Nutrition Label Usage, Diet Health Behavior,

and Information Uncertainty

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Abstract:

The overarching goal of nutrition labeling is to transform credence attributes into searchable cues, which would enable consumers to make appropriate choices at lower search costs. However, despite an abundance of food labeling information, asymmetries regarding appropriate healthy food choices largely persist. Thus, there is need for research that exposes consumer's label usage and their level of concern about their health in order to understand the underlying motivations that may explain consumer behavior with regard to labels. In order to better understand how current food-health behavior and related perceptions over potential future health complications are affected by present labeling usage patterns, this study will estimate 1) the impact of nutrition label usage on individual's perceived diet health concerns using alternative propensity score matching (PSM) techniques; 2) the effect of nutrition label usage on consumer's stated concerns on (a) diet-health, (b) obesity, and (c) general future wellbeing controlling for a wide variety of socio-demographic variables, food-intake and choice related behaviors, and lifestyles factors; and 3) conduct a series of tests and sensitivity analyses to assure robustness of matching indicators and to validate impacts of treatment effects for label users and non-users. The analysis utilizes data from the 2008 *National Health and Wellness Survey* conducted by Nielsen Canada. As the results suggest, consumers are not aware or use nutrition labeling information. In order to change dietary behavior, policy makers may need to adopt instruments that account for differences with regard to food preferences, food shopping habits, and overall usage patterns of food/nutrition labeling information.

Keywords: Socio-economic factors, food labeling, preferences, behavioral factors.
JEL codes: I1, H2

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Introduction

About 60% of Canadians are either obese or overweight (Tjepkema and Sheilds, 2005). The associated costs of physical inactivity and obesity combined have been valued at $9.6 billion (Katzmarzyk and Janssen, 2004). Faced with growing diet-health related problems, there is a need to determine factors that impact Canadian's attitudes, perceptions, and behaviors towards health and diet. Previous research has estimated that obesity is second only to tobacco consumption as a cause of death that could be prevented by behavioral changes (McGinnis and Foege, 1993). On the one hand, consumers may have misconceptions or misinformation about the nutritional content and quality of the foods consumed (Frazão and Allshouse, 2003). Consumers who aim at reducing their calorie intake may not realize the importance of substituting healthier foods into their diet, such as fruit and vegetables. On the other hand, a dominance of other food attributes, such as taste, convenience and cost, may outweigh the benefits of healthful food intake. The existence of self-control problems may lead to a preference of immediate gratification versus future returns. Since consumers do not know whether a lifetime of healthy eating will prevent illness or extend life, they have difficulty passing up current pleasure for future benefits and prefer to indulge in the present instead of consuming healthful foods (e.g. O'Donoghue and Rabin, 1999 and 2000).

Consumers make their purchasing decisions based on a number of factors. Besides the price of the product, factors such as appearance, convenience, and perceived quality determine the decisions made in the marketplace. Assuming the existence of an ideal world, consumers would base their choices on perfect information about product attributes and hence purchase foods that maximize their well-being. However, without perfect nutrition information, the consumer is faced with a more difficult decision when buying food. The consumer does not know the healthfulness of a certain food. Producers may know how their product ranks is in terms of nutritional benefits but they may not see any incentive to share this information with consumers. This asymmetry in nutrition information between producers and consumers causes a market failure.

The overarching goal of nutrition labeling is transform credence attributes into searchable cues, which would enable consumers to make appropriate choices at lower search costs. The majority of economic research on the impact of food labeling has relied on the neoclassical assumptions of perfectly rational consumers who fully incorporate all available information into their food-related choice decisions (e.g. Akerlof, 1970; Lancaster, 1966). Further, consumers are typically assumed to fully understand the information provided to them. Under these assumptions, nutrition labels have long been held as the best available tool to improve the efficiency of food markets by reducing asymmetric information, uncertainty and search cost. However, despite an abundance of food labeling information, asymmetries regarding appropriate healthy food choices largely persist. Only a few studies have been questioning the value of nutrition labeling as a choice decision tool for consumers willing to change diet and health behavior (e.g. Teisl et al., 2001; Kim, Nayga and Capps, 2001; Drichoutis et al., 2009). Other studies have suggested that the continuous proliferation in food labels and diet symbols may increase confusion and mistrust among consumers (Crespi and Marette, 2003). Some empirical studies have produced evidence to show that nutrition label information that overwhelms consumers or is misunderstood can in fact decrease the accuracy of individual’s judgment and subsequent food choice decisions (Feick et al., 1986; Byrdbredbenner, 1994). Other researchers have debated the ‘right’ amount of information consumer can process and its impact on understanding of labeling information and (Wansink et al., 2004).

There has also been criticism regarding the 2 billion dollars that the U.S. food industry spent on the 1994 Nutrition Labeling and Education Act (NLEA) (Balasubramanian and Cole, 2002). Thus, there is need for research that exposes nutrition label usage and consumer's level of concern about their health in order to understand the underlying motivations that may explain consumer behavior with regard to labels.

The objective of this paper is to investigate to what extend frequent usage of nutrition labels affects household meal planner's perceptions. In order to better understand how current food-health behavior and related perceptions of potential future health complications are affected by present labeling usage patterns, this study will estimate 1) the impact of nutrition label usage on individual's perceived diet health concerns; 2) the effect of nutrition label usage on consumer's stated concerns regarding (a) health, (b) obesity, and (c) general future well-being; and 3) conduct a series of tests and sensitivity analyses to assure robustness of matching indicators and to validate impacts of treatment effects for label users and non-users.

The estimation of the determinants of an individual's food label usage patterns in the context of diet and health concerns faces two challenge frequently found in empirical analyses of health and diet behavior based on cross-sectional population data–the likely endogeneity of stated nutrition, health, and perception information and related self-selection bias resulting from voluntary survey participation. The empirical analysis in this paper employs alternative propensity score matching (PSM) estimators (Rosenbaum and Rubin, 1983) to explicitly address these issue two frequent empirical problems.

Reliable evidence regarding the relationship between on consumer health-risk behavior and its impact on food-health information and label usage may inform policy makers about effective design of public health and food labeling policies. Reliable estimates of the complex interplay between health-risk behavior and information behavior will also contributes to the long-standing discussion about the impact of mandatory food-labeling regulation on consumer food choices. Hence, a better understanding of underlying consumer perceptions and motivations with regard to label usage is necessary to formulate effective policy interventions, which may improve market allocation efficiencies and policy outcomes.

2. Background: Healthy Eating Policies

The increased consumption of high-calories foods and the implied consequences for obesity have led to increased debates on how to reverse the trend of increasing body weight (Frazão and Allshouse, 2003). General strategies have consisted in offering better-for-you foods, manipulating food prices of high-calorie and low-calorie foods, and increasing nutrition knowledge through labeling.

Better-For-You (BFY) foods are products where the amount of unhealthy substances has been actively reduced or removed during production (i.e. fats, sugars, salt, and carbohydrates). However, it remains difficult to predict whether the increased availability of BFY products might be able to reverse the increasing consumption trends in energy and fat intakes (Harnack, Jeffery, and Boutelle, 2000). One of the main challenges facing the growing market of BFY foods is to convince consumers that these products taste great, in addition to having nutritional value (Agriculture and Agri-Food Canada, 2011).

The role of the public sector in managing obesity has so far been limited to information distribution (Kuchler, Tegene, and Harris, 2005). Recently, there has been an increase in media and government attention regarding the regulation, legislation and litigation of obesity issues. Overall, small levies on high-calorie foods or price supports on low-calorie foods have provoked many different opposing opinions among researchers, interest groups, the government and the general public (e.g. Bhattacharya and Sood, 2011; Schroeter, Lusk, and Tyner, 2007). Schroeter, Lusk and Tyner (2007) demonstrate a case where a tax on food away from home, an area of food consumption blamed for much of the rise in obesity, could lead to an increase in body weight.

Increasing nutrition knowledge through labeling is another strategy to decrease the prevalence of obesity. In 2005, mandatory nutrition labeling was implemented in Canada in the form of standardized nutrition information panels showing consumers the macro- and micronutrient contained in a food product (Health Canada, 2008). Consumers encounter three types of label information every day. The nutrition fact panel (NF) is the only type of label information created and backed by the Food and Drug Administration (FDA). It is commonly found on the back or side of most pre-packaged food products and provides information such as serving size, nutrient intakes, and percentage of the recommended daily value that is provided by one serving. The FDA regulates the other two types of label information, which are health claims and nutrition claims. However, manufacturers voluntarily create these labels. Thus, products that have a lot of high quality nutrients will usually let this information be known on the label, and products that do not have high quality nutrients will not. If consumers understand this "unfolding process", the difference between their perceptions and actuality may not be significant and the health and nutrition claim labels will not add much to the consumer information base (Caswell, 1992). Furthermore, if nutritional quality is not a top attribute when purchasing food, adding new information in these claim labels will not change a consumer's behavior. The label information could also be difficult to find and use, and would therefore not improve a consumer's information search. However, since consumers are increasingly concerned about diet and nutrition, neither of the previous scenarios is likely. Thus, it is important to include consumer concerns and perceptions into the analysis in order to understand the underlying motivations that may explain consumer behavior with regard to nutrition labels.

3. Model & Data

The evaluation of food policies related to consumer food-health behaviors in response to health interventions such as nutrition labeling has typically relied on empirical evidence produced by observational studies. In their seminal work, Rosenbaum and Rubin (1983) proposed propensity score matching (PSM). PSM compares those individuals who have been affected by a policy or program intervention (treatment group) with individuals who are thought to have not been influenced by the program (control) in question, but otherwise share the characteristics of those in the treatment similar in as many respects as possible (Rubin, 2001). PSM operates on the assumption that the conditional probability, $P(Z)$, is to be uniform between the treated individuals and their matched comparators (controls), while different forms of randomization assure that participants and comparisons are identical in terms of the distribution of observed or unobserved characteristics. As such, PSM presents a statistical comparison of groups based on a model of the estimated probability of participating in the treatment regime. Given the emulation of a randomized control trial, PSM methods can be employed to reduce the bias and increase the robustness in the estimation of treatment effects compared to regression methods commonly found in the literature (e.g. Kim et al., 2000; Variyam, 2008; Lechner, 2002). Widely used and an established analytical tool in the epidemiological literature, PSM has recently attracted the attention of economists interested in the evaluation of policy and program interventions (Heckman et al., 1997; Dehejia and Wahba, 1999; Hitt and Frei, 2002; Becker and Ichino, 2002, Ravallion, 2008, Drichoutis et al., 2009).

Of fundamental interest in the economic evaluation of programs aimed at improving consumer food, nutrition, and/or health behavior is whether a particular policy intervention is effective in accomplishing its primary objectives. For example, is the provision of nutrition and ingredient information to consumers (food labeling) an effective mechanism for combating obesity and other food-intake related diseases? An experimental evaluation with a random assignment of subjects to treatment and control groups has long been the gold standard used to assure that participation in the intervention is the only differentiating factor between the subjects in both groups. However, an experimental evaluation is often not feasible, difficult in its implementation, and costly to the researchers. Hence, the main challenge of program evaluation lies in finding alternative means of designing counterfactual outcomes (e.g. a world without the 1990 U.S. NLEA). Common to issues discussed in the food-health economics literature, counterfactual outcomes are never observed, making statistical methods such as PSM a convenient yet powerful approach to estimating hypothetical outcomes based on observational data.

We employ PSM to answer the question of whether and to what extent frequent attention to and consideration of nutrition labeling information affect consumers' perceived concerns about their future health and obesity status. In doing so we address the possible occurrence of selection bias and reverse causality in the estimation of the labeling treatment effect, where the treatment is endogenous to the related observed outcome. As such PSM represent a parametric (non-parametric) alternative to linear regression analysis suitable for dealing with endogeneity and self-selection bias, problems frequently found in empirical studies involving interactions of food, health, and information parameters (Black and Smith, 2004).

Model Considerations

The economic literature on the estimation of treatments effects has generalized relied on three approaches: Heckman's (1979) treatment effects model as a version of the Heckman sample selection model; difference-in-difference estimators (Card and Kruger, 1994), and propensity score matching (PSM) (Rosenbaum and Rubin, 1983).

The choice of approach thereby relies to at least some extent on the quality (reliability) of available data. For instance, the variables used for the covariate matching of individuals in treatment and control groups determine whether PSM is of advantage to estimate the impact of policy impacts. In addition, the observed variables determine the effectiveness of this procedure to eliminate or at least mitigate sample selection bias (Ravallion, 2008). Hence, concerns about the remaining selection bias in PSM estimates need to be addressed. However, PSM has preferable properties as a tool for estimating mean treatment impacts without making arbitrary assumptions about functional forms and error distributions that are common to alternative econometric techniques. PSM also enables tests of the presence of potentially complex interaction effects among treatment covariate variables. Although it is not possible to test the assumptions of PSM on non-experimental data, Heckman et al. (1997, 1998) used experimental data to identify the conditions under which PSM is able to provide reliable low-bias estimates of a program impact in question.

In order to maximize the advantages of PSM methods in the context of this study, a key role falls to the careful selection of covariate variable involved in the matching of treatment and control group membership. Valid "matching variables" should be those associated both with the probability of treatment participation (e.g. usage of the nutrition facts panel) and with the outcome variable in question (e.g. health / obesity concerns) (Heckman and Navarro-Lozano, 2004). As such, appropriate covariate variables should be independent of the program intervention of interest.

Theoretical Model

The estimated propensity score, for subject *i* (i = 1,…, N) is the conditional probability of being assigned to a particular treatment given a vector of observed covariate variables X_i (Rosenbaum and Rubin, 1983). Let $Y_i = 1$ be the outcome of the i^{th} individual who is affected by a program intervention, and let $Y_i = 0$ be the individual's outcome who is not influenced by the program. The impact of the program is given by $\Delta = Y_i^1 - Y_i^0$. Only Y^1 or Y^0 is realized for each individual. Let D indicate program participation or "treatment" ($D = 1$) and $D = 0$ otherwise. The evaluation problem is then to estimate the average impact of program participation following the intervention on those "treated". Following Rosenbaum and Rubin (1983), if $P(X) = Pr(D = 1 \mid X_i)$ is the probability of program participation, then PSM can be employed to construct a statistical comparison group by matching observations of beneficiary households with observations of non-beneficiaries with similar values of $P(X_i)$. The parameter of greatest interest in the evaluation of the effectiveness of intervention programs and the economic literature is the "average effect of a treatment on treated individuals" or ATT is defined as:

$$ATT= E(\Delta \mid X, D = 1) = E(Y^1 - Y0 \mid X, D = 1) = E(Y^1 \mid X, D = 1) - E(Y^0 \mid X, D = 1), \qquad (1),$$

where X_i is a vector of control variables (subscripts have been dropped). In equation (1), $E(Y^0 \mid X_i, D = 1)$ the counterfactual outcome is not observed.

Relying on the mean outcome of individuals in the untreated group, $E(Y^0 \mid X, D = 0)$, will lead to biased results, because of the high probability that factors which determine participation in the treatment will also determine the outcome variable of interest. Hence, the observed outcomes for individuals in the treatment and control groups might differ even in the absence of the intervention leading to a “self-selection bias”:

$$E[Y^1 \mid X, D = 1] - E[Y^0 \mid X, D = 0] = ATT + E[Y^0 \mid X, D = 1] - E[Y^0 \mid X, D = 0] \qquad (2)$$

In contrast to true randomized experiments, observational studies rely on a set of identifying assumptions to avoid problems associated with self-selection bias as stated in (3). The mean impact of a program intervention is a general factor of interest in many evaluation studies. This parameter, known as the “average effect of a treatment on all individuals in a population” or ATE is defined as:

$$ATT = E[Y^1, D = 1] – E[Y^0, D = 0] \qquad (3)$$

Heckman et al. (1997) notes that the population average treatment effect (ATE) might not be of great interest and relevance to policy decision makers because it includes the effect of an intervention on individuals for whom the program was never directly intended. A third and final outcome measure of interest, the “average effect of a treatment on individuals in the control group” or ATU measures the impact that a program would have had on individuals who did not participate in the intervention. ATU is defined as:

$$ATU = E[Y^1 - Y^0 \mid D = 0]. \qquad (4)$$

To ensure that the matching estimators identify and consistently estimate the treatment effects of interest, PSM requires several assumptions in order to derive consistent estimates for ATT, ATE, and ATU. First, balancing of pre-treatment variables is essential to assuring that the treatment is independent of characteristics after conditioning on observed characteristics estimated in the propensity score model:

$$D \perp X \mid p(X).$$

The conditioning on the propensity score model (*p(X)*) should be comprehensive such that the characteristics between two groups (treated, control) with the same propensity score value will be balanced. Hence, there should be no statistically significant differences between the means of the covariates of the treatment and control groups. The second assumption of (weak) unconfoundedness (conditional independence assumption, CIA) and possible model identification strategy holds when then the potential treatment outcomes are independent of the participation status (treatment assignment), conditional on the propensity score *p(X)*.

$$E(Y^0 \mid Xi, D = 1) = E(Y^0 \mid Xi, D = 0) \quad (5)$$

The assumption implies that selection is solely based on observable characteristics and that all covariates that influence treatment assignment and potential outcomes simultaneously are observed. The third assumption of common support or overlap condition implies that the probability of participation in an intervention, conditional on observed characteristics, lies between 0 and 1:

$$0 < P(X_i) < 1. \quad (6)$$

This assumption is critical to estimation, as it ensures that there is sufficient overlap in the characteristics of the treated and untreated units to facilitate adequate matches. Units with the same *X* values are assumed to have a positive probability of being both participants and nonparticipants.

Hence, covariate matching methods estimate $E(Y^0 \mid X_i, D = 1)$ *by* $E(Y^0 \mid X_i, D = 0)$ using mean outcomes of individuals in the control group matched with individuals in the treatment group directly on all covariate variables (X_i) considered in the model. The complexity of covariate matching increases with large numbers of potential covariate factors. PSM overcomes this problem. As Rosenbaum and Rubin (1983) are able to show, if an outcome (e.g. health concerns) is independent of treatment participation after conditioning on *X*, an outcome can be expected to be independent of treatment participation after conditioning on *P(X)*. Hence, if assumptions (5) and (6) hold when working with observational data, PSM provides an alternative method to experimental validation for estimating $E(Y^0 \mid X_i, D = 1)$ as a means for obtaining unbiased estimates of (1). Since the propensity score is a probability, it ranges in value from 0 to 1.

Data and Estimation

Our empirical analysis utilizes data from the 2008 *National Health and Wellness Survey* conducted by Nielsen Canada. The *National Health and Wellness Survey* has been conducted since 2007 to collect data on consumers' perceptions, attitudes, and behaviors related to food consumption, physical activity, and wellbeing (Nielsen, 2007). The survey was designed to be representative of the Canadian population. In this data set, Canadian households provided information on participant's past and current food choice and consumption behavior with a focus on conscious food-health behavioral changes (e.g. limiting intakes of reducing unfavorable ingredients). The survey contains detailed information on participant's socio-demographic characteristics, their stated concerns about health status, diet habits and behaviors, past and current food purchase and consumption patterns, and frequencies of regular physical exercise. In addition, the survey includes respondents' consideration, understanding and usage of food ingredient, product labeling, and food-health related information as part of their grocery purchase decisions. As such, the survey appears to be particularly valuable for analyses of the potential linkages between food-health related attitudes perceptions, food-health knowledge and information asymmetries in the context of obtaining a better understanding of consumers' food-diet- health concerns and preferences.

This study uses data from 7,630 Canadian adults who are 20 years and older. We include variables from the following categories in the empirical analysis: label information, health and dietary behavior, food purchasing behavior, and demographic information. Table 1 provides an overview of the variables used in the regression models.

[Table1]

The implementation of PSM involves two choices. The first one concerns the model to be used for the estimation of the propensity score, and the second one the variables to be included in this model. With regard to the first objective, we estimate propensity score functions using probit estimators to determine a wide range of covariates associated with a frequent usage of nutrition labels. With regards to our second objective, we estimate a series of PSM models using alternative algorithms for matching labels users and non-users based on a large number of characteristics (treatment covariates)[1].

4. Results

Estimation of Propensity Score

Following Heckman et al. (1997) several statistical methods can be employed to select the best probit model specification when estimating propensity score equations. Following previous literature we evaluate and choose a probit model based on pseudo R^2 as a metric of how well the right-hand side regressors explain respondent's participation probability. Appropriate covariate variables (regressors) should be those associated both with the probability of treatment

[1] Caliendo and Koepening (2005) provide a detailed overview and discuss several matching estimators commonly used in the literature.

participation and with the outcome variable (Heckman and Navarro-Lozano, 2004). Hence, an important role prior to estimating treatment effects falls to the careful selection of covariate variable involved in the matching of treatment and control group to maximize the advantages of PSM methods. As both ATT and ATE estimators are only defined for values the area of common support[2] test of common support were performed prior to estimating PSM equations.

With regard to the first objective, the conditioning of label users and non-users on their characteristics independent of their assignment into a treatment group, we find that label information, differences in past behavioral changes regarding food shopping and nutrition, and not, as commonly upheld, demographic profiles explain consumers' nutritional labeling usage pattern. Tables 2 shows the regression results from the probit estimation of the propensity score function for '*refer_NF_always*.' We find strong evidence that respondents who consider certain nutritional aspects of the information commonly labeled on packaged foods are significantly more likely to refer the nutritional facts panel information on a regular basis (always). The same relationship holds for those who are conscious of salt intake, calorie content, carbohydrates, fiber, fats, allergens, and the specific ingredient make-up of food products. These results can be summarized as to support the majority of previous literature, finding that consumers aware and knowledgeable of nutrition, diet and health are more likely to actively seek or confirm relevant information when making regular food purchase decisions.

The results further suggest that consumers, who always refer to the nutritional facts label, show signs of active diet-health behavioral changes. A high frequency of nutrition facts label usage goes along with existing reductions of various food ingredients and increased their exercise frequency. These consumers have tried to limit their overall intake of salt, carbohydrates

[2] Respondents with the same x value in X are allowed to have a positive probability of falling into the treated or control group.

(calories), and fat (trans-fats and cholesterol). However, label usage does not seem to affect positive diet behavioral change in form of an increase in the consumption of fruits and/or vegetables.

Respondents who are willing to pay more for foods and beverages that have reduced fat, reduced sugar/sugar-free, reduced salt/sodium, or low calories/carbohydrate (*wtp-main*), are more likely to refer to nutritional facts information at every grocery purchase occasion. Furthermore, frequent readers of label information are found to place a high(er) value on foods approved by a nutritionist, medical association, and/or medical professional. However, this valuation does extend to the importance of healthy-sized portions (*purchasefac_readyT*) as part of respondents healthy foods purchase decisions process.

Differences in demographic profiles provide only sparse explanation of consumers' use patterns of nutrition label information, as indicated by the non-significant results of gender, several education levels, income, as well as the age of the household head. However, language, as a proxy for food culture (Carlson et al. 2010) does serve as an indicator of label usage and healthy eating behavior. English-speaking respondents were more likely to always refer to nutrition-facts labels than their non-English-speaking counterparts.

Estimation of Average Treatment Effects

Our second objective was to empirically test, whether a stated high frequency of nutrition label usage did affect respondent's stated concerns regarding future health status, obesity, and more general concerns about their future well-being (health, wellness, lifestyle) compared to the concern levels stated by respondents with less frequent label information usage. Using a series of established PSM estimators we therefore treat label users as the treatment group, and non-user label information as the “pseudo” control group, while controlling and balancing group members based on a wide variety of socio-demographic variables, food-intake, choice related behaviors, and lifestyles factors. Controlling for a large number of matching covariates, we expect to minimize the degree extend of unobserved heterogeneity between treatment and control group membership, thus minimizing the risk of selection bias and model misspecification. To verify the statistical significance of the ATT estimators presented in Table 3, we bootstrapped standard errors with 100 repetitions for each of the matching algorithms.

[Table 3]

Without the necessity of making arbitrary assumptions about functional forms and error distributions, yet with some degree of trust in the quality of the survey data, our results for ATT estimators (the average effect of the treatment on the treated suggest that a high frequency of nutrition label usage is associated with significantly higher levels of stated concerns regarding respondent’s future health status. Third, robustness checks and sensitivity analysis confirm a significant positive association between label usage and stated health concerns. Frequent attention to nutrition labeling, however, does seem to have a significant negative effect on stated concern levels regarding potential future obesity related health complications. The results In Table 3 also emphasize the importance of the covariate matching procedures relative to an unmatched comparison label users and non-user regarding their stated concern levels. The magnitude of effects based on the different PSM matching algorithms is orders of magnitudes than the results of unmatched ATT estimators suggest. Hence, simple statistical comparisons of outcome variables of interest, as a convenient way for providing input into food policy, may be misleading.

5. Summary, Conclusions and Outlook

A better understanding of public food-health concerns and choice patterns will provide important information for policy makers and industry on how to target at-risk households. Our analyses shows that the classic socio-economic variables discussed in the context of consumer behavior and health, i.e. income, education and age of household age, do not explain much of the concerns related to health, diet, and obesity. Healthy eating behavior and use of food labeling information significantly influence people's diet and health awareness. These results suggest that product innovations targeted at health conscious consumers are likely to be successful in the marketplace. The lack of significant results for income, education, and other economic factors suggest that a socio-economic segmentation of Canadian consumers will not allow policy makers and health educators to target at-risk households.

We find that the level of nutrition label usage to be a reliable predictor for people's more general concerns regarding their future health status, and to some extend concerns over anticipated complications with obesity. While unmatched comparisons reveal that label usage contributes significantly to respondents stated health/obesity/wellbeing concerns, the application of different PSM algorithms qualifies this picture. When matched on numerous personal characteristics and diet-food variables, respondents in the label-use "treatment group" do significantly differ in their stated concerns for health and obesity. However, our ability to draw sound policy conclusions remains limited by the inconclusiveness of ATT estimates across matching methods.

Our results further suggest that people worried about food-diet-health issues may or may not “always” seek additional information that would assist them in their food choice decisions. Common knowledge among economist would suggest that, familiarity, habit and an existing knowledge bases on previous purchase and consumption of a large number of food products should also influence the impact label usage may have on overall concerns and related perceptions. Our results so seem to confirm the common conclusion that food-health concerns and information usage behavior appear to be linked, but not in straightforward manner.

Much of the debate of how to best induce behavioral change and healthier eating patterns across North America has focused on the provision of more food-health information as well as front-of-package labeling as a major information vehicle. As the results suggest, consumers are not aware or use nutrition labeling information. In order to change dietary behavior, policy makers may need to adopt instruments that account for differences with regard to food preferences, food shopping habits, and overall usage patterns of food/nutrition labeling information.

References

Agriculture and Agri-Food Canada. 2011. Agri-Food Trade Service. Health and Wellness Trends for Canada and the World. October 2011. Available at www.ats-sea.agr.gc.ca/inter/4367-eng.htm#e (accessed December 4, 2012).

Akerlof, G.A. 1970. The Market for 'Lemons': Quality Uncertainty and the Market Mechanism. Quarterly Journal of Economics, 84(3): 488-500.

Balasubramanian, S.K., and C. Cole. 2002. Consumers' Search and Use of Nutrition Information: The Challenge and Promise of the Nutrition Labeling and Education Act. The Journal of Marketing 66:112-127.

Becker, S.O., and A. Ichino. 2002. Estimation of average treatment effects based on propensity score. The Stata Journal, 2: 358-377.

Bhattacharya J,, and N. Sood. 2011. Who pays for obesity? Journal of Economic Perspectives 25:139-158.

Black, D.A., and J.A. Smith. 2004. How robust is the evidence on the effects of college quality? Evidence from matching. Journal of Econometrics121:99-124.

Byrdbredbenner, C. 1994. Designing a consumer friendly nutrition label. Journal of Nutrition Education 26(4): 180-190.

Card, D., and A.B. Krueger. 1994. Minimum Wages and Employment: A Case Study of the Fast-Food Industry in New Jersey and Pennsylvania, American Economic Review 84(4): 774-775.

Carlson, A., D. Dong, and M. Lino. 2010. Are the Total Daily Cost of Food and Diet Quality Related: A Random Effects Panel Date Analysis. Paper presented at 1st Joint EAAE/AAEA Seminar The Economics of Food, Food Choice and Health, Freising, Germany, September 15-17.

Caswell, J.A. 1992. “Current Information Levels on Food Labels”. American Journal of Agricultural Economics 74(5):1196-1201.

Crespi, J.M., and S. Marette. 2003. Some Economic Implications of Public Labeling. Journal of Food Distribution Research 34(3):83-94.

Dehejia, R.H., and S. Wahba. 1999. Causal Effects in Nonexperimental Studies: Reevaluating the Evaluation of Training Programs. Journal of the American Statistical Association, 94(448):1053-1062.

Drichoutis, A. C., Nayga, R.M.Jr. and P. Lazaridis. 2009. Can Nutritional Label Use Influence Body Weight Outcomes? Kyklos 62(4):500-525.

Feick, L.F., R.O., Herrmann, and R.H. Warland. 1986. Search for nutrition information: a profit analysis of the use of different information sources. Journal of Consumer Affairs 20(2): 173-192.

Frazão, E., and J. Allshouse. 2003. Strategies for Intervention: Commentary and Debate. The Journal of Nutrition 133:844S-847S.

Harnack, L., Jeffery R.W., and K.N. Boutelle. 2000. Temporal Trends in Energy Intake in the United States: An Ecologic Perspective. American Journal of Clinical Nutrition 71:1478-1484.

Health Canada. 2008. Nutrition labelling. Available at: www.hc-sc.gc.ca/f n-an/label-etiquet/nutrition/index_e.html (accessed May 07, 2010)

Heckman, J., Ichimura, H., and P.E. Todd. 1997. Matching as an econometric evaluation estimator: Evidence from evaluating a job training program. Review of Economic Studies, 64 (4): 605-654.

Heckman, J., Ichimura, H., Smith, J.A., and P.E. Todd. 1998. Characterizing selection bias using experimental data. Econometrica 66 (5):1017-1098.

Heckman, J., and S. Navarro-Lozano. 2004. Using matching, instrumental variables, and control functions to estimate economic choice models. Review of Economics and Statistics 86(1):30-57.

Hitt, L., and F. Frei. 2002. Do Better Customers Utilize Electronic Distribution Channels? The Case of PC Banking, Management Science, 48(6):732-748.

Katzmarzyk, P. T., and I. Janssen. 2004. The economic costs associated with physical inactivity and obesity in Canada: An update. Canadian Journal of Applied Physiology 29(2):104.

Kim, S.Y., R. M. Nayga Jr., and O. Capps, Jr. 2000. The effects of food label use on nutrient intake: An endogenous switching regression analysis. Journal of Agricultural and Resource Economics 25(1):215-231.

Kim, S.Y., R. M. Nayga Jr., and O. Capps, Jr. 2001. Food label use, self-selectivity, and diet quality. The Journal of Consumer Affairs 35(2):346-263.

Kuchler, F., Tegene, A., and J.M. Harris. 2005. Taxing Snacking Foods: Manipulating Diet Quality or Financing Information Programs? Review of Agricultural Economics 27(2005):4-20.

Lancaster, K. 1966. A New Approach to Consumer Theory. Journal of Political Economy 74(2): 132-157.

Lechner, M. 2002. Program heterogeneity and propensity score matching: An application to the evaluation of active labor market policies. The Review of Economics and Statistics. 84: 205-220.

McGinnis, J.M. and W.H. Foege. 1993. Actual Causes of Death in the United States. JAMA 270: 2207-2212.

Nayga Jr., R. M., D. Lipinski, and N. Savur. 1998. Consumer's use of nutritional labels while food shopping at home. Journal of Consumer Affairs 32(1):106-120.

Neuhouser, M.L., A.R. Kristal and R.E. Patterson. 1999. Use of food nutrition labels is associated with lower fat intake. Journal of the American Dietetic Association 99:45-46.

Nielsen 2007 and 2008. Health and Wellness Survey. Nielsen Canada.

O’Donoghue, T.O. and M. Rabin. 1999. Doing it Now or Later. The American Economic Review 89:103-124.

O'Donoghue, T.O. and M. Rabin. 2000. The Economics of Immediate Gratification. Journal of Behavioral Decision Making 13:233-250.

Ravallion, M. 2008. Evaluating anti-poverty programs. In T. P. Schultz and J. Strauss (Eds.). Handbook of development economics, 4: 3787-3846. Amsterdam: North Holland.

Rosenbaum, P. and D. Rubin. 1983. The central role of the propensity in observational studies for causal effects. Biometrika 70(1):41-55.

Rubin, D.B. 2001. Using Propensity Scores to Help Design Observational Studies: Application to the Tobacco Litigation. Health Services & Outcomes Research Methodology 2:169-188.

Schroeter, C., Lusk, J., and W. Tyner. 2008. Determining the Impact of Food Price and Income Changes on Body Weight. Journal of Health Economics 27:45-68

Teisl, M. F., N. E. Bockstael, and A. Levy. 2001. Measuring the welfare effects of nutritional information. American Journal of Agricultural Economics 83(1):133-149.

Tjepkema, M., and M. Sheilds. 2005. Nutrition findings from the Canadian Community Health Survey. Overweight Canadian children and adolescents. Statistics Canada.

Wansink, B., S.T., Sonka, and C.M., Hasler. 2004. Front-label health claims: when less is more. Food Policy 29: 659-667.

Tables and Figures

Table 1: Definitions of Variables used in the Regressions

Variable	Definition
Dependent variables	
Refer_NF_always	*= 1 if every time I (we) shop I refer to the Nutrition facts panel on packaged foods and/or beverages*
Concern future health:	*How concerned are you about minimizing future health problems? = 3 if very concerned, = 2 if somewhat concerned,= 1 if not very concerned, =0 if not at all concerned*
Concern sum (H/W/L):	*Sum of stated concern levels about future health problems, losing weight, and improving body image (same scale as concern future health)*
Concern Obesity:	*How concerned are you with obesity in regards to you and/or other members of your household? = 3 if very concerned, = 2 if somewhat concerned,= 1 if not very concerned, =0 if not at all concerned*
Label information	
Question: When reading product labels/packaging, which of the following factors do you consider when deciding to buy packaged food and/or beverages? (all that apply)	
Label_salt	=1 if salt
Label_cal	=1 if calories
Label_carb	=1 if calories
Label_fiber	=1 if fiber
Label_fats	=1 if cholesterol, fat, saturated fat, trans fat
Label_allerg	= Ingredient list to identify allergens
Label_ingr	= Ingredient list to check order or ingredients
Health and dietary behavior	
Question: Which of the following food items, if any, have you, yourself, been reducing the intake of during the past 3 months? (all that applies)	
Reduce_cal	= 1 if calories
Reduce_salt	= 1 if salt
Reduce_carb	= 1 if carbohydrates
Reduce_fat	=1 if fat, cholesterol, fatty acids

Table 1 cont.: Definitions of Variables used in the Regressions

Variable	Definition
Dependent variables	
Increase_f_v	= 1 if have consciously tried to incorporate into the diet of increase the intake of fruit and vegetables during the past 3 months
Exercise_freq	Exercise frequency during an average week, = 4 if more than 3 times per week, = 3 if 2-3 times per week, = 2 once a week, = 1 less than once a week,= 0 never
Food purchasing behavior	
WTP_main	= 1 if willing to pay more or foods and beverages that have reduced fat, reduced sugar or sugar-free, reduced salt/sodium, low calorie, low carbohydrates
Purchasefac_med	= 1 if foods that are approved by a nutritionist/medical association or medical professional is important in purchasing decision of healthy foods
Purchasefac_readyT	= 1 if ready to eat is important factor in purchasing decision of healthy foods
Purchasefac_portions	= 1 if healthy-sized portions is important factor in purchasing decision of healthy foods
Demographic information	
Male	= 1 if respondent is male
English	= 1 if language is English
Edu_HS	= 1 if household head has completed high school and some technical or college
Edu_college	= 1 if household head has completed technical or college and some university
Edu_postgrad	= 1 if household head has completed university
Inc_le_20	= 1 if income ≤ $20,000
Inc_20_29	= 1 if income is $20,000<x≤$29,000
Hhh_35_44	= 1 if age of household head is between 35 and 44 years
Hhh_45_54	= 1 if age of household head is between 45 and 54 years
Hhh_55_64	= 1 if age of household head is between 55 and 64 years
Hhh_65_more	= 1 if household head is older than 65 years
Health_obesity	= 1 if respondent or any other member of the household has been/become obese within the past 12 months

Table 2a: Probit estimation of Propensity Score function for 'Refer_NF_always', n = 7630

	Coefficient	St.Err.
Constant	2.097***	(0.106)
Label information		
Label_salt	0.173***	(0.037)
Label_cal	0.079**	(0.037)
Label_carb	0.161***	(0.038)
Label_fiber	0.202***	(0.035)
Label_fats	0.333***	(0.050)
Label_allerg	0.283***	(0.049)
Label_ingr	0.260***	(0.035)
Health and dietary behavior		
Reduce_cal	0.051	(0.039)
Reduce_salt	0.176***	(0.038)
Reduce_carb	0.106***	(0.039)
Reduce_fat	0.188***	(0.044)
Increase_f_v	-0.018	(0.038)
Exercise_freq	0.079***	(0.012)
Food purchasing behavior		
WTP_main	0.106***	(0.034)
Purchasefac_medical	0.425***	(0.053)
Purchasefac_readyT	-0.087*	(0.044)
Purchasefac_portions	0.156***	(0.037)
Demographic information		
Male	-0.042	(0.044)
English	0.237***	(0.037)
Edu_HS	0.054	(0.056)
Edu_college	0.049	(0.057)
Edu_postgrad	0.154*	(0.060)
Inc_le_20	0.033	(0.059)
Inc_20_29	0.049	(0.053)
Hhh_35_44	-0.029	(0.083)
Hhh_45_54	-0.027	(0.081)
Hhh_55_64	-0.046	(0.082)
Hhh_65_more	-0.035	(0.082)
Health_obesity	0.011	(0.042)
Pseudo-R^2	0.139	

Significance indicated by *, **, and *** at the 90%, 95%, and 99% confidence levels.

Table 3: Average Treatment Effects (ATT), n = 7630 (Different outcome variables, Treatment = Refer_NF_always)

	Average Treatment Effect on Treated [a)]		
Matching Algorithm	Concern Future Health	Concern Sum (Health/Wellness/Lifestyle)	Concern Obesity
Unmatched	0.258*** (0.017) 15.52	0.614*** (0.049) 12.66	0.224*** (0.019) 11.70
Nearest neighbour	-0.025 (0.023) -1.12	-0.319*** (0.066) -4.83	-0.391*** (0.082) -4.79
Radius, Caliper= 0.1	0.085*** (0.013) 6.63	0.022 (0.051) 0.42	0.070 (0.057) 1.22
Radius, Caliper= 0.001	0.040*** (0.014) 2.78	-0.11** (0.05) -2.24	-0.012 (0.065) -1.80
Kernel	-0.007 (0.020) -0.37	-0.222*** (0.052) -4.28	-0.239*** (0.072) -3.34
Stratification	-0.023 (0.02) -1.14	-0.269*** (0.059) -4.56	-0.303*** (0.069) -4.37

a) ATT = average treatment effect on treated. Bootstrapped standard errors for ATT except nearest neighbor, N = 100 replications in brackets. *, **, *** statistically significant at the 10%, 5%, and 1% level.