 1 shows the summary statistics for the key variables used in this study. The variable BMI[38] is generated by using the self-reported data on height (m) and weight (kg). Even though the body mass index is also included in the original data, many of them were missing or not reported. In order to avoid losing large number of observations in this study, we created the BMI variable using the available data in the survey.

4.2 Sample Demographic

---

[37] Nayga, R. M. (1999). Retail Health Marketing: Evaluating Consumers' Choice for Healthier Foods. *Health marketing quarterly*, *16*(4), 53-65.

[38] According to the CDC, the formula for calculating an individual's BMI is $weight\ (kg) / [height\ (m)]^2$.

The majority ethnic group in this survey is non-Hispanic white. The ratio of white in this survey account for about 80.16% of the samples, ranging from 78.94% to 81.25% for each year. The second largest group is African Americans, which range from 12.43% to 13.54% for each year. Asians account for about 3.02% of the samples in the survey, which includes Chinese, Japanese, Korean, Pilipino, Pacific Islander, and Vietnamese. Others includes Native American and other ethnic groups in the sample.

Education attainment is divided into three dummy variables. The three dummies represent 1) individual has some level of education, but never graduated from high school, 2) individual who has completed high school but never attend college, and 3) individual who had studied in college for at least one year. The survey contains about 41.94% of college educated individuals, 36.34% high school graduates, and 21.72% did not complete high school.

In our study, we also use the annual household income level as a control variable. The annual household income level is divided into four dummies, which represent different level of family income of the individual. The four dummies includes family with under $20,000 annual income, from $20,000 to $35,000, $35,000 to $45,000, and $45,000 or above. The samples are proportionately distributed in each income category.

BMI is commonly used to quantify the amount of tissue mass in an individual, and can help to categorize a person as underweight, normal weight, overweight, or obese based on that value. As observed in the sample, the mean value of BMI had constantly increased by year, which indicates the increased of obesity during the 1990s. Furthermore, we also created a dummy variable to identify people who are obese in the sample. As defined by the Center of Disease Control (CDC), individual with a Body Mass Index (BMI) over 30.0 unit is classified at obese. The data also indicates an increasing trend of obesity across years.

4.3 Use of Nutrition Label

One of the most important variables in our study is how often people read the information on a nutrition label. For the purpose of this study, we categorized the variable of nutrition label reading into 5 different levels, 0, 1, 3, 5, and 7. If it is 0, it means the individual never read the information on the nutrition label. On the other hand, if it is 7, it means the individual always read the information on the nutrition label when purchasing a food for the first time.

According to the data, approximately 66% of the people in the sample reported they will read the nutrition information when purchasing a food for the first time versus only 34% of the sample population rarely or never use the information on the nutrition label. Within different education categories, we also notice different label-reading behaviors. For people with lower education achievement, they tend to not use the nutrition label on the package. On the other hand, people with higher education achievement are more likely to use a nutrition label. We also notice people with higher BMI are more sensitive to read the nutrition information than lower BMI group.

5. Empirical Analysis

5.1 Main Analysis

The main focus of this study is to examine whether reducing the imperfect information would improve consumers' food choice and reduce BMI at the current high level. Since nutrition label has been required by law under the provisions of the 1990 Nutrition Labeling and Education Act (NLEA). The nutrition facts and information have been available for consumers in the market during the period when the survey was conducted. Instead of studying the average effect of reading the nutrition label on BMI, we would like to understand how effective it is to different educational group. We expect an average person with higher education would be benefited more from reading the nutritional label and be able to maintain a more ideal BMI or lower the risk of obesity.

To estimate the effect of reading nutrition label on body mass index (BMI), a pooled OLS regression model of the following form is estimated,

$$BMI = \beta_0 + \delta_1(T93) + \delta_2(T95) + \delta_3(T98) + B_1(HighEdu * Read) + \beta_2(CollegeEdu * Read) + \sum \beta_i\,(X_i) + \varepsilon \qquad (1)$$

Where dependent variable, BMI is calculated by the self-reported height and weight. The model includes three year dummies to capture the average year effect on BMI, with 1991 as the base year. X is a vector of individual-level characteristics. The coefficients of interest are β_1 and β_2, which measures the impact of reading nutrition label on BMI for groups with varying educational attainment.

In order to measure the effect of reading nutrition label on the risk of obesity, we also use a pooled logistic regression model for estimation,

$$Logit(Obese) = \alpha_0 + \gamma_1(T93) + \gamma_2(T95) + \gamma_3(T98) + \alpha_1(HighEdu * Read) + \alpha_2(CollegeEdu * Read) + \sum \alpha_i\,(X_i) + \mu \qquad (2)$$

where obese is dummy dependent variable indicating obese individuals with BMI over 30. The variables and time dummies used in this model is same as the one described in the pooled OLS regression model. The coefficient of interest are α_1 and α_2, which identify the effect of reading nutritional label on risk of obesity for group with different educational attainment.

In table II, results from equations (1) and (2) are presented. The coefficient for label reading is positive and statistically significant in both models. According to Drichoutis et al., (2005)[39], consumers are motivated to use nutritional label as they are facing a greater perceived health risk. The positive signs could be illustrating the over-weight individuals are more responsive to nutrition labeling than normal-weight individuals.

The analysis indicates that, on average, an individual with college education who always reads nutrition information reduces his/her BMI by 0.469 units when compared to the individual with the same educational attainment but never reads nutrition information. In the pooled logistic regression, we do not find statistically significant result as in the pooled OLS regression. The coefficients of high school graduate and reading nutrition label fail to be statistically significant in both models, which suggest the impact of reading nutritional label is not statistically different for this group compared the high school graduates to those who did not finish high school education. The significant result of the

[39] Drichoutis, Andreas C., Panagiotis Lazaridis, and Rodolfo M. Nayga. "Nutrition knowledge and consumer use of nutritional food labels." *European Review of Agricultural Economics* 32, no. 1 (2005): 93-118.

key interaction term in the pooled OLS regression model provides strong evidence that the mandated nutrition label was not effective unless the consumers had achieved higher educational attainment. In the theoretical model, imperfect information may cause a rational individual to overconsume the food needed to maintain his/her ideal weight. A nutrition label is one such tools that can eliminate imperfect information for consumers. Yet, it also requires consumers to understand the nutrition information in order to make the rational choice at the point of purchase. Individuals with lower educational attainment may not be able to fully understand how to use it or even how to read it correctly. Considering the NLEA was implemented in 1990, the nutrition information on the label could be somewhat new to certain consumer groups in the market. This could also explain why the estimated coefficient in the logistic model is not significant. It takes time for people to adopt the habit of reading nutrition labels, hence it may take even longer time for nutrition labels to help individuals lower the risk of obesity.

5.2 Effect of Nutrition Labeling Across Time

The nutrition label was mandated for most food products under the provisions of 1990 Nutrition Labeling and Education Act (NLEA). It is reasonable to assume the effect of nutrition label would increase over time as people were adopting the new policy and learning how to make use of the information on the label. In order to illustrate the effect of nutrition label across time, the same regression models were estimated for each year.

$$BMI = \beta_0 + B_1(HighEdu * Read) + \beta_2(CollegeEdu * Read) + \sum \beta_i\,(X_i) + \varepsilon \qquad (3)$$

$$Logit(Obese) = \alpha_0 + \alpha_1(HighEdu * Read) + \alpha_2(CollegeEdu * Read) + \sum \alpha_i\,(X_i) + \mu \qquad (4)$$

Table III reports the estimated coefficients for the key variables from equation (3) and (4). The reading label coefficient is consistently significant in the OLS model, which suggest the over-weight individuals are more responsive to nutrition labeling than normal-weight individuals within the sample period. On the other hand, the logistic model suggests that reading nutrition information does not explain the risk of obesity, except the year of 1998. The coefficients of the key interaction terms are consistently failing to be statistically significant in both OLS and logistic regression models in the year 1991, 1993, and 1995. For the year of 1998, the coefficient for the interaction of college education and reading nutrition label is statistically significant at the 5% level in the OLS model (p-value 0.046) and in the logistic model (p-value 0.034). This result suggests the nutrition label was not effective to higher education population until the year of 1998.

The estimates coefficients imply that individuals with some college education attainment or higher level of education, who always read the nutrition information on the package, will have 1.2 lower BMI score than individuals with same education attainment who never read the nutrition information. Furthermore, individuals who always read the nutrition information can reduce the risk of obesity by 31.87% compare to those who never read the nutrition information under the same college education attainment group.

5.3. Heterogeneity in the Effect of Nutrition Label on BMI and the Risk of Obesity

The study has focused on the average effect of nutrition label on BMI within different education attainment groups. However, there are two potential sources of heterogeneity in the policy's impact across individuals.

First, whether the average effect of nutrition label on BMI varies by gender, ethnicity, and income are analyzed.[40] For gender and income, we do not find any statistically significant result for the key interaction terms in the full model or across time. The only group that has an interruptible result comes from ethnicity. Since the size of the minority ethnic group is relatively small, we divide the sample into non-Hispanic white and others, which includes African Americans, Asians, Native Americans, and other ethnic groups. We use the same specification as stated in equation (3) and (4) to estimate the impact of the interaction terms. The result is reported in Table IV. For the minority ethnic group, the estimated coefficient for the key interaction terms failed to be statistically significant at any conventional level in each year. This suggests the minority ethnic group were not benefitting from reading the nutrition information across different education attainment group. For the non-Hispanic white, we also observe a similar pattern from the year by year model. The key interaction terms are not statistical significant in the first three years of sample, but the coefficient for college education and reading nutrition information is statistically significant at the 5% level in both the OLS and logistic regression model. Also, the high school graduate and reading nutrition information interaction term is significant at the 10% level in the logistic regression model.

This important result illustrates the non-Hispanic white population had adopted the mandated nutrition label law better than the minority ethnic group. One possible explanation to this result is that the minority ethnic group has a very different food consumption habit than the non-Hispanic white. The NLEA only applied to pre-packaged foods, such as canned food, breakfast cereals, bottled drinks, yogurt, potato chips, and fermented vegetables. According to Variyam (2008)[41], if information difference between labels for pre-packaged food and random-weight food is driving the label effects, then the use of labels for pre-packaged food is likely to have a greater impact on nutrient intakes compared with the use of labels for random-weight food. Consider the minority households, such as Asians and Hispanic, the majority of their food consumption came from random-weight food. They usually buy vegetables and meat from the local market and prepare their meal at home. On the other hand, whites are relatively a bigger consumer for pre-packaged food. The insignificant result in the minority ethnic group may be driven by this unobserved consumption behavior.

Second, the effect of nutrition label on BMI may vary across the BMI distribution. For example, over-weight individuals may be more responsive to the available nutrition information than normal-weight individuals. This might mean that the impact of calorie labeling on body weight may be relatively larger among over-weight individuals. Table V shows quantile regression estimates across a wide range of the BMI distribution. The result shows the individuals with BMI at 0.9 quantile has no gain from reading the nutrition label on their BMI. The key interaction terms are found to be insignificant at the 0.9 quantile. The estimated impacts at the 0.1, 0.25, 0.5, and 0.75 quantiles are similar in size and are not significantly different across the BMI distribution. We fail to reject the null hypothesis that the estimated coefficients for the key variables at the 0.1, 0.25, 0.5, 0.75 quantiles are equal to each other. Comparing to the main model, we found the magnitude of label reading effect is the largest at 0.5 quantile or for the median distribution and comparatively larger at the lower

[40] It is important to note that stratification produces smaller sample sizes that often lead to less precise estimates, which limits the ability to make comparisons across groups.

[41] Variyam, Jayachandran N. "Do nutrition labels improve dietary outcomes?" *Health economics* 17, no. 6 (2008): 695-708.

quantiles. As illustrated in fig. 5, the BMI distribution is skewed to the left. This result suggests that label reading has a greater effect on BMI for individuals with lower BMI, but not benefit the people at the highest BMI quantile.

5.3 Estimated Effect Sizes

Using a specification similar to the one shown in the main analysis, equation (1) and (2), results indicate on average for individuals with college education attainment, who always read the nutrition information, BMI reduces by 1.09 compared to the lower education attainment group who never use or read nutrition label. Table VI summarized the marginal effect and total effect for each category. The size of the effect increased to -1.173 if we consider only the year of 1998. Furthermore, the size of label reading impact is even greater if we focus on the non-Hispanic white population in 1998, which would reduce the BMI by 1.192.

To get a better sense of the magnitude of the estimated effect of nutrition label on the risk of obesity, we also report the marginal effect of reading nutrition label on the risk of obesity in Table VI. In the logistic model with four years of observations, we do not find a significant marginal effect for reading nutrition information across education attainments. However, the individuals with college education attainment on average have a lower risk of obesity by 30.39% compare to individuals who did not complete high school education. In 1998, we found that educational attainment is not statistically significant, but the interaction term of college education and reading label is significant at 5% level. The result suggests the individuals with college education attainment who always read the nutrition information would reduce the risk of obesity by 31.87% compared to individuals who did not complete high school education and never read nutrition information. For the non-Hispanic white, the impact of reading nutrition label increases, which on average is associated with lower risk of obesity by 35.97%.

6. Conclusion

The purpose of this study is to illustrate the importance of informational policy and nutrition education in battling the U.S. obesity epidemic. We derive an individual optimal choice of food consumption, non-food consumption, and weight by using the dynamic weight management model introduced by Lakdawalla and Philipson (2009). The imperfect information factor has affected individual's food consumption decision. It reduces the nutrition value of food consumed by the individual consumer causing overconsumption and unnecessary weight gain. Several studies have illustrated the benefits of nutrition label use. We assume that imperfect information, which we describe in the theoretical model, is attributed from two main factors, lack of nutrition information at the point of sales and health knowledge to understand the information.

In our empirical study, we find that the nutrition labeling policy took time for the general population to adopt to be effective. The non-Hispanic white have benefited the most by the mandated nutrition label compared to the minority ethnic group. It reduced the BMI of individuals with college education by 1.192 unit and lowered the risk of obesity by 35.97% in 1998. A more updated study was not possible because NHIS discontinued asking nutrition label use question after 1998. Generally speaking, we find significant reduction of BMI and risk of obesity for higher education groups and reading the nutrition information more often in our main analysis. Nutrition label has been an effective informational policy in facilitating consumers' choice of healthy diet. The policy implication of this study suggests that legislations expanding health education programs for different demographic groups would be an effective policy to promote healthy diet and lower the risk of obesity.

7. Reference:

[1] Lakdawalla D, Philipson T., The Growth of Obesity and Technological Change, Economics and Human Biology, Economics & Human Biology 7.3 (2009): 283-293

[2] J. Alston, D. Sumner, S. Vosti, Farm Subsidies and Obesity in the United States: National Evidence and International Comparisons, Food Policy 33.6 (2008): 470-479

[3] Alston, J. M., Beddow, J. M., & Pardey, P. G. (2009). Agricultural research, productivity, and food prices in the long run. *Science*, *325*(5945), 1209-1210.

[4] Lakdawalla, Darius, and Tomas Philipson. "Labor supply and weight." *Journal of Human Resources* 42, no. 1 (2007): 85-116.

[5] http://dx.doi.org/10.1016/j.amjmed.2014.05.026), are published online in advance of The American

Journal of Medicine, Volume 127/Issue 8 (August 2014) published by Elsevier

[6] Van Ravenswaay, E.O. "Valuing Food Safety and Nutrition: The Research Needs." Value Food Safety and Nutrition. J.A. Caswell, ed., pp. 3-26. Boulder CO: Westview Press, 1995.

[7] Henson, S., and B. Traill. "Demand for Food Safety, Market Imperfections, and the Role of Government." Food Policy 18(1993):152-62.

[8] Caswell, Julie A., and Eliza M. Mojduszka. "Using informational labeling to influence the market for quality in food products." *American Journal of Agricultural Economics* (1996): 1248-1253.

[9] Caswell, J.A., and D.I. Padberg. "Toward a More Comprehensive Theory of Food Labels." Amer. J. Agr. Econ. 74(May 1992):460-68

[10] Andreyeva, T., Long, M. W., & Brownell, K. D. (2010). The impact of food prices on consumption: a systematic review of research on the price elasticity of demand for food. *American journal of public health*, *100*(2), 216.

[11] Park JL, Holcomb RB, Raper KC, Capps O Jr., A Demand Systems Analysis of Food Commodities by US Households Segmented by Income, Am J Agric Econ. 1996; 78(2):290-300

[12] Raper KC, Wanzala MN, Nayga RM Jr., Food Expenditures and Household Demographic Composition in the US: A Demand Systems Approach, Appl Econ. 2002; 34(8):981-992

[13] J. Alston, D. Sumner, S. Vosti, Farm Subsidies and Obesity in the United States: National Evidence and International Comparisons, Food Policy 33.6 (2008): 470-479

[14] J. Beghin and H. Jensen, Farm Policies and Added Sugars in US Diets, Food Policy 33.6 (2008): 480-488)

[15] H. Carman, A Trend Projection of High Fructose Corn Syrup Substitution for Sugar, Amercian Journal of Agricultural Economics 64.4 (1982): 625-633

[16] Blair, Dorothy, and Jeffery Sobal. "Luxus consumption: Wasting food resources through overeating." *Agriculture and Human Values* 23.1 (2006): 63-74.

[17] Wang, Y. Claire, Sara N. Bleich, and Steven L. Gortmaker. "Increasing caloric contribution from sugar-sweetened beverages and 100% fruit juices among US children and adolescents, 1988–2004." *Pediatrics* 121.6 (2008): e1604-e1614.

[18] Vartanian LR, Schwartz MB, Brownell KD., Effects of Soft Drink Consumption on Nutrition and Health: A Systematic Review and Meta-Analysis, AM J Public Health, 2007; 97(4):667-675

[19] Chouinard, H. H., Davis, D. E., LaFrance, J. T., & Perloff, J. M. (2005). The effects of a fat tax on dairy products. *Department of Agricultural & Resource Economics, UCB*.

[20] Yen ST, Lin BH, Smallwood DM, Andrews M., Demand for Non-alcoholic Beverages: The Case of Low-income Households, Agribusiness. 2004; 20(3): 309-321

[21] Jekanowski MD, Binkley JK, Eales J, Convenience, Accessibility, and the Demand for Fast Food, J Agric Resour Econ.2001; 26(1):58-74

[22] J. Alston, D. Sumner, S. Vosti, Farm Subsidies and Obesity in the United States: National Evidence and International Comparisons, Food Policy 33.6 (2008): 470-479

[23] Cutler, D., Glaeser, E., & Shapiro, J. (2003). *Why have Americans become more obese?* (No. w9446). National Bureau of Economic Research.

[24] Caswell, Julie A., and Eliza M. Mojduszka. "Using informational labeling to influence the market for quality in food products." *American Journal of Agricultural Economics* (1996): 1248-1253.

[25] Campos, Sarah, Juliana Doxey, and David Hammond. "Nutrition labels on pre-packaged foods: a systematic review." *Public health nutrition* 14.08 (2011): 1496-1506.

[26] Neuhouser, M. L., Kristal, A. R., & Patterson, R. E. (1999). Use of food nutrition labels is associated with lower fat intake. *Journal of the American Dietetic Association*, *99*(1), 45-53.

[27] Nayga, R. M. (1999). Retail Health Marketing: Evaluating Consumers' Choice for Healthier Foods. *Health marketing quarterly*, *16*(4), 53-65.

[28] Kim, S. Y., Nayga Jr, R. M., & Capps Jr, O. (2000). The effect of food label use on nutrient intakes: an endogenous switching regression analysis. *Journal of Agricultural and resource Economics*, 215-231.

[29] Drichoutis, Andreas C., Panagiotis Lazaridis, and Rodolfo M. Nayga. "Nutrition knowledge and consumer use of nutritional food labels." *European Review of Agricultural Economics* 32, no. 1 (2005): 93-118.

[30] Variyam, Jayachandran N. "Do nutrition labels improve dietary outcomes?."*Health economics* 17, no. 6 (2008): 695-708.

[31] Restrepo, Brandon. "Calorie labeling in chain restaurants and body weight: evidence from New York." (2014).

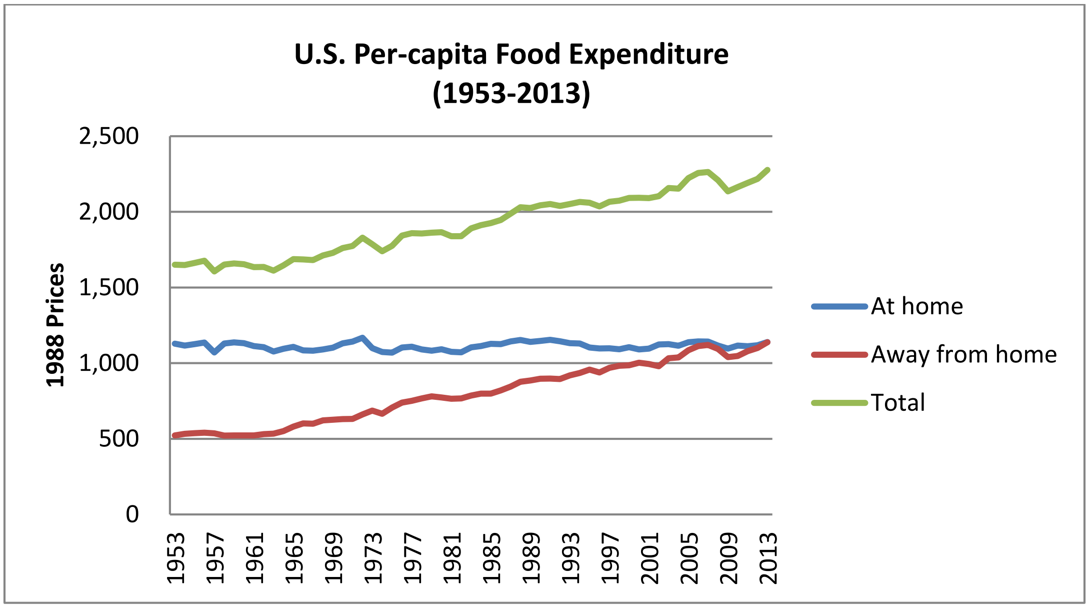

Fig. 1 Per-capita Food Expenditure (Source: USDA ERS)

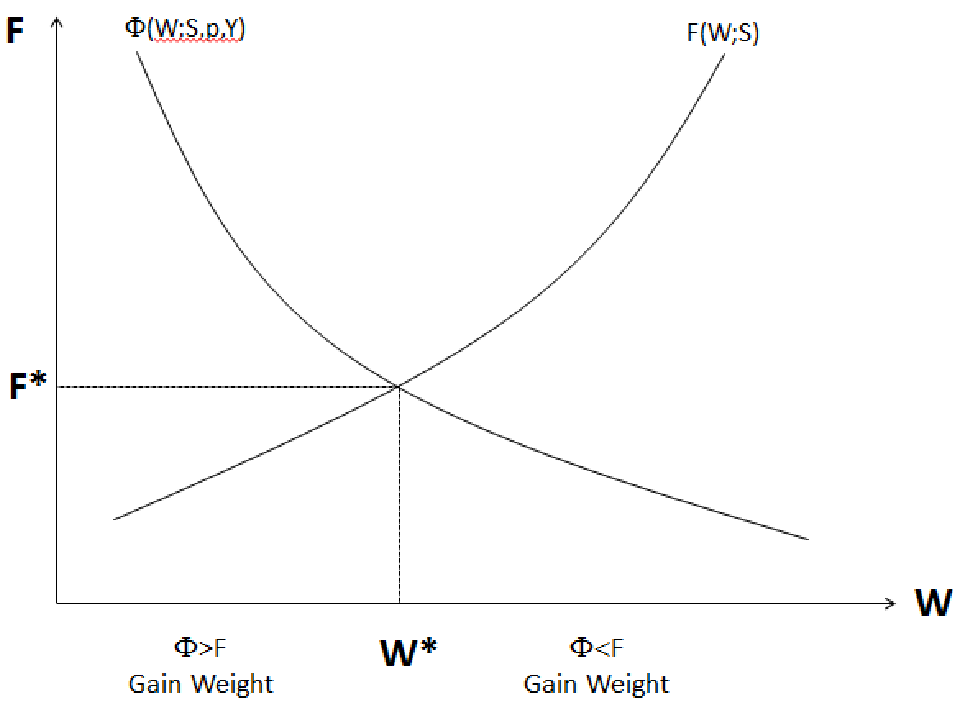

Fig. 2. Steady-state weight and food consumption

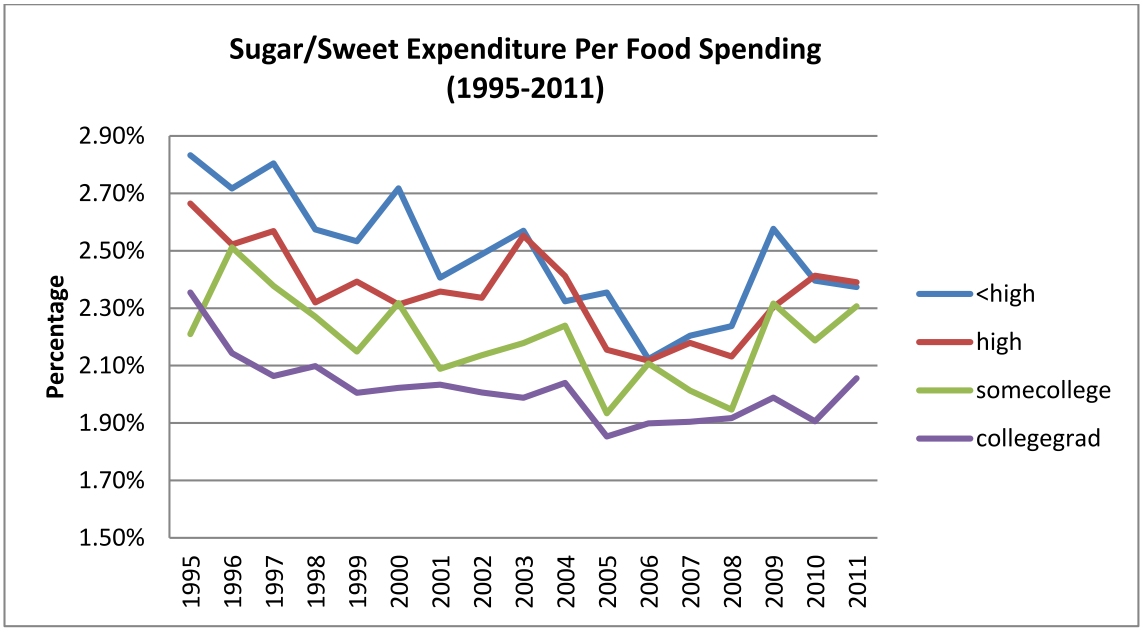

Fig. 3 Percentage of food expenditure spent on sugar/sweetener (Source: CES, BLS)

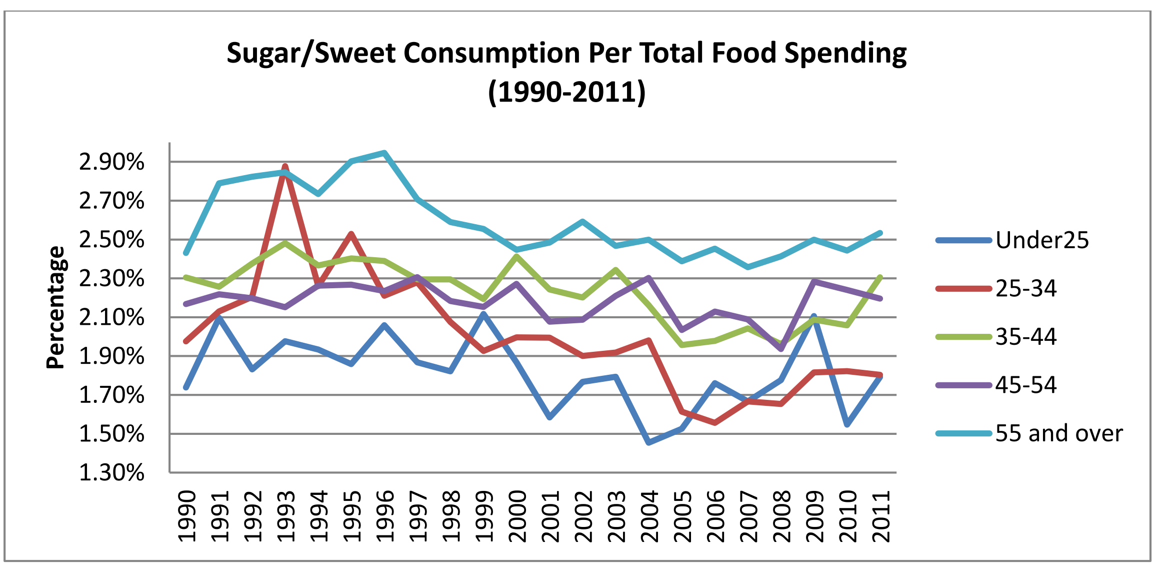

Fig. 4 Percentage of food expenditure spent on sugar/sweetener (Source: CES, BLS)

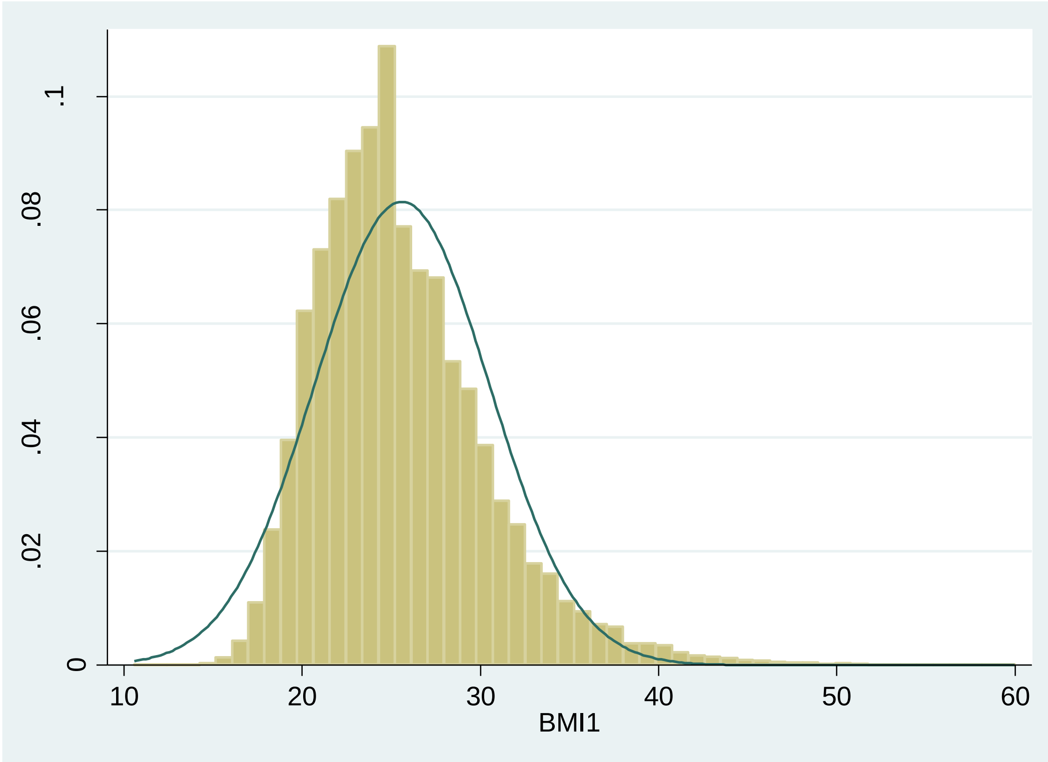

Fig. 5 BMI Distribution in Year 1991, 93, 95, 98 (Source: IHIS)

Tabel I: Sample Summary Statistics

	1991		1993		1995		1998		Year = 1991, 93, 95, 98	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Body Mass Index (BMI)	25.261	4.797	25.543	4.994	25.809	5.082	26.270	4.741	25.606	4.937
1 if Obese (BMI≥30)	0.140		0.156		0.168		0.197		0.159	
Age	44.063	17.952	44.160	17.800	43.986	17.706	44.182	17.523	44.097	17.758
1 if Male	0.464		0.465		0.465		0.473		0.466	
1 if White	0.813		0.811		0.790		0.789		0.802	
1 if Black	0.135		0.132		0.124		0.132		0.131	
1 if Asian	0.026		0.031		0.032		0.033		0.030	
1 if Others	0.026		0.025		0.053		0.046		0.037	
1 if Family Income > 20k	0.311		0.298		0.289		0.281		0.295	
1 if 20k ≤ Family Income < 35k	0.259		0.253		0.255		0.202		0.244	
1 if 35k ≤ Family Income < 45k	0.131		0.130		0.127		0.105		0.124	
1 if Family Income ≥ 45k	0.299		0.319		0.330		0.412		0.337	
1 if Strenuous Work	0.300		0.293		0.294		0.282		0.295	
1 if High School Drop Out	0.226		0.214		0.228		0.199		0.217	
1 if High School Degree	0.378		0.375		0.364		0.330		0.363	
1 if Some College or Above	0.396		0.411		0.408		0.470		0.419	
How Often to Read Nutrition Information (0 = Never, 1 = rarely, 3 = sometimes, 5 = often, 7 = Always)	3.377		3.565		3.532		3.452		3.456	
N	22,333		11,293		9,279		14,581		57,302	

Note: These summary statistics are for the Tabel II regression sample. Individual-level information was drawn from the 1991, 1993, 1995, and 1998 Intergrated Health Interveiw Survey (IHIS).

Tabel II: The Effect of Nutrition Labeling on BMI and Risk of Obesity				
Dep. Var.	**BMI**		**1 if Obese**	
	Coef.	**Std. Err.**	**Coef.**	**Std. Err.**
T93	0.337***	(0.053)	0.115***	(0.033)
T95	0.667***	(0.057)	0.226***	(0.035)
T98	1.113***	(0.050)	0.474***	(0.029)
age	0.287***	(0.009)	0.118***	(0.006)
age^2	-0.003***	(0.0001)	-0.001***	(0.0001)
1 if Male	1.436***	(0.042)	0.037	(0.026)
1 if High School Degree	-0.264***	(0.096)	-0.145***	(0.054)
1 if Some College or Above	-0.659***	(0.097)	-0.362***	(0.057)
1 if 20k ≤ Family Income < 35k	-0.198***	(0.055)	-0.065**	(0.032)
1 if 35k ≤ Family Income < 45k	-0.262***	(0.067)	-0.129***	(0.04)
1 if Family Income ≥ 45k	-0.668***	(0.057)	-0.314***	(0.034)
1 if White	-0.914***	(0.115)	-0.387***	(0.062)
1 if Black	0.844***	(0.126)	0.204***	(0.066)
1 if Asian	-2.701***	(0.166)	-1.544***	(0.138)
1 if Strenuous Work	0.21***	(0.050)	0.084***	(0.029)
How Often to Read Nutrition Information (0 = Never, 1 = rarely, 3 = sometimes, 5 = often, 7 = Always)	0.141***	(0.022)	0.031***	(0.012)
Interaction Term (High School Degree * Reading Nutrition)	-0.029	(0.025)	-0.005	(0.014)
Interaction Term (College Edu. * Reading Nutrition)	-0.067***	(0.024)	-0.006	(0.013)
Constant	18.909***	(0.222)	-3.977***	(0.142)
R-Squared	0.0905		0.0365	
Sample Size	57,302		57,302	

Note: Standard error are in parentheses. Individuals 17 and older are included in these regression. All regressions used sampling weights. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table III: The Effect of Nutrition Labeling on BMI and Risk of Obesity by Year

Dep. Var.	1991		1993		1995		1998	
	OLS	Logit	OLS	Logit	OLS	Logit	OLS	Logit
How Often to Read Nutrition Information (0 = Never, 1 = rarely, 3 = sometimes, 5 = often, 7 = Always)	**0.181*** (0.034)**	**0.038** (0.019)**	**0.166*** (0.051)**	0.038 (0.026)	**0.139** (0.057)**	0.011 (0.027)	**0.156*** (0.046)**	**0.053** (0.023)**
Interaction Term (High School Degree * Reading Nutrition)	-0.062 (0.039)	0.004 (0.022)	-0.022 (0.057)	-0.014 (0.031)	-0.031 (0.065)	0.015 (0.031)	-0.064 (0.053)	-0.033 (0.22)
Interaction Term (College Edu. * Reading Nutrition)	**-0.073* (0.038)**	0.009 (0.023)	-0.051 (0.056)	-0.002 (0.030)	-0.105 (0.065)	0.021 (0.031)	**-0.127** (0.053)**	**-0.054** (0.025)**
R-Squared	0.078	0.0276	0.0729	0.0281	0.0544	0.0238	0.0481	0.0136
Sample Size	22,333		11,293		9,279		14,581	

Note: Controls include but not shown: age, age^2, gender, ethnicity dummies (white, black, and asian), education dummies (high school graduate and some college), strenuous work dummy, and family income dummies (20k-35k, 35k-45k, and 45k or above). Standard errors are reported in parentheses below the coefficients. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Tabel V: Heterogeneity in the Effect of Nutrition Labeling Across the BMI Distribution (Year = 1991, 93, 95, 98)

Quantile	0.1	0.25	0.5	0.75	0.9
How Often to Read Nutrition Information (0 = Never, 1 = rarely, 3 = sometimes, 5 = often, 7 = Always)	**0.155*** (0.021)**	**0.152*** (0.019)**	**0.185*** (0.023)**	**0.143*** (0.037)**	0.065 (0.055)
Interaction Term (High School Degree * Reading Nutrition)	**-0.044* (0.024)**	**-0.039* (0.022)**	**-0.059** (0.027)**	-0.035 (0.043)	0.023 (0.063)
Interaction Term (College Edu. * Reading Nutrition)	**-0.084*** (0.023)**	**-0.085*** (0.021)**	**-0.127*** (0.026)**	**-0.071* (0.041)**	0.033 (0.06)

Note: Controls include but not shown: age, age^2, gender, ethnicity dummies (white, black, and asian), education dummies (high school graduate and some college), strenuous work dummy, and family income dummies (20k-35k, 35k-45k, and 45k or above). Standard errors are reported in parentheses below the coefficients. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Tabel V: Heterogeneity in the Effect of Nutrition Labeling Across the BMI Distribution

Quantile	0.1	0.25	0.5	0.75	0.9
How Often to Read Nutrition Information (0 = Never, 1 = rarely, 3 = sometimes, 5 = often, 7 = Always)	0.177*** (0.0199)	0.158*** (0.019)	0.218*** (0.023)	0.167*** (0.037)	0.082 (0.058)
Interaction Term (High School Degree * Reading Nutrition)	-0.065*** (0.023)	-0.048** (0.022)	-0.09*** (0.027)	-0.04 (0.043)	0.018 (0.067)
Interaction Term (College Edu. * Reading Nutrition)	-0.105*** (0.022)	-0.0898*** (0.0211)	-0.161*** (0.026)	-0.093** (0.041)	0.008 (0.064)

Note: Controls include but not shown: age, age^2, gender, ethnicity dummies (white, black, and asian), education dummies (high school graduate and some college), strenuous work dummy, and family income dummies (20k-35k, 35k-45k, and 45k or above). Standard errors are reported in parentheses below the coefficients. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Tabel VI: Individual with some college education or higher education attainment, Effect of Nutrition Labeling on BMI and Risk of Obesity

OLS Regression Result	Never	Rarely	Sometimes	Often	Always	Marginal Effect
Year = 1991, 1993, 1995, 1998	-0.659	-0.721	-0.844	-0.967	-1.090	-0.061
Year = 1998	-0.480	-0.579	-0.777	-0.975	-1.173	-0.099
Year = 1998, Ethnicity = White	-0.402	-0.515	-0.741	-0.967	-1.192	-0.113
Logit Regression Result	**Never**	**Rarely**	**Sometimes**	**Often**	**Always**	**Marginal Effect**
Year = 1991, 1993, 1995, 1998	30.39%	30.39%	30.39%	30.39%	30.39%	Not significant
Year = 1998	0.00%	5.33%	15.16%	23.97%	31.87%	-0.0548184
Year = 1998, Ethnicity = White	0.00%	6.17%	17.39%	27.27%	35.97%	-0.0636912