The Impact of Nutritional Supplement Choices on Diet Behavior and Obesity Outcomes

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Abstract

Despite decades-old efforts to inform and educate consumers about healthier lifestyles through established dietary guidelines, diet-related diseases are on the rise. At the same time, consumers have developed more favorable attitudes towards nutritional supplements as a perceived alternative way to improve diet quality. Thus, there is a need to understand the role of nutritional supplements in U.S. consumers' diets, given that supplements might serve as a possible policy tool to improve dietary behavior. We use data from the National Health and Nutrition Examination Survey (NHANES) to estimate the impact of nutritional supplements intake on respondent's body weight outcomes, while controlling for diet quality based on individual Healthy Eating Index (HEI-2010) scores. Our analysis applies a set of innovative Propensity Score Matching (PSM) estimators that account for potential selection bias and endogeneity of the self-reported behavior and diet-health outcomes. The empirical analysis demonstrates a negative association between nutritional supplement intake and BMI. Our findings suggest that health-conscious individuals overinvest in health by taking nutritional supplements instead of improving diet quality through more appropriate food choices. Nutritional supplements have been discussed as a disease-preventative input that may enhance the diets and health of at-risk populations. The analysis in this paper suggests that consuming supplements should not be thought of as a replacement for a healthy food-based diet. Our study provides an important contribution to the literature on a key food policy issue and contributes new insight with regard to the relationship between dietary choices and health behavior.

Introduction

The U.S. Food and Drug Administration's (FDA) ban of artificial trans-fats in processed foods emphasizes the growing regulatory oversight regarding diet-health issues in the food industry (Golomb and Bui 2015). Less than optimal dietary patterns have been at the center of the public debate over poor health and chronic disease risks. On average, dietary patterns fall below recommended intake levels for fruits and vegetables, whole grains, and low-fat dairy, while exceeding upper limits for refined grains, saturated fats, sodium, and overall caloric energy (Guenther et al. 2006). Despite the proven health benefits of a diet rich in fruits and vegetables (Agudo 2005; Pérez 2002; Keen and Zidenberg-Cherr 1994), the average U.S. adult only consumes 64% of the vegetable servings and half of the fruit servings recommended by the 2010 Dietary Guidelines for Americans (DGAs) (U.S. Department of Agriculture and U.S. Department of Health and Human Services (USDA/HHS) 2010). At the same time, the consumption of solid fats, alcohol, and added sugars (SoFAAS) is 2- to 3-fold of their recommended limits (Guenther et al. 2006).

Declining produce consumption patterns are commonly attributed to changing socio-demographics, rising demands for convenience foods, growing away-from-home food expenditures and declining food preparation skills. In order to compensate for the nutrient deficit from reduced fruit and vegetable consumption, 62% of U.S. adults consume nutritional supplements at least occasionally, whereas 46% are reported to take supplements regularly (Dickinson and Shao 2006). Preventative health care through greater adherence to dietary guidelines could potentially save up to $43 billion each year in direct medical costs and lost productivity resulting from secondary chronic health problems due to poor diets (e.g. DeVol and Bedroussian 2007).

While previous studies acknowledge the interplay of appropriate food choices and physical exercise in consumer health behavior and outcomes (Beydoun and Wang 2008; Stewart and Blisard 2008; Mancino, Todd, and Lin 2009), little is known about the role and impact of nutritional supplements as an input into consumer diet quality and health status. Furthermore, existing evidence is mixed with regard to the economic impact of nutritional supplements and how the intake thereof could influence a person's dietary behavior. The 2010 DGAs state that nutrients should come primarily from food, and recommends that specific supplementation might be needed for at-risk populations, such as postpartum women, as well as older Americans (USDA/HHS 2010). However, growing evidence suggests that the intake of nutritional supplements may be unnecessary and potentially even be detrimental to human health (Mursu et al. 2011). As such, the 2015 Dietary Guidelines Advisory Committee (DGAC) emphasizes that healthy dietary patterns are to be achieved through recommended food and beverage choices rather than with nutritional supplements except as needed for at-risk populations (USDA/HHS 2015). These inconsistencies highlight the need for research that expands the understanding of the role of nutritional supplements in U.S. consumer's diet-health behavior and whether supplements are currently replacing or supplementing a healthy diet. Consumers may not have access to complete information about the costs and benefits of supplements and their potential effects on diet quality and personal health (Institute of Medicine 2005).

This article provides an important research contribution by providing insights into the relationship between health behavior and its potential linkage to dietary quality outcome measures, utilizing the case of nutritional supplements intake. Our objectives are to identify and quantify (1) determinants of nutritional supplements intake decisions (2) whether and to what extent supplement takers and non-takers differ with regard to diet-health outcomes (e.g. BMI) when differences in diet quality (HEI) are controlled for, and (3) whether and to what extent supplement takers and non-takers differ in diet quality (HEI) outcomes when differences in BMI are controlled for.

Previous studies acknowledge the interdependence of health behavior, dietary choices and health outcomes in terms of their short- and long-term public health impacts (e.g. Balluz et al. 2000; Rock 2007; Bailey et al. 2011; Gahche et al. 2011; Schroeter, Anders, and Carlson 2013; Irz et al. 2015). However, apart from a few exemptions (e.g. Drichoutis, Nayga, and Lazaridis 2005, 2009) the literature on diet-health and behavior typically neglects to incorporate explicit measures of diet or health or does not account for the possible endogeneity of the determinants of behavior. A common limitation is that key determinants of diet-health behavior such as socio-economic factors and unobserved heterogeneity may simultaneously influence individuals' behavior and the stock of diet-health. Consequently, empirical estimates of behavior and the effects of exogenous factors will be biased, potentially leading to misguided policy conclusions. Such bias can be avoided by treating direct measures of diet-health behavior as endogenous determinants of health outcomes and by adopting appropriate modelling procedures to avoid this endogeneity bias and related measurement error.

The analysis in this article builds on Schroeter, Anders, and Carlson (2013), to our knowledge the only study that incorporates health indicators and other lifestyle variables into the study of nutritional supplements intake and food quality. We expand on this topic using a more recent dataset from the 2007-2008 NHANES and updated 2010 Healthy Eating Index (HEI-2010) scores. To overcome the issues of endogeneity and measurement error resulting from the possible self-selection bias in the NHANES data, our approach employs Propensity Score Matching (PSM) estimators to determine the possible link between nutritional supplements intake, food quality and obesity outcomes. Nutritional supplements intake does not directly affect the BMI, yet, it might impact food quality choices, which may in turn influence the BMI.

PSM has emerged as a popular approach in the estimation of causal treatment effects in economic analyses. Given the reliance of the diet-health behavioral literature on cross-sectional observational data, such as NAHENS, the analysis of treatment effects is often complicated by non-linear relationships and limited dependent outcome variables that are possibly endogenous. Compared against established analytical techniques including fixed effects models (e.g. Gleason and Suitor 2003), Heckman-type switching regression modeling (Gould and Lin 1994), and difference-in-difference estimators (Bhatt 2014), PSM methods have been shown to be superior in eliminating the biases resulting from endogenous determinants and self-selection in ensuring the comparability of different groups in the process of outcome evaluations (Kim, Nayga, and Capps, 2001; Crown 2014).

From a policy standpoint, it is important to understand what factors drive consumers' compliance with nutritional recommendations (Irz et al. 2015) and what factors might impact an individual's decision to consume nutritional supplements as likely substitutes in meeting specific diet quality and health outcomes. Results from our study will help to develop a better understanding of the factors that impact nutritional supplements intake and lead to a more efficient and effective promotion of healthy food choices and targeted consumer health education.

Approach

Economists have long been interested in the study of the interdependencies between dietary choices, nutrition and health outcomes in terms of their short- and long-term impacts on diet patterns and public health outcomes (Variyam, Blaylock, and Smallwood 1999). Becker's model of investment in human capital (Becker 1992) and Grossman's seminal work on health capital (Grossman 1972 and 1999) formalize the process by which individuals are endowed with a certain stock of health that deteriorates over a person's lifetime (Kenkel 1995; Thornton 2002; Fayissa and Gutema 2005). The deterioration speed of a person's health status depends, among other things, on investments in health through certain health behaviors.

A diet that follows the recommendations of the 2010 DGAs could be considered as an investment into an individual's health stock and consuming the recommended amount of fresh fruits and vegetables as an investment in health. If an individual substitutes or complements the fruit and vegetable intake with nutritional supplements, the latter would constitute a similar investment in health capital, given that supplements may contribute to the overall utility derived from good health. Consumption choices such as smoking, alcohol intake, lack of exercise, and poor dietary patterns could accelerate the depletion rate of a person's health stock. The depletion of the health stock beyond a certain threshold is associated with a higher probability of early death.

There are many intertemporal utility functions that could serve as a theoretical model for our analysis, such as the one developed by Grossman (1972 and 1999). The empirical analyzes of individual's diet behavior in the context of specific health outcomes is typically complicated by potential endogeneity between key variables of interest and a measurement error resulting from self-selection bias, which is an issue often encountered in consumer survey studies. Due to potential misspecification errors, the use of ordinary least squares estimators (OLS) may lead to biased results (Grilli and Rampichini 2011). Instrumental variable estimators (IV) form a common econometric solution to minimize endogeneity. However, their application is often constrained by the availability of suitable instruments (Park and Davis 2001).

In this study, the nature of the NHANES data and the specific research questions make it even more difficult to find suitable instruments. For these reasons, common IV approaches are deemed less suitable. Propensity Score Matching (PSM), originally developed by Rosenbaum and Rubin (1983), has enjoyed increasing popularity in empirical studies of situations where the effect and outcome of a specific treatment is of interest (Black and Smith 2004; Caliendo and Kopeinig 2008; Drichoutis, Nayga, and Lazaridis 2009). In the economics literature, PSM has been employed to determine the effects of labor market and training courses on individual's wage earnings (Heckman, Ichimura, and Todd 1998; Lechner 1999; Dehejia and Wahba 2002). In health economics and food consumption studies, PSM methods have been utilized to analyze how consumers that were exposed to a particular treatment (e.g. food label usage) differed from those who reportedly did not receive the same treatment (Drichoutis, Nayga, and Lazaridis 2009; Abebaw, Fentie, and Kassa 2010; Campbell et al. 2011). In our study, PSM will account for the potential selection bias of the self-reported nutritional supplements intake and possible endogeneity of the supplement intake in the treatment outcome variable.

Theoretical Model

The rationale behind the PSM approach is to assess the effect of receiving treatment from a pool of treated and non-treated individuals. In this article, consumers who took nutritional supplements during the past 30 days will be referred to as the treatment group (supplement takers) and those who did not consume any supplements will form the control group (non-takers). The propensity score will describe the conditional probability of taking nutritional supplements, given equality in pre-treatment characteristics between both groups. This relationship can formally be expressed as:

$$p(X) \equiv Pr(D = 1|X) = E(D|X), \quad (1)$$

where D represents the intake of nutritional supplements (taker = 1, non-taker = 0), and X is a vector of pre-treatment characteristics (e.g. gender). If the health outcomes are $Y0i$

and $Y1i$ for non-takers and supplement takers, respectively, then the treatment effect for an individual 'i' can be written as:

(2) $$ti = Y1i - Y0i.$$

The propensity score can be estimated with any standard probability model. The population average treatment effect (ATE) and the average effect of treatment on the treated (ATT) are the two commonly cited parameters of interest in literature and are given by:

(3) $$\tau ATE = E(\tau) = E[Y(1) - Y(0)]$$

(4) $$\tau ATT = E(\tau | D = 1) = E[Y(1)|D = 1] - E[Y(0)|D = 1].$$

$Y(0)$ and $Y(1)$ are the two possible outcomes with and without supplement intake. The parameter of interest is the average treatment effect on the treated (ATT), because it gives the difference between expected outcome values of supplement takers and non-takers. Estimating the average treatment effect on the treated is only possible under certain assumptions, because the counterfactual is not observed. Several assumptions need to hold in order to obtain reliable treatment effects using PSM.

The first assumption is balancing the pre-treatment variables on a given propensity score (Becker and Ichino 2002; Caliendo and Kopeinig 2008; Drichoutis, Nayga, and Lazaridis 2009). Thus, for a given propensity score, nutritional supplements takers and non-takers are assumed to have closely matching distributions of observable characteristics X, irrespective of their treatment status. This ensures that treatment is random and takers and non-takers are observationally random.

(5) $$D \perp X \mid p(X),$$

where, *p(X)* is the propensity score. This implies that all variables that influence treatment assignment and potential outcomes simultaneously have to be observed by the researcher.

The next assumption is usually referred to as 'unconfoundedness' or 'conditional independence' assumption (CIA) (Rosenbaum and Rubin 1983; Becker and Ichino 2002; Caliendo and Kopeinig 2008).

(6) $$Y1,Y0 \perp D \mid p(X).$$

This assumption implies that potential outcomes are not dependent on treatment. In other words, variables that can affect both treatment and potential outcomes concurrently have to be observed by the researcher. Another assumption is that of 'overlap' (Becker and Ichino 2002; Caliendo and Kopeinig 2008) given as;

(7) $$0 < P(D = 1|X) < 1.$$

This assumption ensures that individuals with the same characteristics X (e.g. income level) are assumed to have an equal chance of being part of the treatment or control group. Once the above assumptions are satisfied, the propensity score of the ATT can then be estimated reliably.

Empirical Model

The analysis in this article employs data from the 2007-2008 National Health and Nutrition Examination Survey (NHANES) (Centers for Disease Control and Prevention (CDC) 2010). The NHANES is the primary national survey used to assess the health and nutritional status of the U.S. population. Participants in the NHANES are randomly selected civilian residents of the United States. The survey is divided into the physical examination, questionnaire and personal interview components. The interview is used to gather information on demographic, socioeconomic, nutritional, and health related issues. The physical examination component is generally used to conduct laboratory investigations (CDC 2010).

Data from various NHANES survey cycles has been used in a number of similar studies focused on individual's health behavior, food consumption choices, and a multitude of other economic and non-economic research questions (Balluz et al. 2000; Ervin, Wright, and Reed-Gillette 2004; Rock 2007; Bailey et al. 2011; Gahche et al. 2011; Schroeter, Anders, and Carlson 2013). For the purposes of the analysis in this article, only adult NHANES participants of at least 20 years were selected, as this sample typically makes their own food, diet or health behavioral (e.g. nutritional supplements intake) decisions.

From the large pool of available NHANES variables, we selected relevant variables of interest for the analysis from the following categories: nutritional supplements intake (treatment), diet quality and health indicators (outcomes), demographics, and various lifestyle determinants. The descriptive statistics of the data used in the analysis is as displayed in Appendix A. The empirical PSM selection model to be estimated is specified as:

(8) *Supplement = f(HEI , Diabetes, Blood pressure, Male, Age, White, Hispanic, Other race, Citizen, Household size, Married, Divorced, High school, Graduate, HHInc2, HHInc3, HHInc4, HHInc5, Food stamp, Smoker, Alcohol, Very active),*

where *Supplement* is a binary dependent variable that indicates that the individual has consumed nutritional supplements in the past 30 days.

The Healthy Eating Index (*HEI*) is a tool used to measure the diets of Americans against the DGAs. The HEI is composed of twelve sub-components such as HEI Total Fruits, HEI Total Vegetables, HEI Greens & Beans, which carry individual scores that add up to hundred to give the Total HEI. A higher HEI score indicates a diet of higher quality. Using the code written by Kahle and Buckman (2013), we computed the Healthy Eating Index-2010 (HEI-2010) for all NHANES participants in our sample.

With regard to the variables *Diabetes* and *Blood Pressure*, previous literature shows a controversial relationship between these health conditions and nutritional supplements intake. Some reports show no association while others have documented a negative impact (Lyle et al. 1998; Balluz et al. 2000; Satia-Abouta et al. 2003; Harrison et al. 2004).

Based on previous research, we expect supplement intake to be positively associated with *education*, *income*, *female*, *age* and *white* (Ervin, Wright, and Kennedy-Stephenson 1999; Fennell 2004; Garside et al. 2005; Petrovici and Ritson 2006; Bailey et al. 2011). Lifestyle factors such as *smoking*, *alcohol* intake, and an active lifestyle (e.g.

very active) are expected to have a negative relationship with nutritional supplements intake (Nayga and Reed 1999; Fennell 2004; Bailey et al. 2011). We anticipate that *food stamps* recipients might form an at-risk population and may need supplements to boost their diet quality.

An ad-hoc approach to the matching of individuals in order to achieve an optimal balancing of pre-treatment characteristics is unfeasible (e.g. Caliendo and Koepeinig 2008). Instead, our selection of variables in building the propensity score model in equation (8) is guided by economic theory and a sound assessment of previous relevant research. Accordingly, our first step of analysis involves the estimation of equation (8) to achieve the critical identification assumption of unconfoundedness (CIA), a necessary step for the unbiased estimation of treatment effects. The resulting balancing of covariate variables between treatment and control group members is then conveniently expressed in an individual's propensity score as a single-index variable input into the second-stage matching procedure. Matching algorithms commonly applied in PSM studies are: Nearest Neighbor, Caliper (Radius), Stratification and Kernel matching algorithms. The estimation of propensity scores and matching algorithms is performed using the psmatch2 package in Stata (Leuven and Sianesi 2015).

Results

A key feature of the propensity score matching approach is its ability to reduce the self-selection bias and resulting measurement error in treatment effects. In order to validate the quality of matching between nutritional supplements takers and the counterfactual group of non-takers, we perform Rubin's (1991) standard bias test (Table 1). By comparing the difference of the sample means in the treated and matched control sub-samples for each covariate, expressed as a percentage of the square root of the average of the sample variances in both groups, the test allows us to quantify the reduction in selection bias and the quality of the chosen covariate in the propensity score model. Examining the t-test results of unmatched and matched covariates reveals insignificant differences in the matched samples after the propensity score estimation. We also evaluate minor changes in our model specification. Our results are largely insensitive to alternative variables, with the visible exemptions of a few variables (e.g. HEI-Dairy). Overall, the results on matching quality imply that our propensity score specification is reliable and robust. Both propensity score model satisfy the balancing hypothesis (common support), allowing us to test whether nutritional supplement generate significant differences in our selected diet quality and obesity outcomes. In addition, Appendix B presents the mean value of the standard bias measure across the different matching algorithms. For the impact of supplement intake on NHANES participants' BMI, the mean standard bias before matching is roughly 12%. Propensity score matching is able to reduce this bias significantly for all matching algorithms to levels between 1.2% and 2.7%; a range generally considered reliable (Caliendo and Kopeinig 2008).

The focus of this article is to determine whether nutritional supplements takers differ from non-takers with regard to their health outcomes when controlling for differences in diet quality. Supplements are assumed to contribute to an individual's utility derived from good health and are inputs to the person's health production function.

The factors associated with diet-health behavior and specifically nutritional supplements intake decisions are diet quality, health indicators, demographics, and lifestyle. In order to identify and quantify the determinants of supplement intake decisions, the PSM model in (8) was estimated to match all the respondents on a wide range of variables. Table 2 shows the factors associated with the selection into the treatment group of supplement takers.

Table 3 indicates no relationship between health indicator variables and nutritional supplements intake. Previous literature shows mixed results with regard to supplement intake and the presence of a health condition like diabetes or high blood pressure. While some of the studies report that there is a negative relationship between supplement intake and *diabetes* and *blood pressure* (Satia-Abouta et al. 2003; Harrison et al. 2004), others conclude that there is no association between supplement intake and these conditions (Lyle et al. 1998; Balluz et al. 2000). In addition, we found no association between selection into the nutritional supplements intake group and all the components of the HEI-2010.

Table 3 shows that that with the exception of marital status and high school, all of the demographic factors are significant at explaining the probability of being selected into the treatment group. Demographic factors that positively affect the probability of taking nutritional supplements are *age*, *ethnicity*, a higher level of *education*, and a higher *household income*. These results conform to previous research (Ervin, Wright, and Kennedy-Stephenson 1999; Fennell 2004; Garside et al. 2005; Petrovici and Ritson 2006; Bailey et al. 2011; Dickinson and MacKay 2014). We find that *males* are 59% less likely to take nutritional supplements compared to their female counterparts. This finding confirms the results of previous studies (Nayga and Reed 1999; Fennell 2004; Bailey et al. 2011; Dickinson and MacKay 2014). The negative relationship between *male* and supplement intake suggests that females might be more concerned about diet behavior. Our findings suggest that ethnic heritage seems to play an important role in determining selection into the treatment group. In comparison to *African American* individuals, individuals of *other races* are more likely take nutritional supplements.

The negative effect of *household size* on nutritional supplements intake suggests that members of larger households may not consume supplements, given budgetary constraints (Nayga and Reed 1999). Consumers who completed a higher level of *education* may be in a more informed position to take control of their health. Participants who fall in the highest income group have the greatest propensity (69%) to take supplements, which suggests that nutritional supplements may be regarded as luxury goods.

Our results for the lifestyle category show that *food stamp* recipients are 22% less likely to take nutritional supplements compared to other respondents. Food stamps may not be used for the purchase of vitamins and supplements (USDA/FNS 2010). Our result suggests that nutritional supplements are not consumed by one important target group of at-risk consumers who may be in need of complementary supplementation with nutrients.

As has been commonly found in previous related literature (Nayga and Reed 1999; Ishihara et al. 2003; Harrison et al. 2004; Brownie 2005; Li et al. 2010; Schroeter, Anders, and Carlson 2013; Dickinson and MacKay 2014), *smokers* are 17% less likely to take nutritional supplements as compared to non-smokers. This negative relationship may indicate that *smokers* are less concerned about their health. However, we did not find any significant relationship between the heightened consumption of *alcohol* and taking nutritional supplements. Previous research shows that the health impact of alcohol on diet quality is ambiguous. Red wine in moderation has been linked to good health but drinking more than three alcoholic drinks per day has been shown to increase the likelihood of health problems (Klatsky 2010).

Individuals who exhibited active lifestyles are 49% more likely to take nutritional supplements. This is consistent with findings from previous literature (Lyle et al. 1998; Nayga and Reed 1999; Foote et al. 2003; Harrison et al. 2004; Reinert et al. 2007; Rock 2007; Li et al. 2010; Dickinson and MacKay 2014).

Analyzing Health Outcomes of Nutritional Supplements Consumers

In order to deepen the PSM analysis, we used different matching algorithms to build on the estimated PSM model in order to determine whether regular consumers of nutritional supplements may display improved health outcomes, as measured by their BMI. Thus, we aimed at quantifying whether and to what extent supplement takers and non-takers differ in BMI outcomes when variations in diet quality (HEI) are controlled for. We used the factors discussed in Table 2 to determine the selection into the treatment group. Table 4 shows the average ATTs applying different matching algorithms for the comparison of respondents in the nutritional supplements treatment group versus the control group.

The results in Table 4 show a clear distinction between nutritional supplements takers and non-takers in terms of their BMI. Our results suggest that that even though supplement intake is not significantly determined by the individual HEI components, it may have an impact on total diet quality and thus, BMI. The consistent outcome across all the matching algorithms is worth noting: Across the select matching algorithms, supplement takers have a lower BMI of more than 1 kg/(body height in m).[2]

The significant difference in BMI between nutritional supplements takers and non-takers is striking, because the components of the HEI-2010 did not have a significant effect on the selection into the treatment group. Our results expand the findings of previous studies that have found inconclusive results (Drichoutis, Nayga, and Lazaridis 2009). According to Kimmons et al. (2006) individuals who are obese or overweight are less likely to take nutritional supplements. Balluz et al. (2000) note that those who are overweight or obese may have a greater tendency to take supplements because they may be making weight loss attempts or are on a special diet that may include nutritional supplements.

Nutritional Supplements Intake and Diet Quality

In order to quantify whether and to what extent supplement takers and non-takers differ in diet quality (HEI) outcomes when differences in BMI are controlled for, we repeated the matching procedure while controlling for differences in BMI. Table 2 shows the determinants for selection into the treatment group of nutritional supplements taker. In addition to using the variables presented in Table 2, we added the variables *BMI* and *some college* into our model.

The introduction of another education variable resulted in all of the education variables becoming significant at explaining the selection into the treatment of group of being a nutritional supplements taker. *BMI* has a significant negative relationship on selection into the treatment group. Previous research has documented the negative relationship between BMI and nutritional supplements intake (Nayga and Reed 1999; Foote et al. 2003; Ishihara et al. 2003; Radimer et al. 2004; Garside et al. 2005; Kimmons et al. 2006; Reinert et al. 2007; Li et al. 2010; Bailey et al. 2011).

We calculated ATTs to determine whether significant differences exist between supplement takers and non-takers in terms of HEI. Furthermore, we selected three sub-component scores of the HEI-2010 (*HEI total*, *HEI Total Vegetables* and *HEI Total Fruits*) due to the known relationship between fruit and vegetables intake and obesity. Table 5 shows the results of the various matching algorithms.

For the nearest Neighbor matching method and stratification matching, we find a significant positive relationship between *HEI total* and nutritional supplements intake. Thus, the results indicate that supplement consumers have an overall higher diet quality as measured by their HEI total. The positive relationship between nutritional supplements intake and the HEI-2010 confirms the finding in Schroeter, Anders, and Carlson (2013) who used the HEI-2005 (see also Kennedy 2004).

Furthermore, Table 5 shows that consumers of dietary supplements have a higher score of *HEI Total Fruit* compared to respondents who do not take any supplements. For this HEI sub-component, supplement takers are statistically different from non-takers by about 0.01 units. This difference indicates that nutritional supplements takers eat more fruits than non-takers of supplements. We did not find any difference for the *HEI Vegetable*s between nutritional supplements takers and non-takers.

Conclusions

Our study shows that nutritional supplements intake decisions are affected by diet quality, health, demographic and lifestyle factors. This study also suggests a possible link between diet-health behavior (supplement intake) and obesity as measured by BMI. The results show that food stamp recipients and lower income households do not take supplements. These two groups may be at-risk groups who may need supplementation to meet some of their nutritional needs. These results suggest that at-risk populations who need to supplement their diets with supplement are not those currently taking them. On the other hand, individuals of normal weight (individuals with a lower BMI) and individuals who consume more fruits were found to hedge against health risks by frequently consuming nutritional supplements. One way to encourage consumption of nutritional supplements among at-risk groups would be to establish a health policy on consumption, especially with regards to fruits and vegetables and nutritional supplements, in order to target specific at-risk populations.

We find that nutritional supplements intake may have an effect on the overall diet quality of supplement consumers (HEI total), which may impact diet health outcome indicators such as BMI. Thus, consumers of diet supplements may have a lower BMI compared to non-takers. This study suggests a possible link between diet-health behavior and obesity. Given decreasing intakes of fruits and vegetables, it is important to determine the role of nutritional supplements on diet quality.

The results of the study suggest that several health indicators, demographics, and lifestyle variables significantly affect the selection into the treatment group of nutritional supplements takers. Nutritional supplements intake is positively associated with a significantly lower BMI of above 1kg/ (body height in meters)^2, when all other observable characteristics between supplement takers an non-takers are controlled for. We also found that supplement takers are likely to be white, highly educated, of higher household income, non-smokers and of overall higher health status. Nutritional supplements consumers differ from non-takers in terms of diet quality, measured by the HEI-2010.

Finally, given the increasing importance of individuals' dietary choices to consumer diet-health and public policy in the United States, accurate estimates of existing behaviors and their impacts on relevant health outcomes have become essential tools for the purpose of policy guidance. A key component in the quest for improving food policies is the proper treatment of the self-selection bias and resulting mismeasurement in working with cross-sectional observational data, such as NHANES. The econometric analysis carried out in this article contributes to the discussion regarding whether consuming supplements leads to positive diet-health outcomes. Appropriate econometric methods such as PSM can provide reliable insights into an individual's diet and health behavior, which will provide the prerequisite for effective and efficient public policies.

Our study contributes valuable insight towards more effective diet-health education and information campaigns. As such, the results in this study may be useful in guiding policy makers towards more targeted education on the consumption of a healthy diet.

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Tables and Figures

Table 1: Reduction in Self-selection Bias and Covariate Balancing

Variable	Unmatched /Matched	Treated	Control	% bias	% reduction bias	t-test
		Mean				
Diet Quality						
HEI-Total	U					
	M					
HEI-Total vegetables	U	3.153	3.151	3	44.9	1.05(0.29)
	M	3.153	3.154	-1.6		-0.56 (0.57)
HEI-Greens & beans	U	2.193	2.188	2.6	-6.2	0.91 (0.36)
	M	2.193	2.198	-2.7		-0.93 (0.35)
HEI-Total fruits	U	3.071	3.066	3.7	-5.7	1.3 (0.19)
	M	3.071	3.076	-3.9		-1.34 (0.18)
HEI-Whole fruits	U	4.107	4.099	3.6	-12	1.27 (0.2)
	M	4.107	4.115	-4		-1.38 (0.17)
HEI-Whole grain	U	1.952	1.949	3.2	69.4	1.14 (0.25)
	M	1.951	1.952	-1		-0.34 (0.74)
HEI-Dairy	U	5.575	5.576	-0.2	-3101.4	-0.07 (0.95)
	M	5.575	5.566	6		2.11 (0.04)
HEI-Seafood & plant protein	U	2.997	2.989	6.6	29.8	2.34 (0.02)
	M	2.997	3.003	-4.6		-1.59 (0.11)
HEI-Fatty acid ratio	U	3.965	3.964	1	-388	0.37 (0.71)
	M	3.965	3.97	-5		-1.72 (0.09)
HEI-Sodium	U	4.351	4.344	5.3	80.8	1.87 (0.06)
	M	4.351	4.349	1		0.35 (0.73)
HEI-Refined grains	U	6.78	6.772	96.3	64.9	2.24 (0.03)
	M	6.78	6.777	2.2		0.77 (0.44)
HEI-Empty calories	U	11.49	11.481	2.6	15.1	0.93 (0.35)
	M	11.49	11.498	-2.2		-0.76 (0.45)
Health Indicators						
Body mass index	U	28.685	29.299	-9.2	69.0	-3.26 (0.01)
	M	28.695	28.886	-2.9		-1.01 (0.31)
Diabetes	U	0.134	0.115	5.5	15	1.97 (0.05)
	M	0.133	0.149	-4.7		-1.54 (0.12)
Blood pressure	U	0.984	0.983	0.7	-90	0.25 (0.81)
	M	0.984	0.982	1.3		0.45 (0.65)
Demographics						
Male	U	0.4388	0.545	-21.4	97.2	-7.61 (0.00)
	M	0.439	0.436	0.6		0.2 (0.84)
Age	U	55.392	46.159	53.8	93.7	19.11 (0.00)
	M	55.383	55.968	-3.4		-1.16 (0.25)
White	U	0.558	0.401	31.9	100	11.33 (0.00)
	M	0.558	0.558	0		0 (1.0)
Hispanic	U	0.099	0.119	-6.7	85.7	-2.38 (0.02)
	M	0.099	0.098	0.3		0.1 (0.92)
Other race	U	0.171	0.248	-18.8	85.7	-6.66 (0.00)
	M	0.171	0.182	-2.7		-0.99 (0.32)
Citizen	U	0.925	0.828	30	97.4	10.55 (0.00)
	M	0.925	0.928	-0.8		-0.33 (0.74)
High school	U	0.233	0.257	-5.6	52.8	-1.98 (0.05)

	M	0.232	0.221	2.6		0.93 (0.3)
Graduate	U	0.254	0.133	31.2	94.8	11.16 (0.00)
	M	0.254	0.248	1.6		0.5 (0.62)
Married	U	0.624	0.584	8.1	80	2.89 (0.00)
	M	0.624	0.616	1.6		0.57 (0.57)
Divorced	U	0.259	0.209	11.8	73.9	4.19 (0.00)
	M	0.259	0.272	-3.1		-1.02 (0.31)
Household size	U	2.79	3.399	-37.7	95	-13.35 (0.00)
	M	2.791	2.822	-1.9		-0.7 (0.48)
HHInc2	U	0.217	0.229	-3	47.1	-1.08 (0.00)
	M	0.217	0.224	-1.6		-0.56 (0.58)
HHInc3	U	0.194	0.191	0.7	69.4	0.25 (0.81)
	M	0.194	0.193	0.2		0.07 (0.94)
HHInc4	U	0.099	0.077	7.8	84.7	2.76 (0.01)
	M	0.099	0.11	-1.2		-0.38 (0.7)
HHInc5	U	0.166	0.091	22.5	93.8	8.05 (0.00)
	M	0.165	0.161	1.4		0.43 (0.66)
			Lifestyle			
Food stamps	U	0.172	0.305	-28.3	90.2	-9.97 (0.00)
	M	0.172	0.185	-2.8		-1.14 (0.25)
Smoker	U	0.457	0.513	-10.3	99.3	-3.63 (0.00)
	M	0.457	0.456	0.1		0.03 (0.98)
Alcohol	U	0.706	0.719	-2.5	9.1	-0.9 (0.37)
	M	0.705	0.694	2.3		0.8 (0.42)
Very active	U	0.208	0.184	5.7	-7.9	2.04 (0.04)
	M	0.204	0.178	6.2		2.25 (0.03)

Table 2: Determinants of Dietary Supplement Intake

Variables (Y= Supplement)	**Coefficients**	**Standard Error**
	Diet Quality	
HEI-Total vegetables	-0.282	2.906
HEI-Greens & beans	0.122	0.955
HEI-Total fruits	0.840	1.206
HEI-Whole fruits	-0.957	0.743
HEI-Whole grain	0.689	2.088
HEI-Dairy	-0.511	0.745
HEI- Seafood & plant protein	-0.383	0.571
HEI- Fatty Acid Ratio	-0.617	0.851
HEI-Sodium	0.658	0.528
HEI-Refined grains	0.727	0.537
HEI-SoFAAS calories	0.117	0.480
	Health indicators	
Diabetes	-0.026	0.094
Blood pressure	-0.189	0.243
	Demographics	
Male	-0.590***	0.066
Age	0.032***	0.002
White	0.444***	0.084
Hispanic	0.336***	0.119
Other race	0.230**	0.104
Citizen	0.458***	0.113
Household size	-0.090***	0.023
Married	0.113	0.096
Divorced	0.018	0.112
High school	-0.032*	0.075
Graduate	0.403***	0.088
HHInc2	0.202**	0.084
HHInc3	0.324***	0.091
HHInc4	0.488***	0.120
HHInc5	0.694***	0.112
	Lifestyle	
Food stamps	-0.218***	0.076
Smoker	-0.165***	0.063
Alcohol	0.101	0.065
Very active	0.491***	0.085
Constant	-6.458	5.966
Number of observations	5,063	
Log-likelihood	-3102.18	
Pseudo R^2	0.114	

***, **, and * indicate significance at the 99%, 95%, and 90% level. The common support criterion was imposed to assure maximum overlap between propensity scores of control and supplement taker group (Heckman et al 1998).

Table 3: Determinants of Selection into Dietary Supplement Intake Group

Variables (Y= Supplement)	**Coefficients**	**Standard Error**
	Health indicators	
BMI	-.0136***	0.005
Diabetes	0.0522	0.097
Blood pressure	-0.210	0.243
	Demographics	
Male	-0.580***	0.0661
Age	0.0348***	0.002
White	0.399****	0.084
Hispanic	0.342***	0.120
Other race	0.262**	0.105
Citizen	0.340***	0.114
Household size	-0.0749***	0.023
Married	0.115	0.097
Divorced	0.0129	0.113
High school	0.333***	0.088
Some college	0.708***	0.089
Graduate	0.823***	0.104
HHInc2	0.157*	0.085
HHInc3	0.239***	0.092
HHInc4	0.378***	0.122
HHInc5	0.571***	0.114
	Lifestyle variables	
Food stamps	-0.161**	0.074
Smoker	0.399***	0.084
Alcohol	0.0920	0.065
Very active	0.440***	0.086
Constant	-2.080***	0.347
Number of observations	5063	
Log-likelihood	-3072.87	
Pseudo R^2	0.122	

***, **, and * indicate significance at the 99%, 95%, and 90% level. The common support criterion was imposed to assure maximum overlap between propensity scores of control and supplement taker group (Heckman et al 1998).

Table 4: Average Effect of Treatment on the Treated (ATT) for Dietary Supplement Intake on BMI

Matching Algorithm	**Coefficient**	**Standard Error**
Nearest Neighbor Matching	-1.480***	0.316
Radius Matching (r= 0.1)	-1.150***	0.221
Radius Matching (r= 0.001)	-1.234***	0.238
Kernel Matching	-1.141***	0.210
Stratification Matching	-1.071***	0.237

Note: ***, **, and * indicate significance at the 99%, 95%, and 90% level (Standard errors in parentheses). Bootstrapped standard errors of ATT estimates using 100 repetitions.

Table 5: Average Effect of Treatment on the Treated (ATT) for Dietary Supplement Intake on Healthy Eating Index (HEI) and select subcomponents

	Nearest Neighbor Matching	**Radius Matching** (R=0.1)	(R=0.001)	**Kernel Matching**	**Stratification Matching**
HEI total	0.0813*	0.0341	0.0432	0.0514	0.0596*
	(0.048)	(0.035)	(0.041)	(0.034)	(0.035)
HEI total vegetables	0.0047	0.0013	0.0019	0.0023	0.0029
	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)
HEI total fruits	0.0125*	0.0072*	0.0090*	0.0092**	0.0103***
	(0.007)	(0.004)	(0.005)	(0.004)	(0.003)
HEI sofaas calories					

Note: ***, **, and * indicate significance at the 99%, 95%, and 90% level (Standard errors in parentheses). Bootstrapped standard errors of ATT estimates using 100 repetitions.

Supporting Material

Table A: Descriptive Statistics of Variables

Variable	Description	Suppl=1 Mean (St.dev.)	Suppl=0 Mean (St.dev.)
	Dietary supplement intake		
Supplement	= 1 if respondent has taken any dietary supplements in the past 30days	1 (0)	0 (0)
	Diet Quality		
HEI Total	Total Healthy Eating Index 2010 (HEI-2010)	54.63 (1.08)	54.58 (1.09)
HEI-Total vegetables	HEI-2010 for total vegetable	3.15 (0.08)	3.15 (0.08)
HEI green beans	HEI-2010 for greens and beans	2.19 (0.19)	2.19 (0.19)
HEI total fruit	HEI-2010 for total fruit	3.07 (0.14)	3.07 (0.15)
HEI whole fruit	HEI-2010 for total whole fruit	4.11 (0.21)	4.10 (0.22)
HEI whole grains	HEI-2010 for total whole grains	1.95 (0.09)	1.95 (0.09)
HEI dairy	HEI-2010 for total dairy	5.58 (0.15)	5.58 (0.15)
HEI SFPP	HEI-2010 for total seafood and plant proteins	3.00 (0.13)	2.99 (0.12)
HEI far	HEI-2010 for total fatty acid ratio	3.97 (0.11)	3.96 (0.11)
HEI na	HEI-2010 for total sodium	4.35 (0.13)	4.35 (0.13)
HEI rg	HEI-2010 for total refined grains	6.78 (0.13)	6.77 (0.13)
HEI sc	HEI-2010 for total empty calories	11.49 (0.35)	11.48 (0.36)
	Health indicators		
Body Mass Index	=Weight (kg)/ $(\text{Height (m)})^2$	28.64 (6.37)	29.25 (6.90)
Diabetes	=1 if respondent has been told by doctor or health professional to have diabetes	0.13 (0.34)	0.12 (0.32)
Blood pressure	=1 if respondent has been told by doctor or health professional to have high blood pressure	0.96 (0.19)	0.95 (0.22)
	Demographics		
Male	=1 if respondent is male	0.44 (0.50)	0.54 (0.50)
Age	Age of respondent in years	55.26 (17.18)	46.16 (17.25)
White	=1 if respondent is non-Hispanic white	0.55 (0.50)	0.39 (0.49)
Black	1 if respondent is non-Hispanic Black	0.17 (0.38)	0.23 (0.42)
Hispanic	=1 if respondent is Hispanic	0.10 (0.30)	0.12 (0.33)

Other race	=1 if respondent is none of the races above	0.17 (0.38)	0.25 (0.43)
Citizen	=1 if respondent was born in the USA	0.92 (0.27)	0.82 (0.38)
Household size	Total number of individuals in household	2.81 (1.53)	3.42 (1.72)
Married	1 if respondent is married/common law	0.62 (0.49)	0.58 (0.49)
Divorced	=1 if respondent is divorced or separated	0.26 (0.44)	0.21 (0.41)
Single	=1 if respondent is single/never married	0.12 (0.33)	0.21 (0.41)
High school	=1 if respondent went to high school	0.23 (0.42)	0.26 (0.44)
Some college	=1 if respondent went to some college	0.29 (0.45)	0.23 (0.42)
Graduate	=1 if respondent graduated from college and above	0.25 (0.44)	0.13 (0.33)
HHInc1	=1 if annual household income 0.35(0.48) is between $0-$24,999	0.30 (0.46)	0.39 (0.49)
HHInc2	=1 if annual household income is between $25000-$49,999	0.21 (0.41)	0.22 (0.42)
HHInc3	=1 if annual household income is between $50,000 - $ 74,999	0.19 (0.39)	0.18 (0.39)
HHInc4	1 if annual household income between $75,000 - $ 99,999	0.10 (0.30)	0.08 (0.26)
HHInc5	1 if annual household income is $100,000 and over	0.17 (0.37)	0.09 (0.28)
	Lifestyle		
Food stamp	1 if respondent has ever received food-stamps	0.17 (0.40)	0.31 (0.54)
Smoker	=1 if respondent has smoked at least 100 cigarettes in entire life and is currently smoking	0.45 (0.51)	0.51 (0.60)
Alcohol	Alcohol =1 if respondent has consumed at least 12 alcoholic beverages in last year	0.70 (0.55)	0.72 (0.48)
Very active	=1 if respondent's self-rated daily activity is very vigorous	0.17 (0.37)	0.22 (0.41)

Note: Descriptive statistics based on unmatched HNHANES sample data.

Table B: Standard Bias for different matching algorithms

Before matching	
Mean absolute bias	11.9
Pseudo R^2	0.114
LR χ^2 (p-value)	797.31 (0.00)
Nearest Neighbor	
Mean absolute bias	1.6
Pseudo R^2	0.002
LR χ^2 (p-value)	12.83 (0.999)
Radius caliper (0.1)	
Mean absolute bias	2.2
Pseudo R^2	0.002
LR $\chi2$ (p-value)	13.41 (0.921)
Radius caliper (0.001)	
Mean absolute bias	1.3
Pseudo R^2	0.001
LR $\chi2$ (p-value)	6.44 (0.999)
Kernel	
Mean absolute bias	1.2
Pseudo R^2	0.001
LR χ^2 (p-value)	7.37 (1.00)
Stratification	
Mean absolute bias	2.7
Pseudo R2	0.013
LR $\chi2$ (p-value)	82.91 (0.000)