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A theoretical and empirical investigation of nutritional label use

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Abstract Due in part to increasing diet-related health problems caused, among others, by obesity, nutritional labelling has been considered important, mainly because it can provide consumers with information that can be used to make informed and healthier food choices. Several studies have focused on the empirical perspective of nutritional label use. None of these studies, however, have focused on developing a theoretical economic model that would adequately describe nutritional label use based on a utility theoretic framework. We attempt to fill this void by developing a simple theoretical model of nutritional label use, incorporating the time a consumer spends reading labels as part of the food choice process. The demand equations of the model are then empirically tested. Results suggest the significant role of several variables that flow directly from the model which, to our knowledge, have not been used in any previous empirical work.

Keywords Nutritional labelling · Nutrition information · Health · Nutrition knowledge · Theoretical model · Utility · Consumer behaviour

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Introduction

Over the last decade considerable attention has been paid to nutritional labelling of food products mainly due to their expected contribution to consumer's informed choices towards meeting dietary guidelines. The nutritional value of foods, communicated to the consumer on the nutritional label as well as through other means, has been one important factor that influences consumers' food choices. Nevertheless, the burden of diet-related diseases and obesity has been observed worldwide. Obesity in particular, has been found to be highly correlated with diseases such as gallbladder disease, hypertension, stroke, certain types of cancer, high blood pressure, coronary heart disease and type II diabetes. Obesity, which has risen threefold or more since 1980 in some areas of North America, the United Kingdom and Eastern Europe [1], is linked with the increased consumption of energy-rich foods high in saturated fats and sugars and reduced physical activity.

Nutritionists and economists think of nutrition information of food products as an important issue that may help consumers make healthier food choices [2]. Mandatory nutritional labelling regulations have been introduced in some countries (e.g., United States, Canada, Australia, New Zealand). In E.U. countries, the debate was launched when, in January 2003, the Commission initiated a consultation among Member States and stakeholders related to the revision of the current regulation (90/496 EOC) and the preparation of a proposal amending, among other things, the provision of nutritional information from voluntary to mandatory.

A number of studies have focused on the empirical perspective of nutritional label use. For example, Drichoutis et al. [3], Guthrie et al. [4], Kim et al. [5, 6] and

Nayga [2, 7] empirically investigated the factors that affect nutritional food label use.

There is no consistency, based on the literature, of whether the effect of some factors is positive or negative on label use. For example, there has been no consensus on the effect of age or income on nutritional label use (e.g., [3, 6, 8–12]). For other factors, the literature points to a one-direction relationship. For example, education has been found to positively affect label use and females have been found more likely to use nutritional labels than males [2–6, 12–15]. Household size has also been found to have an effect on label use. Specifically, smaller households are more likely to engage in nutrition information search behaviours than larger households [3, 4, 15]. Meal planners are less likely to engage in nutrition information search [3] (for more information about the nutritional label use literature, see Drichoutis et al. [16] for a thorough review).

Even though many of these applications claim to use the theoretical basis of Stigler's theory [17], i.e., the consumer will continue to acquire and process information as long as the additional costs do not outweigh the additional benefits, there has been little or no use of this theory in guiding the empirical process. The underlying concept in Stigler's theory is that spending more time searching for information (e.g., price or nutrition information) in order to grasp the associated benefits reduces the available time for other activities (which constitutes the cost of information search). Stigler's theory, however, provides little guidance on what factors determine information search intensity and therefore offers little empirical help. It would be useful if theory could identify possible determinants of information search, which may be overlooked by intuition.

To fill this void, we attempt to develop a theoretical model of nutritional label use, which incorporates the time a consumer spends reading nutritional labels as part of his/her food choice process. Because we consider label use to be a health-enhancing activity, we also use the health capital concept introduced by Grossman in his seminal article [18]. In Grossman's model of the demand for health, health is a capital good produced via time and money and thus determines the amount of time available for market and nonmarket activities and the amount of income available to purchase nonhealth goods. Within the context of Becker's household production function framework [19], health is treated as a durable item. Thus, individuals inherit an initial stock of health capital that depreciates with age and can be increased by investment. Net investment in the stock of health equals gross investment minus depreciation. Direct investments in health include the own time of the consumer, medical care, diet, exercise, and recreation.

While a number of theoretical and empirical extensions and applications of the framework for studying the demand for health have appeared based on Grossman's model, no other known article has introduced nutritional label use as a health-enhancing activity. We show that the theoretical model provides specific empirical guidance, which is not obvious with mere intuition. The next section of the article focuses on the development of the theoretical model from which the empirical model is based. The following sections discuss the use of data from a survey conducted in the city of Athens in Greece to estimate the demand equations of interest, the measurement of the variables, the models, results, and then conclusions.

The theoretical model

We assume that there are three composite commodities in the market. The first group of commodities, which we treat as a single product, is an "unhealthy" food product that we denote as B, whereas the other group includes "healthy" foods that we denote as G. The third group denoted as Z includes all other commodities. As consumption commodities, the quantities of the two foods G and B and the quantity of Z enter the utility function directly. Consumers also get utility from the health stock H they possess and from other time components. Let the utility function of a typical consumer be:

$$U = U(H, G, B, Z, W, E, N, R; S_1) \tag{1}$$

which is quasi-concave and twice differentiable. S_1 is a vector of demographic variables and other demand shifters, W is working time, E is time spent on health-enhancing activities (e.g., sports or exercise time in general), N is time spent on gathering nutrition information (e.g., label use time, reading nutrition-related articles) and R is residual time. U has the following property: $U(H, 0, 0, Z, W, E, N, R; S_1) = 0$, which suggests that food is essential for the individual. Consumption of goods is such that $U_G > 0$, $U_B > 0$ and $U_Z > 0$. The direct positive effect of the three goods in the utility signifies that these products can provide a pleasurable consumption experience. However, $U_{GG} < 0$, $U_{BB} < 0$ and $U_{ZZ} < 0$ because each added unit of the goods will produce less consumption pleasure. Likewise, $U_H > 0$ and $U_{HH} < 0$. In addition, following Becker [19], DeSerpa [20] and Evans [21], we define time components as specific arguments in the utility function.

Consumers produce health according to the health-production function:

$$H = H(G, B, W, E, N_I; S_2, k, n) \tag{2}$$

We define N_I as the stock of nutritional information possessed by the individual where $H_{N_I} > 0$. S_2 is a vector of demographic variables and other demand shifters. Similar to the health production function concept, nutritional information is produced according to the production function,

$$N_I = N_I(mN; N_k, S_3) \tag{3}$$

The consumer can invest in his/her stock of nutrient information by gathering nutritional information (e.g., by reading nutritional labels of food products), and this investment is facilitated by nutrition knowledge N_k. Equation (3) shows that the consumer can invest in the amount of nutritional information he/she possesses by acquiring new information (or by refreshing his/her knowledge). m reflects the efficiency of the consumer to derive and process information from one unit of time N that he/she spends gathering information ($0 \le m \le 1$). For example, if $m = 1$ then all the time he/she allocates reading nutritional labels is health enhancing. The m variable can be considered a human capital variable that is fixed in the short run. The S_3 variable includes demographic variables plus the information sources.

In the health production function (2), G and B are inputs in the production of health. The assumption that foods can either increase or decrease the level of health is commonly used when trying to model healthy and unhealthy consumption (e.g., [22]). Therefore, since G is a "healthy" food, its consumption will increase the individual's stock of health: $H_G > 0$. On the other hand, B is an "unhealthy" food and therefore its consumption will decrease the individual's stock of health: $H_B < 0$.

E and W are time inputs in health production that directly affect the level of health. We assume that the time spent in health-enhancing activities, such as exercise, contributes positively to health: $H_E > 0$. Working time W is also assumed to affect the level of health stock either positively or negatively: positively due to healthy components of work (e.g., physical activity on job) or negatively due to unhealthy components of work (e.g., job strain). The k and n variables capture the healthy and unhealthy components of work, respectively (e.g., strain, physical activity or satisfaction at/from work). Such factors are well known to affect health [23–25]. S_2 is the stock of human capital that refers to the knowledge, information, ideas, skills and health of individuals [26].

From the individual's point of view, both market goods and own time are scarce resources. Following neoclassical consumer theory, we assume that the consumers' market wage rate is w, and Y is unearned income. The goods budget constraint equates the value of outlays on goods to income, under the assumption that the consumer does not save:

$$P_G G + P_B B + P_Z Z = wW + Y \tag{4}$$

Here P_G, P_B, and P_Z are the prices of G, B and Z, respectively. Similarly, the individual faces a binding time constraint and can choose the time he/she will spend on the different activities in order to exhaust a time endowment equal to T, where T equals the length of the decision period (e.g., 24 h for a period of 1 day):

$$W + E + N + R = T \tag{5}$$

The equilibrium quantities of the choice variables can now be found by maximizing the utility function given by Eq. (1) subject to the constraints given by Eqs. (2)–(5).

The derived conditional demand function of label use time from the above optimization process is:

$$N = N^*(m, P_G, P_B, P_Z, w, Y, T, S_1, S_2, S_3, N_K, n, k) \tag{6}$$

Market prices are assumed constant. Since no data were collected on the respondent's market wage rate w, we will use working time as a proxy for opportunity cost of time [27]. Furthermore, instead of the unearned income Y, we will use household's annual income I as a proxy. Equation (6) then reduces to:

$$N = N^*(m, W, I, S_1, S_2, S_3, N_K, n, k) \tag{7}$$

Substituting Eq. (7) into the nutrition information production function Eq. (3), we also get the following function:

$$N_I = N_I^*(mN^*; N_k, S_3) \tag{8}$$

Equations (7) and (8) are used to empirically test our theoretical model.

The data

Since no available secondary data exist with respect to the variables we want to use, a consumer survey, using personal interviews, was conducted during December 2005–April 2006. The questionnaire developed was pre-tested on a small sample of consumers during November 2005. The main survey covered the Greater Athens area in Greece. A multistage stratified sampling method was used for the survey. In total, we selected 95 areas (consisting of one or more unified blocks) covering the entire Greater Athens area. The systematic sample that was drawn from each area was then visited during the morning hours and if a contact could not be established, a letter was distributed to them explaining the purpose of the survey and asking for their participation. If a household could not be located (e.g., if the household moved), it was replaced with another household when possible. The households were then revisited during the afternoon hours. A total of 2,565 households were selected to participate in the survey corresponding to a sampling fraction of 0.8‰. Of these, 263 households were not found (e.g., moved) and 240 of them were replaced, thus reducing the initial sample to 2,542 households. We were not able to establish contact with 1,277, and 899 households refused to cooperate. Hence, 366 households agreed to participate in the survey yielding response and cooperation rates of 14.40 and 28.93%, respectively [28]. Refusal rate was about 35.37%, and the no-contact rate was about 50.24% [28].

When the household agreed to participate in the survey, we asked to interview the major food shopper or we randomly chose one of the household shoppers if more than one individual did the grocery shopping. An average interview lasted for about 22 min; in total more than 129 h of interviews were conducted. Individuals who failed to respond to a question or to report their socioeconomic and demographic information were dropped from the sample. Hence, the number of respondents used in the analysis was 356.

Table 1 compares the key demographics of the respondents and the overall synthesis of their households with that of the 2001 census for Athens. Since respondents were the major grocery shoppers of the household, their demographics would not be exactly representative of the population. However, when we compare the synthesis of the households with that of the 2001 census, we find that the figures are very close (Table 1). In addition, considering the fact that the population of Athens accounts for half of the population of Greece, our sample shows some potential for extrapolating results at the country level (at least for nonrural populations).

Measurement of variables and econometric modelling

To estimate Eqs. (7) and (8), we employed the specifications below:

$$LABUSE = \begin{pmatrix} b_0 + b_1 WWEEKH + b_2 STRAIN + b_3 NFLX + b_4 PHDEM + b_5 WALK + b_6 NKNOW \\ + b_7 EFFIC + b_8 PLANNER + b_9 INVOLV + b_{10} HCLAIMTR + b_{11} ISMEDIC \\ + b_{12} ISFRIEN + b_{13} ISELSE + b_{14} ISNO + b_{15} EXER + b_{16} OBESE + b_{17} OVWEIGHT \\ + b_{18} UNWEIGHT + b_{19} NOSMOKE + b_{20} SMSTOP + b_{21} HHEAD + b_{22} GEND \\ + b_{23} AGE + b_{24} HSIZE + b_{25} EDUC_2 + b_{26} INC_2 + b_{27} INC_3 + b_{28} INC_4 \end{pmatrix} + u \quad (9)$$

$$NI = \begin{pmatrix} b_0 + b_1 LABEFFIC + b_2 ISMEDIC + b_3 ISFRIEN + b_4 ISELSE \\ + b_5 ISNO + b_6 NKNOW + b_7 GEND + b_8 AGE + b_9 EDUC_2 \\ + b_{10} INC_2 + b_{11} INC_3 + b_{12} INC_4 \end{pmatrix} + v \quad (10)$$

Equations (9) and (10) above empirically represent Eqs. (7) and (8) discussed earlier. The description of the variables used in these last two equations and their descriptive statistics are presented in Table 2. Table 3 presents the correspondence between the variables of the theoretical model based on Eqs. (7) and (8) and the variables from the empirical forms represented by Eqs. (9) and (10).

The S_1 and S_2 variables introduce into the model several demographic variables and demand shifters that have been found to affect label use. Drichoutis et al. [16] in their recent literature-review paper on label use, summarize and categorize several variables and their expected influences on label use. Many of these variables are used in the present study. For example, Celsi and Olson [29] found that consumers will spend more time attending to information as their involvement increases. The *PLANNER* and *INVOLV* variables are thought to capture this effect. The role of claims has also been explored with respect to label use (e.g., [30–32], and therefore the variable *HCLAIMTR* is introduced to test if the perceived believability of health and nutrition claims influences label use. Drichoutis et al. [3] showed the effect of several attitudinal and behavioural factors on label use, and therefore we introduce some lifestyle factors to explain label use (i.e., *OBESE*,

Table 1 Demographic characteristics by gender and age

	Gender (%)		Age (%)							
	Males	Females	0–9	10–19[a]	20–29	30–39	40–49	50–59	60–69	≥70
2001 census	47.66	52.34	9.11	11.15	16.38	16.35	14.60	11.75	10.33	10.32
Household synthesis	49.62	50.38	7.66	11.78	14.85	14.66	15.33	15.04	10.25	10.44
Surveyed sample	36.52	63.48	0.00	0.60	7.83	21.08	23.49	20.18	14.76	12.05

[a] The survey was addressed to the major grocery shoppers who, in all cases, were above 18 years old. Therefore the row labelled “surveyed sample” includes only a few cases for the age category of 10–19 years old

Table 2 Names and descriptions of variables

Variable	Variable description	Scale	*N*	%	Mean	SD
LABUSE	Label use while shopping (1–5 scale)	1–5			2.596	1.442
	Always		39	10.96		
	Often		88	24.72		
	Neither often nor rarely		40	11.24		
	Rarely		68	19.10		
	Never		121	33.99		
*LABUSE*EFFIC*	The product of the predicted values for label use and efficiency in reading nutritional labels (*EFFIC*)	0–5			1.059	1.302
INVOLV	Degree of involvement with food	0–2			1.497	0.682
PLANNER	Respondent is the major meal planner = 1, otherwise = 0	0, 1	264	74.16	0.742	0.438
WWEEKH	Work hours of a typical week				18.465	21.735
CLAIMTR	Respondent believes that very few or no products carry trustful nutrition or health claims = 1, otherwise = 0	0, 1	133	37.36	0.374	0.484
STRAIN	Respondent suffers from strain = 1, otherwise = 0	0, 1	25	7.30	0.073	0.261
NOFLEX	Respondent has no workday or work-hour flexibility = 1, otherwise = 0	0, 1	71	19.94	0.199	0.400
PHDEM	Respondent's job is physically demanding = 1, otherwise = 0	0, 1	43	12.07	0.121	0.326
WALK	Respondent has to walk or stand often while working = 1, otherwise = 0	0, 1	77	21.63	0.216	0.412
ISMEDIC	Primary source of nutrition information is nutritionists, physicians, etc. = 1, otherwise = 0	0, 1	30	8.43	0.084	0.278
ISMEDIA[a]	Primary source of nutrition information is TV, radio, newspapers, books, etc. = 1, otherwise = 0	0, 1	184	51.68	0.517	0.500
ISFRIEN	Primary source of nutrition information is friends, relatives, etc. = 1, otherwise = 0	0, 1	68	19.10	0.191	0.394
ISELSE	Primary source of nutrition information is something other than above = 1, otherwise = 0	0, 1	12	3.37	0.034	0.181
ISNO	Respondent does not get informed at all regarding nutrition information = 1, otherwise = 0	0, 1	62	17.42	0.174	0.380
OBESE	Respondent is obese (BMI ≥ 30) = 1, otherwise = 0	0, 1	60	16.86	0.169	0.375
OVWEIGHT	Respondent is overweight (25 ≤ BMI < 30) = 1, otherwise = 0	0, 1	145	40.73	0.407	0.492
NWEIGHT[a]	Respondent has normal weight (20 ≤ BMI < 25) = 1, otherwise = 0	0, 1	151	42.42	0.424	0.495
NOSMOKE	Respondent has never smoked = 1, otherwise = 0	0, 1	155	43.54	0.435	0.497
SMSTOP	Respondent has smoked in the past but does not smoke now = 1, otherwise = 0	0, 1	59	16.57	0.166	0.372
SMOKE[a]	Respondent smokes = 1, otherwise = 0	0, 1	142	39.89	0.399	0.490
HHEAD	Respondent is household's head = 1, otherwise = 0	0–1	273	76.69	0.767	0.423
GEND	Respondent is male = 1, otherwise = 0	0, 1	130	36.52	0.365	0.482
AGE	Respondent's age				49.770	14.866
HSIZE	Household size				2.933	1.161
$EDUC_1^a$	Respondent has up to junior high school education = 1, else = 0	0, 1	85	23.88	0.239	0.427
$EDUC_2$	Respondent has high school education = 1, else = 0	0, 1	155	43.54	0.435	0.496
$EDUC_3$	Respondent has university education or higher = 1, else = 0		116	32.58	0.326	0.469
INC_1	Annual household income is < €10,000 = 1, else = 0	0, 1	72	20.22	0.202	0.402
INC_2	Annual household income is €10,000–20,000 = 1, else = 0	0, 1	126	35.39	0.354	0.479
INC_3	Annual household income is €20,000–40,000 = 1, else = 0	0, 1	123	34.55	0.346	0.476
INC_4^a	Annual household income is > €40,000 = 1, else = 0	0, 1	35	9.83	0.098	0.298

Table 2 continued

Variable	Variable description	Scale	N	%	Mean	SD
NKNOW	Nutrition knowledge	0–9			5.503	1.310
	Experts' advice	0, 1	170	47.75	0.478	0.500
	Food source$_1$	0, 1	159	44.66	0.447	0.498
	Food source$_2$	0, 1	69	19.38	0.194	0.396
	Food source$_3$	0, 1	13	3.65	0.037	0.188
	Food choice$_1$	0, 1	272	76.40	0.764	0.425
	Food choice$_2$	0, 1	260	73.03	0.730	0.444
	Dietary recommendation$_1$	0, 1	318	89.33	0.893	0.309
	Dietary recommendation$_2$	0, 1	344	96.63	0.966	0.181
	Dietary recommendation$_3$	0, 1	354	99.44	0.994	0.075
NI	Nutrition information stock	0–7			4.567	1.226
	Proteins/whole milk versus skimmed milk	0, 1	126	35.39	0.354	0.479
	Calories/butter versus margarine	0, 1	36	10.11	0.101	0.302
	Vitamins/white versus whole wheat bread	0, 1	294	82.58	0.826	0.380
	Fat/yoghurt versus whipping cream	0, 1	331	92.98	0.930	0.256
	Cholesterol/whole milk versus skimmed milk	0, 1	283	79.49	0.795	0.404
	Fiber/white versus whole wheat bread	0, 1	304	85.39	0.854	0.354
	Cholesterol/butter versus margarine	0, 1	252	70.79	0.708	0.455
EFFIC	Efficiency reading nutritional labels	0–1			0.688	0.308
	Locate information$_1$	0, 1	288	80.90	0.809	0.394
	Locate information$_2$	0, 1	299	83.98	0.840	0.367
	Locate information$_3$	0, 1	256	71.91	0.719	0.450
	Manipulate information$_1$	0, 1	168	47.19	0.472	0.500
	Manipulate information$_2$	0, 1	159	44.66	0.447	0.498
	Choose between foods	0, 1	300	84.27	0.843	0.365

[a] Variables omitted for estimation purposes

Table 3 Correspondence between theoretical and empirical variables

Variables in theoretical model	Variables in empirical model
N	*LABUSE*
N_I	*NI*
m	*EFFIC*
W	*WWEEKH*
I	INC_1, INC_2, INC_3
N_k	*NKNOW*
n, k	*STRAIN*, *NOFLEX*, *PHDEM*, *WALK*
S_1, S_2	*INVOLV*, *PLANNER*, *CLAIMTR*, *OBESE*, *OVWEIGHT*, *UNWEIGHT*, *NOSMOKE*, *SMSTOP*, *HHEAD*, *GEND*, *AGE*, *HSIZE*, $EDUC_2$, $EDUC_3$, INC_1, INC_2, INC_3
S_3	*ISMEDIC*, *ISFRIEN*, *ISELSE*, *ISNO*, $EDUC_2$, $EDUC_3$, INC_1, INC_2, INC_3, *AGE*, *GEND*

OVWEIGHT, *NOSMOKE*, *SMSTOP*). Other typical demographic factors (e.g., education, income) are used in Eq. (9) as possible determinants of label use.

Similarly, the S_3 variable includes demographic variables plus the information sources that have been found to affect nutrition knowledge [3] (or stock of nutrition information in our case). As in Blaylock et al. [33], we distinguish between two types of knowledge on nutrition. The first type is knowledge of *general* nutritional concepts, which we call nutrition knowledge, and the second type is *specific* knowledge of the nutrient content of foods, which, for this article, is identical with the concept of nutrition information stock.

To measure label use (N), we first asked consumers to think of many food products that carry nutritional labels. To avoid confusion each respondent was then shown an 11×7 cm nutritional label indicating that this is what a typical nutritional label looks like (details on the format of the label are described later). Following Drichoutis et al. [3], Guthrie et al. [4], Nayga [7], and Szykman et al. [34], we used a self-reported measure for label use. Ideally, accurate measures of label use time would have been preferred. However, no known study has managed to derive such kinds of measures. One study on label use has used the verbal protocol analysis [35], where individuals were trained to think aloud while shopping, and therefore the actual behaviour was recorded. This method, however is time consuming and costly and, therefore, has not been popular or used, at least in label-use studies. In our study, we measured nutritional label use by asking respondents how often they use nutritional labels when grocery shopping. Possible answers were *never*, *not often, medium, often* and *always*. Only 11% of the sample (39 cases) indicated that they always use nutritional food labels when grocery shopping, and 24.7% (88 cases) indicated they often use food labels. Medium and not often use were reported by 11.24% (40 cases) and 19.1% (68 cases) of the sample, respectively. Most respondents (34% or 121 cases), reported that they never use nutritional food labels while grocery shopping.

The healthy and unhealthy components of work (n, k) were proxied by job strain, work flexibility, physical demands of work, and the requirement of working or standing while at work. The type of occupational stress having a negative impact on workers' health is defined as job strain [36–38]. Job strain occurs when job demands are high, and job decision latitude is low. High job demands can be associated with intense pressure of work provoked by performing tasks at high speed and by being subjected to tight deadlines. Job latitude can be measured by job decisions at work on the individual level. Therefore, working respondents were asked how often they face tight deadlines, how often they have to work at a fast pace, and how often they can change their pace of work or the order of their tasks [36, 39] on a five-point Likert scale ranging from *never* to *very often*. Respondents who stated that they *often* or *very often* work at a fast pace and/or face tight deadlines, while simultaneously not being able to change the pace of the work or the order of the tasks were qualified as having job strain. Therefore, the corresponding variable (*STRAIN*) takes the value of 1 and 0 otherwise. Non-working respondents were assumed to have no job strain.

To measure work flexibility, we asked respondents if the working days and the working hours are inflexible, somewhat flexible or very flexible. Respondents that stated that either working days or working hours were inflexible were classified as having no job flexibility (*NOFLEX*). Respondents not working were seen as having flexibility and were aggregated with those having flexibility. Respondents were also asked to evaluate the physical demands of their work on a seven-point Likert scale from *very, very light* to *very, very exerting* [40]. When respondents stated that the physical demands of their work are exerting or more, the variable (*PHDEM*) was given a score of 1 and 0 otherwise. Similarly, respondents were asked how often they have to stand or walk while at work on a seven-point Likert scale ranging from *never* to *always*. When respondents stated that they have to walk or stand while at work *often* or more, the variable (*WWALK*) was given a score of 1 and 0 otherwise.

Following Byrd-Bredbenner et al. [41], each consumer was shown a typical nutritional label in order to test consumer's efficiency (*EFFIC*) in deriving information from nutritional labels. The labels were printed on an 11×7 cm white paperboard and were formatted using the "Big 8" format (i.e., showing the amount of eight key nutrients: energy, protein, carbohydrates, fat, sugar, saturated fat, fiber and sodium). The consumers were then asked a series of six questions. The first three questions tested their ability to locate quantitative information on the label. Respondents were asked how much total carbohydrates, proteins and saturated fat, respectively, were in 100 g of the food. The next two questions tested consumers' ability to calculate quantitative information, used to evaluate their diet-planning computational ability. Participants were asked: If you ate 500 g of this food, how many calories would you get? If you ate 200 g of this food, how much fat would you get? The last question tested consumers' ability to choose between foods. A new label was shown to them using the same format with the previous label and consumers were then asked to indicate the healthiest food choice. For each correct answer, consumers were assigned a score of 1, and for each wrong answer they were assigned a score of 0, thus yielding a score between 0 and 6 for each consumer. The scale was then divided by 6 to rescale the variable and make it consistent with the theoretical model presented in the previous section (although we realize that this is just a linear transformation, and therefore does not affect results). About 80.9, 84, and 71.9% of the respondents were able to correctly locate the requested quantitative information from the label with regards to carbohydrates, proteins, and saturated fat, respectively. The percentages dropped to 47.2 and 44.7% when consumers were asked to manipulate quantitative information in the next two questions, respectively. Finally, about 84.3% of the respondents were able to choose correctly between the two food alternatives based on the nutritional information shown to them.

To measure nutrition knowledge (*NKNOW*), we asked a series of questions derived from the Nutrition Knowledge questionnaire [42]. The questions examined consumers' knowledge on four sections: dietary recommendations, sources of nutrients, choosing everyday foods and diet-disease relationships. These four sections were composed of nine questions. Among others, we asked consumers to state what kind of fat should they cut down (saturated or monounsaturated), which foods mainly contain saturated fats (vegetables, dairy or both), if they agree or disagree that some foods contain a lot of fat but no cholesterol, and if brown sugar is a better dietary alternative than white sugar. Two more questions examined consumers ability to choose the healthiest food alternative (e.g., choose between beef steak, pork steak, sausages, and turkey in terms of fat), and the last three questions tested consumers knowledge of diet-disease relation (consumers were asked if they agree or disagree that eating less saturated fat, more fruits/vegetables, and less salt can help in fighting heart diseases). Correct answers were assigned a score of 1, while incorrect answers were assigned a score of 0 thus yielding a score between 0 and 9 for each respondent.

Nutrition information stock (*NI*) is measured as the knowledge of the specific nutrient content of foods. We used seven questions of pairwise comparison of foods regarding the nutrient content of foods [3, 33, 42]. Consumers were asked to compare certain foods (e.g., butter vs. margarine, whole milk vs. skim milk, white bread vs. whole wheat bread) and were asked to indicate which has more cholesterol, fat, fiber, calories, etc. (see Table 2). For each correct answer the respondents were assigned a score of 1 and a score of 0 for an incorrect answer, thus yielding a score between 0 and 7 for each respondent. At this point it would be useful to elaborate on the conceptualization of knowledge about nutrition in this study. We conceptualize two distinct forms of knowledge about nutrition. The first form is knowledge of *general* principles about nutrition (e.g., awareness of experts' advice or dietary recommendations). The second form is the *specific* knowledge about the nutrient content of foods (e.g., if a food is low/high in a nutrient or which of a pair of foods has more/less of a nutrient). One would expect an endogenous relation of nutrition knowledge with label use, i.e., higher nutrition knowledge may affect the likelihood of reading labels but also reading labels may affect nutrition knowledge. In fact this has been verified by a past study [3]. However, the measure of nutrition knowledge used in past studies is a combination of what we conceptualize as *general* knowledge and *specific* knowledge. The endogeneity issue could be a result of the failure to recognize the distinct forms of nutrition knowledge. In our model, we assume that *general* knowledge can affect label use behaviour (since it may facilitate comprehension of nutrient information) but not the other way around, i.e., increased use of labels will not provide the individual with more information about general principles of nutrition. However, we recognize that increased use of labels can and will affect the *specific* nutrition knowledge, which in our study is identical to the nutrition information stock. Note that this distinction of nutrition knowledge has also been made by Blaylock et al. [33].

The measure of involvement with food was constructed as follows: respondents were asked how important to them, while grocery shopping, each of five food attributes were, i.e., brand name, taste, nutrition value, ease of preparation and price. Possible answers ranged from *not important at all* to *very important*. For each food attribute that respondents rated as *important* or *very important*, a score of 1 was assigned, otherwise a score of 0 was assigned, thus yielding a total score between 0 and 5 for each individual.

Respondents were asked to report their body weight and height. We used these variables to calculate the body mass index (BMI), according to the formula: BMI = weight/height.[1] Self-reported weight and height are usually subject to reporting error. Underweight people tend to overreport their weight, and overweight people tend to underreport their weight. Cawley and Burkhauser [43] provide equations based on the National Health and Nutrition Examination Survey III, so that researchers can predict true weight and height from datasets with self-reported weights and heights. The coefficients from their equations were multiplied by the self-reported values from our dataset to construct measures of weight and height corrected for reporting error. The assumption that has to be made is that of transportability, i.e., that the relationship between true and reported values is the same in both datasets. The rest of the variables are described in Table 2. Individuals with a BMI over 30 are classified as obese. Individuals with a BMI between 25 and 30 are overweight, those with a BMI between 20 and 25 are considered to have normal weight, and those with a BMI under 20 are underweight.

The outcome variable in Eq. (9) is a discrete choice variable which calls for the use of what are known as Qualitative Response models [44, p. 663]. For ranking (ordinal) dependent variables, an ordered logit model is considered appropriate. The fitted (predicted) values from this estimation are used in Eq. (10), multiplied by efficiency (*EFFIC*) and thus forming a new variable (*LABUSE***EFFIC*), which is consistent with the theoretical

[1] In the analysis we had to collapse the underweight category with the normal weight category because of the few cases in the underweight category and also due to the fact that there were only women who were underweight in our sample.

model variable (mN).[2] The latter equation was estimated via ordinary least squares. Since many variables in the models were not statistically significant, we suspected the presence of multicollinearity. To test for multicollinearity, we calculated the variance inflation factor (VIF) for the regressors of each equation. In a regression context, the VIF is a measure of the effect $VIF_k = 1/(1 - R_k^2)$, where R_k^2 is the R^2 obtained when the kth regressor is regressed on the remaining variables. As there is no direct counterpart to R^2 in logistic regression, VIF cannot be computed in this case, but we can use the VIF test in OLS regression to test for multicollinearity in logistic regression. Therefore, we used the VIF measure in both equations. The VIF values are far below the problematic values, which are considered to be values in excess of 10. Hence, we find no degrading collinearity problems among the variables in our model.

Results and findings

Table 4 presents the results for Eq. (9). Our discussion of the results for Eq. (9) is based on the statistical significance of the marginal effects and discrete changes, which were calculated as the means of all other variables.[3] Discrete changes were calculated for the dummy variables only. The parameter estimates for Eq. (10) are presented in Table 5.[4]

Table 4 shows that label use is affected by several socioeconomic factors, but most importantly by factors that flow directly from the theoretical model, thus amplifying its usefulness. Respondents with job strain (*STRAIN*) are 9.2% more likely to use nutritional labels often than those with no strain. Similarly, respondents with no flexibility (*NOFLEX*) are more likely to report medium use of nutritional labels. This is an indication of the importance of work-related factors on label use. It may show that consumers try to compensate for the negative effect of work on their health with a more healthful diet, which could be achieved through increased label use. However, the job-related variables are not statistically significant across all categories of label use. More research is needed to definitively assess the effect of job-related variables on label use.

Keeping in mind the previous comment, respondents with physically demanding (*PHDEM*) jobs are more likely to report medium use of nutritional labels. This result makes more sense if we think that those doing heavy work may need a more nutritious diet that will allow them to deal with the increased physical demands of their job. In a similar fashion, those with nonsedentary jobs (*WALK*) are 12.9% more likely not to use nutritional labels and 3.9% less likely to always use nutritional labels than those with sedentary jobs. This result may suggest that those with nonsedentary jobs perceive their jobs as contributing to their everyday exercise and health and thus may find unnecessary the use of nutritional labels as a means to a healthier diet.

The statistical significance of efficiency of reading nutritional labels (*EFFIC*) also reinforces the theoretical model. The results suggest that respondents who are more able to derive information from nutritional labels are more likely to use them. This finding has important implications for policy makers and marketers since it shows that increased label use can be realized with better comprehension of nutritional information. This also calls for the use of consumer-friendly and easy-to-use label formats.

We also find that overweight respondents (*OVWEIGHT*) are more likely to use labels than normal weight respondents, but there is no effect of obesity on search for nutrition information. It may be that the overweight perceive label use as a good means for dietary management purposes and small weight changes. On the other hand, obese respondents (*OBESE*) may not regard nutrition information as capable of helping alter their body weight, since the reduction changes needed can be substantial compared to the overweight.

As expected, males (*GEND*) and older respondents (*AGE*) are less likely to use nutritional labels. The finding on males has been verified by several studies [3, 4, 6, 15], and once more confirms that men are less interested in nutrition, perhaps because they are less likely to agree that nutritional labels are useful [45]. The latter result regarding age can be associated with the lower processing capacity of older people, and the fact that older people tend to perceive labels to be less understandable [8]. Furthermore, household heads (*HHEAD*) are more likely to use nutritional labels, which is probably driven by the responsibility sentiment toward the other members of the household regarding their nutrition and health.

Finally and not surprisingly, respondents who stated that very few products carry trustful nutrition and health claims (*CLAIMTR*) are less likely to use nutritional labels. This finding suggests the importance of trust in nutritional label use. We should also note that education only slightly affects some categories of label use, and income has no effect on nutrition information search.

Results for Eq. (10) are also very interesting. The product of the fitted values of label use with efficiency (*LABUSE*EFFIC*), a variable which flows directly from the theoretical model, is statistically significant and

[2] To test the validity of using a variable as a product of two other variables, we also tried estimating Eq. (10) using m and N as separate variables. This estimation produced the same results.

[3] The parameter estimates are available upon request.

[4] Since the number of observations in some label-use categories may be small, we experimented by estimating Eqs. (9) and (10) when some categories of the label-use variable were collapsed together. Results remained practically unchanged, and therefore we decided to continue with the original formulation since this is more informative.

Table 4 Marginal effects and discrete changes for label-use equation

Variables	Label use = never	Label use = rarely	Label use = medium	Label use = often	Label use = always
INVOLV	0.0157	0.0021	–0.0020	–0.0102	–0.0056
ISMEDIC	0.0598	0.0048	–0.0087	–0.0371	–0.0189
ISFRIEN	0.0116	0.0015	–0.0015	–0.0075	–0.0041
ISELSE	–0.0994	–0.0251	0.0067**	0.0702	0.0475
ISNO	0.0670	0.0058	–0.0095	–0.0418	–0.0215
PLANNER	–0.0263	–0.0032	0.0034	0.0169	0.0091
CLAIMTR	0.1453**	0.0133*	–0.0199**	–0.0907**	–0.0479**
WWEEKH	0.0006	0.0001	–0.0001	–0.0004	–0.0002
STRAIN	–0.1296*	–0.0358	0.0067	0.0923*	0.0664
NOFLEX	–0.0934	–0.0188	0.0087**	0.0640	0.0395
PHDEM	–0.0825	–0.0174	0.0074*	0.0569	0.0356
WALK	0.1296*	0.0071	–0.0195	–0.0782**	–0.0390**
OVWEIGHT	–0.0852*	–0.0129	0.0099*	0.0562*	0.0320*
OBESE	0.0853	0.0062	–0.0125	–0.0525	–0.0265
NOSMOKE	0.0059	0.0008	–0.0007	–0.0038	–0.0021
SMSTOP	–0.0535	–0.0095	0.0057	0.0360	0.0212
HHEAD	–0.1565**	–0.0070	0.0239**	0.0934**	0.0462**
GEND	0.1529**	0.0132*	–0.0212*	–0.0950**	–0.0500**
AGE	0.0055**	0.0007**	–0.0007**	–0.0036**	–0.0020**
HSIZE	–0.0064	–0.0009	0.0008	0.0042	0.0023
$EDUC_2$	–0.0577	–0.0082	0.0070	0.0378	0.0211
$EDUC_3$	–0.1129*	–0.0202	0.0116*	0.0759	0.0455
INC_1	–0.0662	–0.0120	0.0069	0.0447	0.0265
INC_2	–0.0925	–0.0153	0.0102	0.0616	0.0359
INC_3	–0.0685	–0.0109	0.0078	0.0455	0.0261
NKNOW	–0.0235	–0.0032	0.0029	0.0153	0.0084
EFFIC	–0.1626*	–0.0219*	0.0204*	0.1060**	0.0581*
Threshold parameters[a]	Coefficient	Std. error	*t*-Statistic		
MU_1	0.921	0.0889	10.346		
MU_2	1.456	0.1034	14.074		
MU_3	3.112	0.1766	17.620		
Fit measures for ordered logit model					
% Correct predictions	42.70				
Log likelihood	–504.8397				
Restricted log likelihood	–539.8184				
McFadden R^{2} [b]	0.065				
x^2 (*P*-value)	69.96 (1.13E-06)				

* $P < 0.10$, ** $P < 0.05$

[a] These are threshold parameters that separate the adjacent categories, estimated with the other model parameters. The first threshold parameter MU(0) is typically normalized to zero

[b] $1 - (\log L_{unrestricted}/\log L_{restricted})$

positive. This variable can be interpreted as the proportion of label-use time that is useful for the consumer in terms of deriving information from the labels, and it shows that as this increases so does nutrition information stock. The result for this variable indicates the importance of efficiency and label use together on enhancing the stock of nutrition information.

Furthermore, it is interesting that nutrition knowledge (*NKNOW*) positively affects nutrition information stock, thus showing that increased *general* knowledge of nutrition principles may facilitate acquisition of *specific* nutrient content knowledge. However, nutrition knowledge as shown in Table 4 does not affect label use. These findings imply that information campaigns will not necessarily

Table 5 Estimated coefficients for nutrition information stock equation

Variables	Coefficient	*P*-values
Constant	2.4523**	0.000
ISMEDIC	–0.3838*	0.079
ISFRIEN	–0.1838	0.243
ISELSE	0.0067	0.984
ISNO	–0.1980	0.245
*LABUSE*EFFIC*	0.2129*	0.000
$EDUC_2$	0.5065**	0.002
$EDUC_3$	0.6432**	0.001
INC_1	–0.3404	0.160
INC_2	–0.3423	0.129
INC_3	–0.2535	0.236
AGE	0.0134*	0.002
GEND	–0.2155	0.103
NKNOW	0.2285**	0.000
R^2	0.237	
Adjusted R^2	0.208	
F-value	8.16	0.000

* $P < 0.10$, ** $P < 0.05$

encourage people to read nutritional labels but will rather make consumers more efficient producers of *specific* knowledge, in case consumers decide to read the labels.

It also appears that information sources play a role in the acquisition of nutrition information. People who use specialists, such as doctors or nutritionists (*ISMEDIC*), as their primary source of information have lower stocks of specific information than people whose main source of nutrition information is the media. It is possible that individuals who are informed mainly by specialists are aware only of very specific issues that are motivated by their special medical or physical condition.

In addition, higher education ($EDUC_2$, $EDUC_3$) leads to higher nutrition information stock, which emphasizes the role of schooling on knowledge. There is also a positive effect of age (*AGE*) on nutrition information. This result may indicate the role of market experience if combined with the result from the label use equation that older people are less likely to use nutritional labels. This may also indicate that a possible reason why older individuals do not pay attention to nutritional information is that they have a higher stock of nutrition information knowledge.

Conclusion

In this article, we attempted to fill a void in the nutritional-labelling literature by developing a theoretical model that hopefully will provide a framework and standard approach for empirically exploring consumer label use. In order to test the demand equations derived from the model, we collected data from personal interviews of primary grocery shoppers. No other known study has based an estimation on a utility-theory model specific to label use. Our results suggest the significant role of several variables that flow from the theoretical model and that are used for the first time, to our knowledge, as possible determinants of label use. The results can also be used as a guide by marketers in segmenting the market between label users and nonusers since we identified the profile of consumers more likely to engage in label-usage behaviour. According to the results, the profile of consumers more likely to read nutritional labels while shopping is as follows: a younger female with higher nutrition knowledge and higher efficiency in deriving information from the label, a consumer who is head of the household and exercises at least once a week, under job strain, with no flexibility in changing workdays or work-hours, having a physically demanding job and being trustful toward nutrition and health claims. In addition, label use, along with efficiency and certain demographic factors, was shown to affect the level of nutrition information stock.

Due to the nature of the survey we conducted (i.e., the representativeness of our sample), our results can be generalized to the population of Athens, which accounts for half the population of Greece. Ideally, however, future research should test the robustness of our results on semi-urban and rural populations, and see if there are urbanization effects, as other researches have suggested [10, 12]. Replicating our study in other parts of Europe would also be beneficial, especially since marketers are anxious to know how to target consumers with the new mandatory nutritional-labelling regulations that the European Union is contemplating implementing. Future studies can also use our theoretical model as a guide in developing specific theoretical and empirical models for other types of label use (e.g., eco-labelling, food-safety labels, country of origin) and information search behaviour. Several of the assumptions of the theoretical model could also be relaxed in future work with the use of longitudinal rather than cross-sectional data. For example, longitudinal data, if available, can be used to allow some variables (e.g., the efficiency variable, job strain variables) to change over time in the model and therefore test the dynamic effects of these variables. Moreover, future studies should attempt to collect data on the state of individuals' health and test the interactions and effects of these health states or measures on nutritional label use.

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