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Abstract
The overarching goal of nutrition labelling is to transform intrinsic credence attributes into searchable cues, which would enable consumers to make informed food choices at lower search costs. This study estimates the impact of nutrition label usage on Canadian consumers’ perceived diet-health concerns using alternative propensity score matching (PSM) techniques. We apply a series of tests and sensitivity analyses to overcome issues of endogeneity and selection bias frequently found in studies of diet-health behaviour and to validate the impact of exposure to nutrition facts labels for users vs. non-users. Our results support the notion that consumer uncertainty and related food-health concerns are linked to their information behaviour, but not in straightforward manner. Dominant subjective food attributes, such as taste, convenience and affordability, may in fact outweigh the benefits of information about healthier, alternative food choices. In order to change dietary health behaviour, food manufacturer and policy makers alike need to adopt communication instruments that better account for differences in preferences, shopping habits and overall usage patterns of nutrition labelling information.

KEYWORDS
health concerns, nutrition labelling, propensity score matching, self-selection bias, treatment effects

1 | INTRODUCTION

The overarching goal of publicly mandated nutrition labelling is to transform intrinsic credence attributes into searchable cues, which would enable consumers to make better informed-food choices at lower search costs. However, the effectiveness of nutritional labelling is questionable at best. Despite an abundance of research on its format, and the potential impact on consumers’ food choices and subsequent health outcomes, there remains controversy about whether the provision of additional nutrient information will effectively instill nutritional knowledge and whether it can change consumers’ dietary habits (Garde, 2008). Despite the breadth and depth of studies on nutrition labelling, evidence regarding the potential linkage between the actual use of nutrition information and growing diet-health concerns among consumers is scant (Hieke & Taylor, 2012).

Thus, there is a need to determine whether and to what extent nutrition labels are an effective food policy tool in mitigating consumers’ diet-health concerns. The objective of our study is analyse the relationship between nutrition label usage and household meal planner’s stated concerns and perceptions regarding their (and their household’s) future general health and obesity status. The analysis utilizes survey data of 8,114 individuals collected during the 2008 National Health and Wellness Survey (NHWS) conducted by Nielsen Canada, a market research company. Our data encompasses a wide range of variables on consumers’ perceptions, attitudes and behaviours related to food consumption, physical activity, well-being, with a focus on conscious food-health behavioural changes. We utilize a Grossman-style health production framework with propensity score matching (PSM) as an economic program evaluation method. PSM has recently gained attention in the food economics literature (Drichoutis, Lazaridis, Nayga, Kapsokefalou, & Chrysochooidis, 2008).

Reliable evidence regarding the relationship between food-health information behaviour and nutrition label usage and its impact on individual’s perceptions of health risks may be valuable to policy makers interested in the design of more effective public health policies. Estimates of the complex interplay between information behaviour and health-risk perceptions will contribute information to the long-standing

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discussion about the impact of nutrition labelling on consumer food choices and associated public health outcomes.

1.1 Related economic literature on nutrition labelling

Economic research on the impact of nutritional labelling has largely relied on Lancaster’s (1966) and Akerlof’s (1970) neoclassical assumptions of perfectly rational consumers who fully incorporate all available information into their food-related choice decisions. Furthermore, it is usually assumed that consumers fully understand the provided information. Under these assumptions, nutrition labelling could improve market efficiency by reducing information asymmetries and search cost associated with following healthier lifestyles. In this case, nutrition labelling could be an effective policy tool in mitigating poor nutritional choices and related health outcomes.

With this premise of improving health outcomes, the food industry spent an estimated $2 billion dollars on the implementation of the 1994 U.S. Nutrition Labeling and Education Act (NLEA) (Caswell, Ning, Liu, & Mojuszka, 2003). The NLEA provides the Food and Drug Administration (FDA) with specific authority to require nutrition labelling of most foods. As such, the FDA mandates nutrition fact panels (NFP), commonly found on most pre-packaged food products. NFPs provide standardized information on serving size, and nutrients contents on a percentage basis of the recommended daily intake values that are provided by a single serving.

In recent years, food manufacturers and independent organizations have pledged more than $50 million dollars to develop and roll out a large number of voluntarily nutritional and health claim labels, often summarized as ‘front-of-package-labels’ (FOP) (Wansink, Sonka, & Hasler, 2004). While the FDA also regulates FOP claims, only food manufacturers of goods that contain large amounts of high quality nutrients typically choose to add this information (Food and Drug Administration, 2013). After a five-year implementation phase, mandatory nutrition labelling also came into effect in Canada in January of 2007. The Canadian nutrition labelling appears in the form of standardized NFPs that are closely modelled after the 1994 U.S. NLEA regulations, providing consumers with information on macronutrients and micronutrients contained in food products (Health Canada, 2008).

However, several studies have been questioning the value of nutrition labelling as a choice decision tool to change consumers’ diet and health behaviour (e.g., Drichoutis, Nayga, & Lazaridis, 2009; Kim, Nayga, & Capps, 2001). Given the multitude of complexities that rule consumer attitudes and behaviour, it is challenging to modify consumers’ dietary intake (Kiesel, McCluskey, & Villas-Boas, 2011).

Previous research even suggests that the proliferation in nutritional labelling may increase consumer confusion and mistrust (Andrews, Burton, & Kees, 2011; Crespi & Marette, 2003). Complex nutrition label information may overwhelm consumers or be misunderstood (Andrews et al., 2011), and decrease the accuracy of an individual’s judgment and subsequent food choice decisions (e.g., Wansink, 2003). In fact, this over-provision of information may lead to ‘tyranny of choice’ situations, where consumers will avoid any food-health decision due to the increasing risk of misperception and miscalculation. In fact, Todd and Variam (2008) report a decline in nutrition label usage, with higher rates among less educated shoppers.

Thus, there exists a controversy in previous literature on nutrition labelling: one the one hand, existing knowledge of diet-health and especially diet-disease linkages might play a significant role in consumers’ use of nutrition labels, which could positively influence food choice (Schwartz, 2004). On the other hand, existing health concerns might serve as a valid proxy for consumers’ uncertainty regarding nutrition label information as an input in a well-informed food choice decision process.

Moreover, econometric issues such as the likely endogeneity of stated food-health related perceptions on behaviour, selection bias in the recruitment of study participants and general difficulty of finding suitable instrumental variables have been plaguing cross-sectional empirical analyses of food and health-behavioural data (i.e., Park & Davis, 2001). To explicitly address these methodological issues, our empirical analysis uses a large-scale representative survey data set and PSM estimators (Rosenbaum & Rubin, 1983). The PSM estimators take account of the potential reverse causality and self-selection bias associated with direct comparisons of stated concerns between nutrition label users and non-users. We use alternative PSM algorithms (Caliendo & Kopeinig, 2008) to estimate robust treatment effects regarding the impact of label usage on food-health concerns, when the treatment is endogenous to the outcome.

2 METHODOLOGY

2.1 Theoretical framework

We place our analysis of health concerns and nutrition labelling in the context of a Grossman-style health production framework. We assume that consumers derive utility from consuming foods that belong to three broad categories: health-enhancing, health-decreasing and health-neutral products. The quasi-concave and twice differentiable utility function further includes a vector of lifestyle factors (e.g., time spent working) that are assumed to directly affect the individual health status, vectors of demographics and other demand shifters. Of specific interest to us is the frequency of reading nutrition labels. Consumers are assumed to possess an initial stock of health and nutrition knowledge to evaluate labelling information. Following Grossman’s line of reasoning, consumers can invest into nutrition information, which would build up their stock of knowledge.

However, the Grossman framework neglects to account for several latent factors that often remain unobserved in conventional economic models. Yet, these factors may play an important role in explaining consumers’ food behavioural intentions. We, therefore, conduct the analysis in the context of Ajzen and Fishbein’s (1985) Theory of Reasoned Action (TRA). The TRA’s conceptual framework and its social psychological foundation have been applied to several topics including health and food behaviours (Ajzen, Albarracin, & Hornik, 2007; Bagozzi, Wong, Abe, & Bergami, 2000).

The TRA predicts that an individual’s intention to perform a behaviour (e.g., reading nutrition labels) is a latent variable that depends on attitudes towards performing the behaviour, their relative importance and subjective norms (Figure 1). The latter, may not play a significant role in determining behavioural intentions for low-involvement food products.
that do not have a strong symbolic association. We, therefore, alter the original model and replace subjective norms with food preferences as a determinant of the intention to obtain product label information. Moreover, another important extension of the original TRA is habit as a determinant of food-related behaviour (Saba & Di Natale, 1998). Habit can be thought of as an unconscious aspect of human behaviour or as an automatic reaction. Habits in food choice decisions are characterized by a high frequency of purchasing and low consumer involvement in the decision-making process (Liu, Wisdom, Roberto, Liu, & Ubel, 2013). While preferences and habits are dependent on intrinsic motivations (e.g., concerns about health issues), the attitudes toward performing a specific action are dependent on the individual’s beliefs that a particular behaviour leads to an outcome. Furthermore, the evaluation of the outcome may also include other predictive factors such as the individuals’ perceived behavioural control over future food-health outcomes (Sparks, Hedderley, & Shepherd, 1992). These properties give the TRA predictive as well as explanatory power, providing us with valuable insights for understanding the relationship between food-health concerns and label usage.

According to the TRA, the likelihood of an individual’s behaviour is dependent on a rational decision-making process. Therefore, the stronger the individual’s attitude towards nutrition information and the more positive the balance between food-related habits and the motivation to obtain labelling information, the stronger the intention to read label frequently will be. The relationship between intention and actual behaviour in turn is dependent on moderating variables such as the direct experience with the attitude object and the possession of skills (e.g., existing food or nutrition knowledge) required to perform the behaviour (Ajzen & Fishbein, 1980).

2.2 | Model framework

In the economic evaluation of programs aimed at improving consumer food, nutrition and/or health behaviour, it is of fundamental interest to determine whether a particular policy intervention is effective in accomplishing its primary objective. Is the provision of nutrition and ingredient information on food labels an effective mechanism for assisting consumers in making more informed and better food consumption choices, thus combating concerns about food-intake related diseases? While an experimental evaluation with a random assignment of subjects to treatment and control groups would be the gold standard approach, it is often not feasible, difficult in its implementation and costly to the sponsor. Hence, the main challenge of program evaluation lies in the design of counterfactual outcomes—a world without nutrition labelling—in our case. However, counterfactual outcomes are never observed, making statistical approaches to estimating treatments effects valuable policy evaluation tools.

In the food economics literature, the estimation of treatments effects using propensity score matching (PSM) has gained increasing popularity as the evaluation of consumer food-health policy interventions, such as the 1994 NLEA nutrition labelling mandate, typically relies on empirical evidence from observational data (e.g., Drichoutis et al., 2009). In their seminal work, Rosenbaum and Rubin (1983) proposed PSM as an approach suitable to reduce self-selection bias and to increase the robustness in the estimation of treatment effects from observational data (e.g., Lechner, 2002).

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 a treatment regime, that is, use of nutrition labelling information.

We use PSM to answer the question of whether and to what extent frequent consideration of nutrition labelling 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 labelling treatment
effect, where the treatment is endogenous to the observed outcome. PSM has advantages over its econometric alternatives (e.g., Heckman two-stage models), as it does not require arbitrary assumptions over functional forms or error distributions and enables tests of the presence of potentially complex interaction effects among covariate variables (Caliendo & Kopeinig, 2008).

To maximize the advantages of PSM, a key role falls to the careful selection of covariate variables. Valid ‘matching variables’ should be associated both with the probability of treatment participation (e.g., usage of nutrition labelling information) and nonparticipation, yet, be independent of the intervention outcome (e.g., stated health and/or obesity concerns) (Heckman & Navarro-Lozano, 2004).

The estimated propensity score (PS), for subject \( i \) \( (i = 1, \ldots, N) \) is the conditional probability of being assigned to the treatment given a vector of observed covariate variables, \( X_i \) (Rosenbaum & Rubin, 1983). Thus, \( Y_i = 1 \) is the level of stated health or obesity concerns of the \( i \)th individual who has stated to frequently use nutrition labelling as part of their food choice decision process. And \( Y_i = 0 \) is the label non-user’s stated concern level. The impact of label usage is then given by \( \Delta = Y_i^1 - Y_i^0 \). Either \( Y_i^1 \) or \( Y_i^0 \) is realized for each individual. Let \( D \) indicate treatment, \( D = 1 \), and \( D = 0 \) otherwise. The evaluation task is then to estimate the average impact of frequent label usage on those reported to use labels, the ‘treated’. Following Rosenbaum and Rubin (1983), if \( P(D = 1 | X) \) is the probability of program participation, then PSM can be used to construct a statistical comparison group by matching observations of label users with observations of non-users with similar values of \( P(D) \). The parameter of interest in this evaluation process is the ‘average effect of treatment on treated individuals’ or ATT is defined as:

\[
ATT = E(D|X, D = 1) - E(D=0|X, D = 1)
\]

where \( X_i \) is a vector of covariate variables (subscripts have been dropped).

Relying on the mean outcome of individuals in the untreated group, \( E(Y^0 | X, D = 0) \), will likely lead to biases, as the probability of nutrition label usage will also determine health and obesity concern levels. Hence, stated concern levels between label users and non-users might differ even in the absence of mandated food labelling leading to a ‘self-selection bias’:

In contrast to true randomization, PSM with observational data relies on a set of identifying assumptions to avoid problems associated with self-selection bias. Therefore, the mean impact of a program intervention, the ‘average effect of treatment on the population’ or ATE, is a general factor of interest in many evaluation studies.

While a population average treatment effect of nutrition labelling may not be of direct interest to food policy, knowledge of the ‘spillover’ effect of labelling beyond those who claim to obey it, may be of relevance to policy makers nevertheless.

Since the observational data used in our analysis provides information on important determinants that influence treatment selection and related outcomes, we assume that health and obesity concerns and label usage can be considered independent conditional on observables in the data, thus satisfying the Conditional Independence Assumption (CIA) as one of the identifying assumptions of PSM (Caliendo & Kopeinig, 2008).

The second identifying assumption, the conditioning of treatment selection variables on a PS model (\( p(X) \)), should be such that the characteristics between the two groups in the evaluation with the same PS value will be balanced. In other words, two survey participants in our data with the same PS, one label user and one non-user, can be compared on their reported health and obesity concerns after balancing the distributions of their characteristics.

And the third assumption of common support (overlap condition) assures that the probability of using labels to inform food choice decisions, after conditioning on observed characteristics, lies between 0 and 1, thus facilitating adequate matching. Subjects with the same \( X \) values are thus assumed to have a positive probability of being both label users and non-users. Hence, if participant’s stated health and obesity concerns are independent of label usage after conditioning on characteristics \( X \). Then, concern levels should also be independent of group selection after conditioning on \( P(X) \). If the above assumptions are adhered to, then PSM provides a superior alternative to estimating unbiased treatment effects with observational data compared to other instrumental variable methods (Rosenbaum & Rubin, 1983).

3 DATA AND PROPENSITY SCORE ESTIMATION

3.1 Data

Our analysis utilizes data from the 2008 National Health and Wellness Survey (NHWS) conducted by Nielsen Canada. The NHWS has been conducted to collect data on consumers’ perceptions, attitudes and behaviours related to food consumption, physical activity and wellbeing (Nielsen, 2007). We use data of 8,114 consumers of a total sample of 10,273 Canadian household meal planners.1 These households provided information on their past and current food choice and consumption behaviour with a focus on conscious food-health behavioural changes. The survey was designed to be representative of the Canadian population. The select sample includes adult participants of 20 years and older, who reported nutrition label usage, and those who report socio-demographic or other relevant parts of the survey for our study. Table A1 compares selected demographics of the survey sample with those of the 2011 Canadian Census. Females, older participants and college education are oversampled, while younger participants aged 18-24 and family households are under-sampled. Hence, the survey reflects a slight self-selection bias towards female meal planners with a presumable interest in food, diet and health matters.

The 2008 NHWS contains detailed information on participant’s demographic and socio-economic characteristics, their stated diet, health and obesity concerns as well as existing health conditions (e.g., high blood pressure), frequency of physical exercise and alcohol intake.

1Although the information elicited in the survey targets the entire household, the survey respondent is defined as the adult household member responsible for the majority of food related activities.
Dietary habits and behaviours are captured in terms of meal types and frequencies (e.g., snacking), past and current food purchase and consumption patterns, and recent conscious reductions and/or increases in the intake of unfavourable (e.g., fats, sodium, cholesterol) or favourable (e.g., fruits and vegetables, omega 3) ingredients and foods. The survey also elicits respondent's food and nutrition knowledge, ingredient usage patterns, labelling and nutrition information as part of their every-day grocery purchase decisions. The latter detailed set of variables includes household meals planner's choice of purchasing factors (e.g., affordability, convenience, nutrition), attention to specific label information (e.g., salt or fat level) and willingness to pay for foods with specific favourable properties.

The breadth and depth of this survey appears to be particularly valuable for analyses of the linkages between food-health attitudes, perceptions and related knowledge in the context of information asymmetries that impede the effectiveness of nutritional labelling in mitigating consumers' food-diet-health concerns.

3.2 Propensity score estimation

The first step in estimating the PS involves the selection of variables to be included in the estimation of the PS model. We follow Heckman and Navarro-Lozano (2004). In addition, select variables from several NHWS categories in line with economic theory and those found to be relevant in previous related studies: health status, food information sources, dietary behaviour, food purchasing behaviour and demographics. We model the treatment-control balancing process through the following PS function for respondent’s frequent use of mandated nutrition labels when making product choice decisions (binary):

\[
\text{LabelUseChoice} = f (\text{Health status, Food info sources, Dietary behavior, Food purchasing behavior, Demographics})
\]

We estimate the model in Equation 2 with the objective of minimizing the systematic unobserved heterogeneity between label users and non-users, thus minimizing the risk of selection bias and model misspecification.

4 RESULTS

4.1 Estimation of propensity score

Our PS model specification includes variables that have been found to play a significant role in explaining food-health related behaviours, perceptions and concerns (Schroeter, Anders, & Carlson, 2013). Table 1 provides an overview of the variables included in the preferred PS model.

In addition to the dependent variable ‘Label_use_choice’ in the PS model, we are interested in two separate diet-health related outcome variables: Respondent’s stated concerns regarding their (and their household’s) future general health status (Concern_future_health) and concerns regarding future complications due to obesity for themselves or members of their household (Concern_obesity).

The preferred PS model shown in Table 2 satisfies the necessary PSM identifying conditions under a binary logit specification.

We find strong evidence that respondents who have been diagnosed with high blood pressure and therefore seek specific dietary information (i.e., salt content) commonly labelled on packaged foods as part of their food choice decisions are significantly more likely to refer to nutrition labelling on a regular basis. The same relationship holds for those respondents who have been diagnosed as obese and consequently seek fat content information when grocery shopping.

In addition, the frequent use of nutrition labelling to inform purchase decisions is linked to an individual’s awareness regarding the use of dietary symbols and specific media sources to update food-related knowledge and food purchasing decisions. These results support previous literature, that household meals planners knowledgeable about nutrition, diet and health issues are more likely to seek information about nutritional content or composition when making purchase decisions. However, our results also expand the literature (e.g., Howlett, Burton, & Kozup, 2008) by suggesting that a diet-health related diagnosis, such as being told to watch salt and/or fat intake, may affect an individual’s propensity to regularly use nutrition labelling.

Table 2 shows that respondents who always use nutrition labels expressed difficulties in meeting their self-stated goals with regard to diet-health behavioural changes, such as reducing or eliminating one or more unhealthy foods or ingredients from their habitual consumption patterns (Difficulty_reduce). However, label usage does not seem to affect positive diet behavioural change, such as increasing the consumption of fruits and/or vegetables. A high frequency of label usage is associated with emphasizing affordable, healthier and more nutritious product options

(Purchase_factor_affordable). This result supports the recent suggestion for lower-priced health food options (Chen, Liu, & Binkley, 2012).

Differences in demographic profiles provide significant explanation of meal planners’ frequency of label usage. While Male carries a negative sign, as expected, higher educational attainment, higher household income and a household head falling into the ‘baby boomer’ age cohort, positively contribute to the propensity of frequent nutrition label usage.

We use language as a proxy for food culture (for more information, see Carlson, Dong, & Lino, 2010). As Table 2 shows, English-speaking respondents were more likely to always refer to nutrition labels compared to their non-English-speaking counterparts.

4.2 Estimation of average treatment effects

Our objective is to empirically test whether a stated high frequency of nutrition label usage does significantly affect a respondent’s stated concerns regarding future health status, and diet-health concerns about their future obesity status, compared to those respondents with less frequent or no reported label usage.

We follow Callendo and Kopeinig (2008) who suggest a comparative ‘trial and error’ approach to the application of alternative PSM matching algorithms: one-to-one, nearest neighbor, kernel matching, local linear, spline smoothing and radius matching with varying calipers. We bootstrap standard errors with 100 repetitions for each matching
algorithms to verify the statistical significance of ATT estimates based on robust standard errors.

The economic interpretation of the ATT results in Table 3 provide clear evidence that a high frequency of nutrition label usage is associated with significantly lower levels of stated concerns regarding respondent’s future health and obesity status. For all matching procedures, the estimated ATTs are significant and carry negative signs, with slightly larger effects on an individual’s future health status. The matching results form a contrast to the results for the unmatched comparison of label-users and non-users, which indicates a positive relationship between label usage and stated concerns levels. Matching respondents on personal and behavioural characteristics through PSM adds a level of certainty and robustness regarding the true effect of nutrition label usage on individual’s confidence about potential future health and obesity issues. Our findings emphasize how misleading simple statistical comparisons of mean outcomes could be in a policy context.

For comparison purposes, Table 4 presents the estimates of a naive OLS model explaining the impact of all PSM variables plus the endogenous nutrition label usage selection variable on the two outcome variables of interest.

### TABLE 1 Overview of survey data and variables used in the analysis

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
<th>Mean</th>
<th>St. dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dependent variables</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Question: When shopping for household groceries, do you refer to the Nutrition Facts table on packaged foods and/or beverages when making the final product choice decisions?</strong></td>
<td>Label_use_choice = 1 if yes, = 0 if no</td>
<td>0.227</td>
<td>0.419</td>
</tr>
<tr>
<td><strong>Question: How concerned are you about minimizing future health problems?</strong></td>
<td>Concern_future_health = 3 if very concerned, = 2 if somewhat concerned, = 1 if not very concerned, = 0 if not at all concerned</td>
<td>2.347</td>
<td>0.664</td>
</tr>
<tr>
<td><strong>Question: How concerned are you with obesity in regards to you and/or other members of your household?</strong></td>
<td>Concern_obesity = 3 if very concerned, = 2 if somewhat concerned, = 1 if not very concerned, = 0 if not at all concerned</td>
<td>0.731</td>
<td>0.443</td>
</tr>
<tr>
<td><strong>Health Status</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Statement: Please scan the health conditions/ailments that you or any other members of your household have experienced within the past 12 months. (all that apply).</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>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)</strong></td>
<td>Health_bloodp *label_salt = 1 if diagnosed health condition = high blood pressure and label information = salt</td>
<td>0.184</td>
<td>0.388</td>
</tr>
<tr>
<td></td>
<td>Health_obesity *label_fats = 1 if diagnosed health condition = obesity and label information = cholesterol, fat, saturated fat or trans fat</td>
<td>0.152</td>
<td>0.359</td>
</tr>
<tr>
<td><strong>Food information sources</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Question: Have you seen/read of dietary or nutrition-related symbols/logos or endorsements (other than the Nutrition Facts) on packaged food/beverage products?</strong></td>
<td>Seen_logo = 1 if yes</td>
<td>0.548</td>
<td>0.498</td>
</tr>
<tr>
<td><strong>Question: Which of the following are your TOP 3 sources of information on the topic of healthy eating?</strong></td>
<td>Source_media = 1 if internet, television, magazines</td>
<td>0.640</td>
<td>0.480</td>
</tr>
<tr>
<td><strong>Dietary behaviour</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Question: Which of the following food items do you find to be the most challenging to reduce in your household’s diet?</strong></td>
<td>Difficult_reduce = 1 if any of: calories, carbohydrates, cholesterol, fat, salt/sodium or sugar</td>
<td>0.554</td>
<td>0.497</td>
</tr>
<tr>
<td><strong>Food purchasing behaviour</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Question: Thinking about healthy foods, which of the following factors are most important in your purchase decision? (top 3 factors)</strong></td>
<td>Purchase_factor_affordable = 1 if affordable healthy alternatives</td>
<td>.094</td>
<td>.292</td>
</tr>
<tr>
<td><strong>Demographic information</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male = 1 if respondent is male</td>
<td>0.305</td>
<td>0.461</td>
<td></td>
</tr>
<tr>
<td>English = 1 if language is English</td>
<td>0.796</td>
<td>0.404</td>
<td></td>
</tr>
<tr>
<td>Edu_postgrad = 1 if household head has completed university</td>
<td>0.232</td>
<td>0.422</td>
<td></td>
</tr>
<tr>
<td>Income_$70k_more = 1 if household income is more than $70,000</td>
<td>0.489</td>
<td>0.499</td>
<td></td>
</tr>
<tr>
<td>Hh_age_55_64 = 1 if age of respondent is between 55 and 64 years</td>
<td>0.231</td>
<td>0.421</td>
<td></td>
</tr>
<tr>
<td>Hh_size&gt;7 = 1 if household size is larger than 7 people</td>
<td>.003</td>
<td>.058</td>
<td></td>
</tr>
</tbody>
</table>
confidence levels. *, ** and *** indicate statistical significance at the 90%, 95% and 99% level.

The test results suggest that all matching algorithms are able to achieve a satisfactory balance between the covariates in the matched label users sub-groups, thus significantly reducing the inherent selection bias and measurement error of naïve ad-hoc comparisons. How well the selected covariates explain the probability of treatment is indicated by the comparison of pseudo- \( R^2 \) values before and after PS matching, with little to no remaining systematic difference left in the distribution of characteristics between the members of both groups, and pseudo- \( R^2 \) s should be close to zero. Finally, rejection of the joint significance of all regressors using a likelihood ratio test further indicates a good balancing of model covariates.

**TABLE 2** Logit estimation of propensity score function for ‘Label_use_choice’, \( n = 8,114 \)

<table>
<thead>
<tr>
<th>Demographic information</th>
<th>Coefficient</th>
<th>SE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male</td>
<td>-0.479***</td>
<td>(0.05)</td>
</tr>
<tr>
<td>English</td>
<td>0.239***</td>
<td>(0.06)</td>
</tr>
<tr>
<td>Edu_postgrad</td>
<td>0.259***</td>
<td>(0.07)</td>
</tr>
<tr>
<td>Income_$70k_more</td>
<td>0.169***</td>
<td>(0.05)</td>
</tr>
<tr>
<td>Hh_age_55_64</td>
<td>0.216***</td>
<td>(0.05)</td>
</tr>
<tr>
<td>Hh_size&gt;7</td>
<td>-0.426</td>
<td>(0.41)</td>
</tr>
<tr>
<td>Pseudo-R²</td>
<td>0.108</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>8,114</td>
<td></td>
</tr>
</tbody>
</table>

*, ** and *** indicate statistical significance at the 90%, 95% and 99% confidence levels.

**TABLE 3** Average treatment effects on treated, treatment: Label_use_choice, \( n = 8,114 \)

<table>
<thead>
<tr>
<th>Matching algorithm</th>
<th>Concern_future_health</th>
<th>Concern_obesity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unmatched</td>
<td>0.101** (.02)</td>
<td>.014* (.01)</td>
</tr>
<tr>
<td>One-on-One</td>
<td>-0.082* (.037)</td>
<td>.005 (.026)</td>
</tr>
<tr>
<td>Nearest neighbour (n = 10)</td>
<td>-0.042* (.02)</td>
<td>-0.026* (.01)</td>
</tr>
<tr>
<td>Radius, Caliper = 0.1</td>
<td>-0.032* (.02)</td>
<td>-0.026* (.011)</td>
</tr>
<tr>
<td>Radius, Caliper = .01</td>
<td>-0.046** (.01)</td>
<td>-0.031* (.02)</td>
</tr>
<tr>
<td>Kernel</td>
<td>-0.033* (.02)</td>
<td>-0.026* (.01)</td>
</tr>
<tr>
<td>Local linear regression</td>
<td>-0.045** (.02)</td>
<td>-0.027** (.01)</td>
</tr>
<tr>
<td>Spline smoothing</td>
<td>-0.045** (.02)</td>
<td>-0.028** (.01)</td>
</tr>
<tr>
<td>Mahalanobis metric</td>
<td>-0.006 (.05)</td>
<td>-0.009 (.03)</td>
</tr>
</tbody>
</table>

\*ATT = average treatment effect on treated using psmatch2 in Stata (Leuven & Sianesi, 2003). Bootstrapped standard errors in parentheses for ATT except nearest neighbor (\( N = 100 \) replications).

4.3 Matching quality

An important quality criterion in the evaluation of the efficiency of matching algorithms is their ability to balance the distribution of relevant PS covariates. We apply Rubin’s (1991) standardized bias (SB) measure to quantify the remaining treatment-control group differences after conditioning on the propensity score. Table 5 presents the means of the SB before and after matching across matching algorithms. For the frequency of referring to nutrition labels, the mean standard bias before matching is 21%. After matching, this bias is reduced significantly for all matching estimators to levels between 1.4% and 2.5%, which are generally considered reliable (Caliendo & Kopeinig, 2008). Our SB results perform better than the SB reductions reported in a comparable study by Drichoutis et al. (2009).

The test results suggest that all matching algorithms are able to achieve a satisfactory balance between the covariates in the matched label users sub-groups, thus significantly reducing the inherent selection bias and measurement error of naïve ad-hoc comparisons. How well the selected covariates explain the probability of treatment is indicated by the comparison of pseudo- \( R^2 \) values before and after PS matching, with little to no remaining systematic


5 | DISCUSSION AND CONCLUSIONS

Our results and subsequent robustness checks support the hypothesis that individual’s food-health concerns and relevant information behaviour, the frequency of reading of nutrition labels, appear to be linked. As our results in Table 3 show, this relationship is not straightforward. An unmatched comparison between label readers and nonreaders reveals that the former appear to state greater concerns over future health and obesity status. A key result of our analysis is that when the underlying characteristics of label readers and nonreaders are accounted for, this relationship is reversed. We find the effect of label reading on stated concerns to be negative. As such, we find evidence that nutrition labelling may have a positive and mitigating effect on consumers’ diet-health concerns, which confirms its use as a potentially effective food policy tool. When compared against a naïve OLS regression, in which label usage has no significant effect on either stated concern, our methodological approach highlights the importance of matching (PSM) between individuals in treated and control groups in order to make inferences about the effectiveness of policy interventions.

Our empirical results (Table 2) also indicate the important role of food attitudes and attribute preferences, such as taste, convenience and affordability, play in the context of making healthier food choices. In our survey data of Canadian consumers, we elicit these attributes in the form of purchase factors (e.g., Purchase_factor_affordable) and find that a high frequency of label usage is associated with placing importance on affordable and healthier product options. The existence of self-control problems may thus lead to a preference of immediate gratification vs. future returns (Hassan, Shiu, & Michaelidou, 2010). Since consumers are not able to assess whether a lifetime of healthy eating will prevent illness or extend one’s life expectancy, they may face difficulties in passing up current gratification for future benefits from healthful foods (e.g., O’Donoghue & Rabin, 1999). A recent study showed that consumers with low self-control make more healthful food decisions in response to traffic-light nutrition labels, which is not true for consumers with high self-control (Koenigstorfer, Groeppel-Klein, & Kamm, 2014).

An existing level of individual consumer knowledge based on previous food purchases and consumption of a large variety of food products could also affect concerns and related perceptions. One of the main challenges facing the growing market of ‘better-for-you’ foods is to convince consumers that these products are tasty, in addition to having nutritional value (Agriculture and Agri-Food Canada, 2011). Thus, it remains difficult to predict whether the increased availability of ‘better-for-you’ reduced-ingredient or front-of-package labelled products in the Canadian retail market might be able to reverse current consumption trends (Howlett et al., 2008).

The growing public policy challenge of obesity in Canada and the United States coupled with the enduring information asymmetry have induced Health Canada and the U.S. FDA to consider changing the format and content of nutrition fact panels (NFP). And despite consumers’ general interest in the linkages between food and health, a widespread debate over alternative means of providing nutritional information on food labels is documented in the literature (Grunert & Wills, 2007; Hieke & Taylor, 2012). The evidence suggests that many consumers tend to ignore the NFP information in their grocery purchase decisions. Grunert and Wills (2007) suggest that some consumers dislike the lengthy and complex NFP label explanations and would prefer shorter FOP claims (Koenigstorfer et al., 2014). A recent industry analysis showed that about 50% of the surveyed U.S. consumers indicated that they read nutrition labels ‘most of the time’ or ‘always’ (Acosta Sales & Marketing, 2014).

Our analyses suggest that the ‘classic’ socio-economic variables, that is, income, education and age, do not sufficiently explain the complex relationship between Canadian consumers’ nutrition knowledge, concerns about diet, health, obesity and food choice behaviour (Schroeter et al., 2013). We rather find that an individual’s understanding of what constitutes healthy eating behaviour and frequent use of nutrition labelling information significantly influences their health awareness and diet. Along the same line, having been diagnosed with a diet-related disease significantly affects an individual’s propensity to refer to and use nutrition label information. Howlett, Burton, Heintz Tangari,
and Bui-Nguyen (2012) suggest a link between sodium label use and hypertension and Howlett et al. (2008) suggests a link between labeling of fats and heart disease. Our results extend the literature regarding linkages between consumer information behaviour and critical food-health outcomes for individuals with high blood pressure and those directly diagnosed to be obese. We suggest that differentiated product innovations appealing to health conscious and health constrained consumers are more likely to be successful in the marketplace.

Our study also provides a unique contribution to the discussions over the optimal design of standardized nutrition labelling, given that robust empirical evidence based on large-scale data about whether and how different forms of nutrition label information affect consumer behaviour still remains scarce (e.g., see Hieke & Taylor, 2012). We aim at narrowing this gap in research knowledge by determining how the frequency of nutrition label usage might affect consumer perceptions regarding future health status. We provide evidence that a consistent usage of nutrition label information in everyday grocery purchase decisions is a reliable predictor for consumers’ perceived concerns. Given that we utilized Canadian data, our results have to be interpreted in light of the specific geographic circumstances of this study. Therefore, factors such as the structure of the Canadian grocery retail market, predominant food culture and broader food policy framework conditions present during the time of data collection in 2008 would suggest that our results should be extrapolated to countries and markets with fundamentally different conditions. As pointed out by Hurt, Kulisek, Buchanan, and McClave (2010), it is important to view nutrition labelling together with other strategies or regulations of nutritional content to significantly alter eating habits to prevent obesity-related consequences. Our study suggests that medical providers may act as an important early-warning system with regard to establishing individual healthy lifestyle habits. Consumers, who have been advised to reduce their sodium intake, are more informed shoppers in the grocery setting who seek out and use the nutrition labels more frequently.

A better understanding of public food-health and obesity concerns, consumer information behaviour and food choice patterns in the context of food policy interventions has been at the center of attention by policy makers, marketing managers and applied economists. Consumers show a strong interest in their health and wellness and technology has presented at 1st Joint EAAE/AAEA Seminar The Economics of Food, Freising, Germany.


REFERENCES


Carlson, A., Dong, D., & Lino, M. (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, Freising, Germany.


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## APPENDIX

### TABLE A1  Sample demographics vs. 2011 Canadian census

<table>
<thead>
<tr>
<th></th>
<th>Gender (%)</th>
<th>Age (%)</th>
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