Journal of Agricultural and Resource Economics 49(3):514–528 ISSN: 1068-5502 (Print); 2327-8285 (Online)

doi: 10.22004/ag.econ.342182

Health News Environment and the Distribution of Diet Quality

Yizao Liu, Rebecca Cleary, and Andrea Carlson

This article investigates the relationship between the health news environment and the healthfulness of consumers' food purchases. We estimate an unconditional quantile regression model using household-level purchase data from 2015–2018 and find that more health information is associated with a better diet. The relationship is slightly stronger at the lowest quantile of the Healthy Eating Index distribution, although we cannot reject equivalence with the estimate at the mean for most quantiles. Further, the association between health information and diet quality is weaker in households with higher education, implying that high education households are less likely to be affected by media information.

Key words: health information, Healthy Eating Index (HEI), IRI Consumer Network Data, Purchase to Plate Crosswalk (PPC), unconditional quantile regression

Introduction

Improving diet quality or healthfulness has long been a target of public health policy because of its direct impact on human health. Various factors, policies, and interventions to improve diet quality have been discussed, including providing better access to a healthy food environment (Volpe, Okrent, and Leibtag, 2013; Allcott et al., 2019), nutrition and income assistance programs such as SNAP (Hastings, Kessler, and Shapiro, 2021; Katare, Binkley, and Chen, 2021), school food programs (Smith, 2017; Cleary et al., 2021), nutrition labels (Buyuktuncer et al., 2018; Christoph and An, 2018), and food reformulations (Alé-Chilet and Moshary, 2022). One possible factor that might affect diet quality is media exposure to health and nutrition information, including media stories. In 2020, US adults spent an average of 13 hours per day using a combination of various media, including internet, television, radio, and magazines (eMarketer, 2021). Media stories on television, radio, newspapers, especially online health information, have further resulted in more consumers actively searching for and acquiring health knowledge from online sources (Diviani et al., 2015). By providing a very low-cost way for consumers to receive health information, exposure to mass media may have a considerable impact on consumers' awareness of the importance of a healthy diet and food choices.

Lower information costs tend to increase the probability that heterogeneous consumers will choose healthier food products (Zhu, Lopez, and Liu, 2016). Consumers may learn about the importance of a healthy diet and how to eat healthier over time from media health information (Smed, 2012) and make healthier food choices. However, today's consumers are also surrounded by

Yizao Liu (corresponding author, yul459@psu.edu) is an associate professor in the Department of Agricultural Economics, Rural Sociology, and Education at the Pennsylvania State University. Rebecca Cleary is an assistant professor in the Department of Agricultural and Resource Economics at Colorado State University. Andrea Carlson is an economist in the US Department of Agriculture Economic Research Service.

The findings and conclusions in this manuscript are those of the authors and should not be construed to represent any official USDA or US Government determination or policy. The analyses, findings, and conclusions expressed in this study also should not be attributed to Circana/Information Resources, Inc. (IRI).

Review coordinated by Jeffrey J. Reimer.

an overwhelming amount of information about health and diet from different sources, including healthcare providers, news coverage on new health findings, food advertisements, and word-of-mouth among consumers. Sometimes, the health information is confusing and conflicting, sending contradictory messages about health benefits of certain foods, eating behaviors, or nutrition information (Im and Huh, 2017). Consequently, confused consumers may be less likely to comply with expert nutrition and health advice, even when there is no ambiguity that compliance will lower health risks (Nagler, 2014). Overall, the net impact of health information on consumers' diet quality is still uncertain and needs to be empirically examined.

Health information plays an important role in public health. Many healthcare professionals, organizations, and governments use health campaigns to raise awareness, promote healthy diets, encourage healthy behaviors, and curb harmful behaviors. For example, former First Lady Michelle Obama started a health promotion campaign, "Let's Move," in 2010 to provide families access to health education and foster healthier environments to reduce the rates of childhood obesity. Both traditional and online media outlets provided extensive coverage on the First Lady's engagements during the campaign, reaching a much wider audience (Andersen, Wylie, and Brank, 2017). In 2017, MTV ran a campaign on World AIDS Day to encourage young people to get tested for HIV, which received 1.2 million hits in 5 hours and became the number one trending topic in 9 minutes (Butteriss and Bradley, 2019). While a successful campaign typically aims to expose a high proportion of a large population to health messages through media, the knowledge of the direction and magnitude of the impact of health information is of critical importance for policy makers when evaluating the true effectiveness of a health campaign.

This article investigates the relationship between health information from the media and the healthfulness of consumers' retail food purchases. We measure the amount of health- and diet-related information available to consumers using the number of media stories on newspapers, magazines, television, radio, and online sources covering healthy diets collected from the NexisUni database. The healthfulness of food purchases is measured by the 2015 Healthy Eating Index (HEI-2015), a validated index of dietary quality measuring adherence to key recommendations in the *Dietary Guidelines for Americans 2015–2020* (DGA-2015). We use household-level retail food purchase data from 2015–2018 matched to USDA nutrition data (Carlson et al., 2019) to estimate the HEI-2015 based on food-at-home purchases for each household. We estimate a panel unconditional quantile regression model of household diet quality to investigate across the distribution of diet quality, as the tails of diet quality are clinically important. Those with the poorest diet quality are more at risk for diet-related chronic diseases (e.g., hypertension, diabetes, and cardiovascular disease) as well as more limited mobility than those with higher quality diets.

Recent literature has shown that many consumers use media information as an important primary source of information on health-related decisions, including dietary choices (Verbeke, 2008) and health care choices (Beck et al., 2014; Suenaga and Vicente, 2022). A number of previous studies have examined the effect of media information by focusing on public information campaigns, published scientific articles, or mass media stories on consumer demand in specific food categories, such as shell eggs (Brown and Schrader, 1990), meat and fish (Tonsor, Mintert, and Schroeder, 2010), fruits and vegetables (Smed, 2012), and bottled water (Huang and Liu, 2017). Most of these studies find that information about the long-term health effects of dietary choices may have small effects on food demand. Information about food safety issues—including high-risk, low-probability events such as food scares—are in some cases found to have larger effects on consumption (e.g., Liu, Lien, and Asche, 2016; Rieger, Kuhlgatz, and Anders, 2016). Unlike previous literature, this article focuses on the overall healthfulness of all retail food purchases and calculates the household's monthly HEI score over time. In contrast to isolated food groups, the collective assessment of households' overall food purchases yields a reasonably accurate estimate of their general diet quality. This approach considers the role of health information more comprehensively, accounting for possible consumer substitution across various food groups.

A number of empirical studies have found heterogeneity in consumer behavior in the search and use of health information, depending on consumer demographics and health status (Campos, Doxey, and Hammond, 2011) or risk perceptions and risk attitudes (Yang and Goddard, 2011). Other studies have investigated the heterogeneous demand reaction to health news (Smed, 2012). Browning, Hansen, and Smed (2019) examine the dynamic consumers responses and find that the short- and long-run information impacts vary across individual households. In line with the previous literature, this article further examines the heterogeneous impact of health news across households with different education levels.

We find that more health information in the media is associated with healthier food purchases. There is a slightly stronger link between health information and diet quality at the lowest quantiles of the HEI distribution, although we cannot reject equivalence with the estimate at the mean across most quantiles. For households with very unhealthy food purchases, providing more health information is associated with a larger increase in diet quality compared to households in the middle and upper quantiles of the HEI distribution. We also find that the association between health information and the healthfulness of food purchases is weaker in households with higher education, suggesting that high-education households may be less likely to be affected by media information. These findings suggest that current media campaigns aimed to increase the number of accurate media stories on nutrition and healthy diets might be effective in encouraging the purchases of healthier food and beverages but may be slightly more effective for households with the least healthy retail food purchases. Public campaigns may want to consider improving information accuracy, particularly over health-related news and information, where misinformation tends to proliferate. Further, there is the potential for tailoring targeted media campaigns to appeal more effectively to communities with lower levels of education and higher rates of unhealthy food purchases. However, further research is necessary to determine the specific focus and effectiveness of these initiatives in promoting healthier food choices across diverse demographic segments.

Data

The 2015–2018 IRI Consumer Network Panel (IRI-CNP) and the Purchase-to-Plate Crosswalk (PPC) released by USDA Economics Research Service are the core data for our analysis. The IRI-CNP data contain demographic information for a sample of US households and record all households' retail purchases of food for at-home consumption at the barcode level, including quantities, prices, discounts, and coupons.[1] Households are incentivized to record all of their barcoded purchases using a handheld, in-home scanning device. Our final sample includes over 90,000 households that belong to the "static panel" of households that reliably scan their purchases throughout the year and which have assigned sample weights to result in nationally representative consumer purchases.[2]

While the IRI data include some nutrition data, they are not sufficient. We import data from the USDA's Food and Nutrient Database for Dietary Studies (FNDDS) (Martin et al., 2014) and Food Pattern Equivalent Database (FPED) (Bowman et al., 2014) via the Purchase-to-Plate Crosswalk (PPC) (Carlson et al., 2019). The crosswalk includes a linking database that links over 95% of individual items purchased by IRI-CNP participants to the USDA databases and conversion factors which convert the purchase weight to the edible weight. The edible weight is used in the USDA nutrition data and represents the weight of the food after the inedible parts (e.g., skins, bones, seeds, and shells) are removed.

Similar to other studies employing household scanner data to assess nutritional quality (Hastings, Kessler, and Shapiro, 2021), the IRI-CNP data confront certain limitations. They do not include food intended for consumption away from home, such as in restaurants or schools. Additionally, the data

[1] Foods purchased from restaurants, fast food, delis and other establishments where the primary food sold is prepared food are not included in the IRI data.

[2] The number of households in the "static panel" varies by month.

primarily capture purchases of packaged items with barcodes, omitting random-weight products.[3] As household purchase data, we cannot identify the dietary intake of individual household members or ensure equitable product allocation within households. Recent studies, however, indicate that household food purchases offer a reasonably accurate estimate of overall diet quality (Vepsäläinen et al., 2022).

Healthy Eating Index-2015

The HEI-2015 is an index of adherence to key recommendations in the DGA-2015, with scores ranging from 0 to 100, with 100 representing a diet that perfectly adheres to the recommendations. Since we use the scores in a regression analysis, we calculate household-level HEI-2015 scores for each household in a month. While the HEI was originally designed to use with dietary intake data, it has been used with food availability (Miller et al., 2015), household food acquisition (Mancino et al., 2018), and retail scanner data (Carlson et al., 2019). Our HEI scores are based on household retail food purchases similar to Chrisinger et al. (2018), except that our HEI scores are calculated on the monthly level rather than for each purchase occasion. In general, household food purchase data has been shown to be consistent with overall diet quality measures from recalls but may differ on specific nutrient intake. For this reason, we limit our investigation to the total HEI score and do not analyze the individual HEI components separately.

Table 1 presents the weighted descriptive statistics. In our sample, the mean monthly HEI-2015 is 49.95, which is lower than estimates based on a simple average of individual scores using dietary recall data (54) or FoodAPS data for large grocery stores (52) (Mancino et al., 2018). Sweitzer et al. (2017) find that expenditures in the IRI-CNP are lower than in the Consumer Expenditure survey and the National Food Acquisition and Purchase Survey (FoodAPS). Higher income and larger households were more likely to underreport than other households. Underreporting is particularly apparent for produce, eggs, seafood, and processed vegetables. More importantly, the PPC only covers about half of produce purchases made by IRI-CNP participants because participants do not record quantities for random-weight items. Since fruits and vegetables comprise 20% of the HEI-2015 score, underreporting of produce and processed fruits and vegetables—as well as not being able to include almost half of produce sales in the HEI estimate—are likely the main reason for differences between our estimates and others.

A Measure of Health Information in the Media

Consumers' knowledge of the healthy diet and nutritional information might be affected by information provided by mass media. To measure the amount of health and diet related information available to consumers, we use the NexisUni database to search for media stories covering healthy diets. The database—the world's largest electronic database for legal and public-records–related information—provides access to over 15,000 news, business, and legal sources. We consider newspapers, magazines, television, radio, and online sources in our study. Specifically, we searched for all media stories that contained keywords in three categories related to the topic of health and diet: (i) healthy diets, healthy food, healthy dinner, healthy lunch, healthy breakfast, healthy eating, healthful diet, healthy snack; (ii) MyPlate, food pyramid, food group, my pyramid; (iii) weight loss, diet plan, diet recommendation. We use the total number of media stories in each month in a state as proxies for the amount of information available to consumers.

Table 1 reports the summary statistics for media coverage data. On average, in each month there are 2,596 media stories covering health information related to diet. Figure 1 presents how media coverage changed over our sample period. Overall, the amount of health information is relatively stable, with the numbers being slightly higher in 2015 and 2016.

[3] Random-weight items are foods that consumers or stores package themselves, such as loose fruits and vegetables, granola, or bulk coffee beans.

Table 1. Summary Statistics, Estimated Using Survey Weights (N = 2,906,400)

	All Sample	
Variable	**Mean**	**S.D.**
Household HEI-2015 of retail food purchases	49.9515	12.3185
Health news	2,596.3800	388.2719
Education		
Less than high school	0.0031	0.0558
High school	0.1759	0.3807
College	0.6195	0.4855
Postgraduate	0.2015	0.4011
Race and ethnicity		
Hispanic	0.0769	0.2664
White	0.7613	0.4263
Black	0.1214	0.3266
Asian	0.0433	0.2036
Other races	0.0739	0.2617
Income ($thousands)	74.1706	55.0340
Employed part-time	0.2210	0.4149
Employed full-time	0.6251	0.4841
Presence of children	0.3237	0.4679
Household size	2.5544	1.4533
Q1: Jan, Feb, March	0.2489	0.4324
Q2: April, May, June	0.2520	0.4342
Q3: July, Aug, Sept	0.2510	0.4336
Q4: Oct, Nov, Dec	0.2480	0.4319

Notes: State summary statistics are not available to maintain confidentiality of the data. The households are weighted using the projection factors.
Source: Author estimates using data from NexisUni; the IRI Consumer Network, 2015–2018; USDA's Food and Nutrient Database for Dietary Studies, Food Pattern Equivalent Database; and the Purchase to Plate Crosswalk.

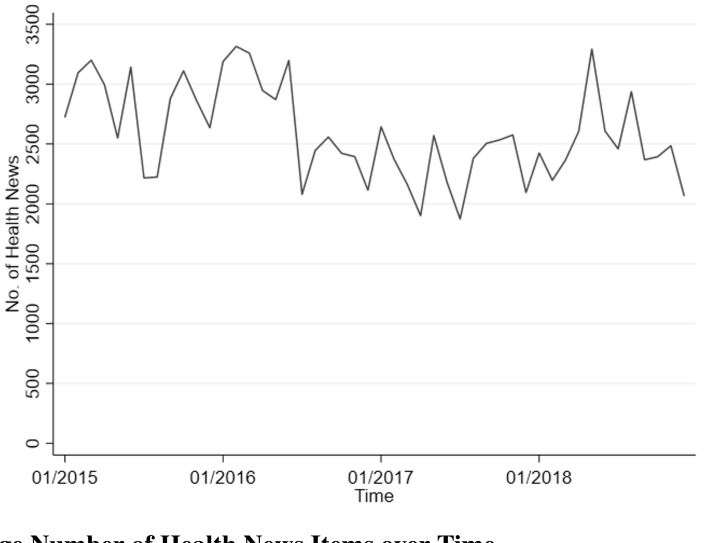

Figure 1. Average Number of Health News Items over Time
Source: Author estimates using NexisUni Data.

Other Covariates

Demographic information of households is included into our analysis to evaluate the heterogeneous effects of health information across education level. Table 1 also reports these weighted summary statistics.[4] Education has been found to be positively associated with dietary quality, and we include indicators for household education levels. To control for differences in income, we include the midpoints of the eight income brackets included in the IRI-CNP data; the weighted median income in our sample is $74,170. From our base data, we also include household size; the average household size in our sample is 2.55. Household composition also has a link with dietary quality, and we include a dummy variable for children, equal to 1 if there is at least one child under the age of 18 in the household and 0 otherwise. On average, 32% of households in the sample report having children. Employment type may also impact the time that households have available to purchase and prepare healthful; we include indicators for full- and part-time employment of the household head(s) (the excluded group is not employed). We include indicators for the race (White, Black, Asian, other, or mixed) and ethnicity (Hispanic) of the principal survey respondent because dietary quality can differ by race and ethnicity. We also include market and seasonal (calendar quarters) indicators to control for purchase differences across space and that vary within the year. These sociodemographic indicators also control for different levels of underreporting by IRI-CNP households.

Model

Econometric Approach and Specification

To determine the impact of media stories on different quantiles of diet quality, we utilize the unconditional quantile regression (UQR) approach proposed by Firpo, Fortin, and Lemieux (2009). UQR offers several distinct advantages over the conditional quantile (CQR) approach, namely that the UQR measures the unconditional association of health information in the media on household diet quality and does not depend on the covariates available or their specific values. The primary advantage of the UQR approach is that the estimated coefficient of the UQR measures the association of health news stories on household diet quality *unconditional* on the presence or specific values of the covariates. In contrast, the estimated coefficients of the CQR measure the association of the number of health news stories on a quantile of household diet quality conditional on the specific values of the other covariates, and the interpretation of the estimated association is limited, particularly in the presence of multiple covariates (Borah and Basu, 2013). In policy analysis, the unconditional relationship between the covariates and household diet quality is often relevant. UQR is therefore recommended when addressing questions of policy relevance (e.g., the association of the health news story environment and household diet quality Borah and Basu, 2013).[5] This UQR approach has been used to provide policy recommendations in a food and/or health context to measure medication adherence (Borah and Basu, 2013), the relationship between income and health biomarkers (Carrieri and Jones, 2017), and the relationship between BMI and food label use (Bonanno et al., 2018).

We assume a simple linear relationship between the healthfulness of household h's retail food purchases in market *m* at time *t*, H_{hmt}, and the amount of health information in the media in market m where the household lives at time *t*, $INFO_{mt}$. The one-period lag of the health information, $INFO_{m,t-1}$, is also included in the model to capture the potential carryover effect of health information that may last more than one period. Most households stay multiple years in the IRI-CNP. To incorporate the panel feature of our data, we conduct a panel UQR regression with the household fixed effects. The relationship is given in the following expression:

[4] Demographic information is collected on a yearly basis by IRI. Demographics that change within the year (e.g., births, deaths, moves) will only be reflected when IRI distributes their annual survey.

[5] For a complete discussion on the differences between conditional mean, conditional quantile, and unconditional quantile estimation, see Borah and Basu (2013).

$$(1) \qquad H_{hmt} = \beta_0 + \beta_1 INFO_{mt} + \beta_2 INFO_{m,t-1} + \boldsymbol{Season}_t + \boldsymbol{Market}_h + \boldsymbol{HH}_h + e_h,$$

where β is a conformable vector of parameters to be estimated and e_h is an error term. ***Season*** and ***Market*** are vectors of dummy variables for seasonality and market, and $\boldsymbol{HH_h}$ denotes the household fixed effects.

To estimate the panel UQR specified in equation (1), we employ the recentered influence function (RIF) method introduced by Firpo, Fortin, and Lemieux (2009). The RIF summarizes the impact of an individual observation on a given quantile of household diet quality. Firpo, Fortin, and Lemieux's method uses RIFs to estimate unconditional partial effects of infinitesimal changes in the distribution of the covariates on a given quantile of household diet quality. We follow Firpo, Fortin, and Lemieux and assume a linear relationship between the RIF of a given quantile of household diet quality and the covariates. Under the assumption of linearity, we can use ordinary least squares (OLS) to capture how marginal changes in the distribution of the covariates affects a given quantile of household diet quality. However, instead of using the τth quantile of household diet quality, q_τ, as the dependent variable, we use its RIF, and the expectation of the RIF regression function for the household can be specified as

$$(2) \quad E\left[RIF\left(H_{hmt}; q_\tau \mid X\right)\right] = \beta_0 + \beta_1 INFO_{mt} + \beta_2 INFO_{m,t-1} + \boldsymbol{Season}_t + \boldsymbol{Market}_h + \boldsymbol{HH}_h + e_h,$$

where X includes $INFO_{mt}$, $INFO_{m,t\text{-}1}$, $\boldsymbol{Season}_t$, $\boldsymbol{Market}_h$, and $\boldsymbol{HH}_h$. The parameter estimates can be interpreted as the unconditional marginal effects at each quantile. We employ the RIF algorithm developed by Firpo, Fortin, and Lemieux (2009) within the Stata 18 framework.

Identification

There are potentially two types of endogeneity related to health news stories. It is worth noting that our health information is collected at the aggregate state level. That is, we only know how many pieces of health news stories are available to all consumers in a state in a month but not the individual reception (consumption) of health news stories. In addition, our measure of the information volume may not include all the information that a consumer could receive, and not all consumers are exposed to the health information. The individual reception of the health news stories might depend on individual subscriptions to media sources, which may vary across household demographics. Although the arrival of news is exogenous to individual consumers when making food-related decisions, with the use of the state-level health news environment, there might be a potential concern of endogeneity in the sense that there might be more health news in states with higher levels of health and income. To alleviate this concern, we use the average obesity rate and average income at the state and annual level as instruments for the number of health news pieces. It is less likely that a household's HEI will be affected directly by the state average. We use a control function approach to estimate the unconditional quantile regression models with instruments. Our conducted endogeneity test affirms its presence, and the instrument tests support the statistical validity of our chosen instruments.

However, it is crucial to note that this analysis faces additional sources of endogeneity. The ways in which individuals receive and respond to information can vary significantly. Some households may be more health-conscious, actively engaging with health news and making healthier food choices, while others may not be paying attention to health news. Unfortunately, data on the specific reception of information at the household level are unavailable to us. Consequently, we are unable to address the endogeneity arising from the unobserved reception of health information and its impact on the HEI.

Additionally, our analysis does not incorporate a causal mechanism to explain how health news stories might influence individual food consumption and, consequently, their HEI. Developing such causal mechanisms would require a theoretical framework, which is beyond the scope of our current study. Thus, while we can partially mitigate the endogeneity related to the health news environment, we refrain from making any claims about causal effects.

Table 2. Relationship between Healthy Eating Index and Health News: Panel Unconditional Quantile Regressions (N = 2,906,400)

		Panel UQR Regressions						
	FE	Q05	Q10	Q25	Q50	Q75	Q90	Q95
Variable	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Health news	0.0011***	0.0011***	0.0011***	0.0011***	0.0010***	0.0011***	0.0010***	0.0010***
	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)
Lag Health news	0.0007***	0.0009***	0.0008***	0.0008***	0.0007***	0.0006***	0.0006***	0.0006***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Season FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Values in parentheses are robust standard errors. Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level, respectively. Demographic variables are omitted from the regression because there are minimal variation in demogrphics within a household over time. Household fixed effects (FE), season fixed effects, and market fixed effects were included in the regressions but are omitted here for brevity. Both the fixed effects and panel unconditional quantile regressions are estimated with instruments described in the Model section.
Source: Author estimates using data from NexisUni; the IRI Consumer Network, 2015–2018; USDA's Food and Nutrient Database for Dietary Studies, Food Pattern Equivalent Database; and the Purchase to Plate Crosswalk.

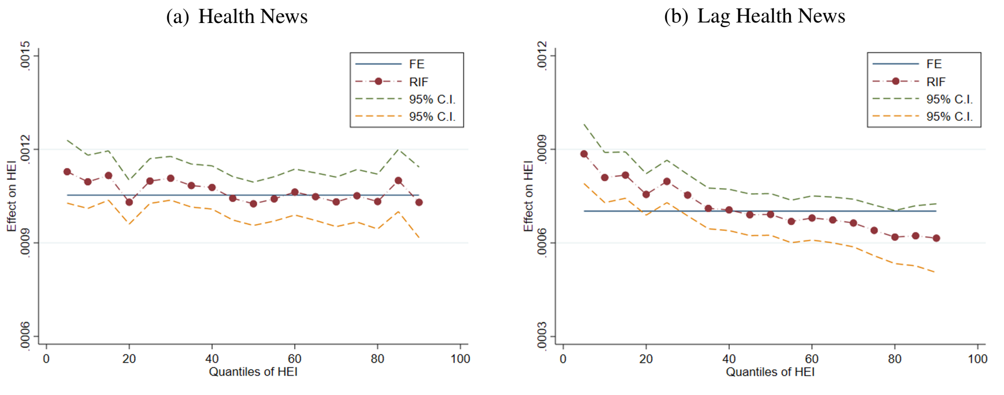

Figure 2. Estimated Relationship between Healthy Eating Index and Health News

Notes: The figures are drawn using estimates from Table 2. Household, season, and state fixed effects were included in the regressions.
Source: Author estimates using data from NexisUni; the IRI Consumer Network, 2015–2018; USDA's Food and Nutrient Database for Dietary Studies, Food Pattern Equivalent Database, and the Purchase to Plate Crosswalk.

Results

Panel UQR Regressions

Table 2 shows the results of the panel UQR described in equation (2). Column 1 includes the results from the fixed effect (FE) regression at the mean and columns 2–8 present the results of the panel UQR regression at the 5th, 10th, 25th, 50th, 75th, 90th, and 95th percentiles of households HEI, respectively. Further, to make the interpretation of our coefficients of interest easier, Figure 2 plots the estimated coefficients for panel UQR regressions at every 5 percentiles of the HEI distribution along with their 95% confidence intervals. For comparison, the FE regression results are also plotted as a straight line.

Figure 2a shows the relationship between health information and HEI. The FE analysis at the mean suggests that one piece of health news is associated with an increase in HEI by 0.0011 points for an average household in a month. Since the average number of 2,596 pieces of news a month, health information is associated with a contribution to a household's HEI by 2.86 points a month.[6] The results imply the importance of health information: With the constant flow of health news from various media sources, it is possible for health information to have a continued contribution to a household's purchases of healthy foods.

The panel UQR regressions indicate that the relationship between health information and HEI is positive and statistically significant across all quantiles of the HEI distribution but varies in magnitude along the distribution. Specifically, the association between health information and HEI is slightly higher at the lowest quantiles of the HEI distribution. However, the differences across quantiles are very small and the FE estimate lies within the confidence interval for most quantile estimates. Therefore, we are not able to reject equivalence with the estimates at the mean for most quantiles. For households with very unhealthy food purchase baskets, providing more health information is slightly associated with larger increases compared to very healthy households. One possible explanation could be that households with very unhealthy food choices might have a lower baseline awareness of nutritional information or the health implications of their food selections. Therefore, the introduction of health information could lead to more significant changes in behavior in these households. Further, households with unhealthy food habits might be more slightly motivated to make positive changes when provided with health information. In addition, lagged health news also has a positive and significant impact on HEI, but the magnitude is smaller compared to the current period health news, which suggests that the health media stories viewed 1 month ago could be forgotten by the next month.

As a robustness analysis, we further conduct a UQR analysis with household demographic variables, without including the panel features. The results, presented in Table S1 in the online supplement (see www.jareonline.org), are consistent with the panel RIF results: One piece of health news is associated with an increase in HEI by 0.0011 points for an average household in a month at the mean. Similar to the panel RIF regression results, we find that the differences across quantiles are very small, and the two-stage least squares (2SLS) panel regression estimate at the mean lies within the confidence interval for most quantile estimates, and we are not able to reject equivalence with the estimate at the mean for most quantiles.

Health Information and Education

Personal health literacy refers to the degree to which individuals have the ability to find, understand, and use information and services to inform health-related decisions and actions for themselves and others.[7] From newspapers to online blogs, the constant, large stream of health news can make it difficult for consumers to distinguish reliable information. They could be confused by the vast amount of, and sometimes conflicting, health-related news they received or have difficulty understanding the benefit or problems of certain diets or nutrition. Therefore, the relationship between health news and diet quality could vary depending on the levels of health literacy of a consumer. In this section, we use the highest education level in a household as a proxy of the household's level of health literary and evaluate the heterogeneous association between health news and healthfulness of retail food purchases across households with varying education levels. Health literacy has been shown to have a relationship with education level: People with lower education were found to demonstrate lower health literacy skills compared with people with higher education (Lee et al., 2010).

We classify education levels obtained by the household heads into three categories and use two dummy variables: *High School* and *College and above*, using less than high school as the reference.

[6] One of the ways that Guenther et al. (2014) validate the HEI as a measure of diet quality is by finding a difference in scores between men and women of about 2 points.

[7] The definition of health literacy was updated in August 2020 with the release of the US government's Healthy People 2030 initiative (https://health.gov/healthypeople/priority-areas/health-literacy-healthy-people-2030).

Table 3. Relationship between Healthy Eating Index and Health News across Education Levels (N = 2,906,400)

		RIF Regressions						
	OLS	**Q05**	**Q10**	**Q25**	**Q50**	**Q75**	**Q90**	**Q95**
Variable	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Health news	0.0020***	0.0024***	0.0022***	0.0018***	0.0020***	0.0019***	0.0024***	0.0021***
	(0.0004)	(0.0009)	(0.0007)	(0.0005)	(0.0005)	(0.0005)	(0.0007)	(0.0008)
Health news × High school	−0.0010***	−0.0012	−0.0010	−0.0007	−0.0010**	−0.0010*	−0.0016***	−0.0015*
	(0.0004)	(0.0009)	(0.0007)	(0.0005)	(0.0005)	(0.0005)	(0.0007)	(0.0008)
Health news × College	−0.0008**	−0.0014	−0.0012*	−0.0007	−0.0009*	−0.0006	−0.0011	−0.0008
	(0.0004)	(0.0009)	(0.0007)	(0.0005)	(0.0005)	(0.0005)	(0.0007)	(0.0008)
High school	2.7886***	4.6610**	3.7954**	2.5036*	2.8373***	2.0968	3.4964**	3.1816
	(0.9484)	(2.2268)	(1.6939)	(1.3094)	(1.1722)	(1.3053)	(1.7043)	(2.0814)
College	4.7239***	6.1607***	5.5480***	4.4698***	5.0016***	4.1049***	5.2245***	4.6546**
	(0.9435)	(2.2183)	(1.6861)	(1.3026)	(1.1661)	(1.2995)	(1.6987)	(2.0756)
Demographic variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Season FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Values in parentheses are robust standard errors. Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level, respectively. Demographic variables, season fixed effects (FE), and state fixed effects were included in the regressions but are omitted here for brevity. 2SLS = two-stage least squares; RIF = recentered influence function.
Source: Author estimates using data from NexisUni; the IRI Consumer Network, 2015–2018; USDA's Food and Nutrient Database for Dietary Studies, Food Pattern Equivalent Database; and the Purchase to Plate Crosswalk.

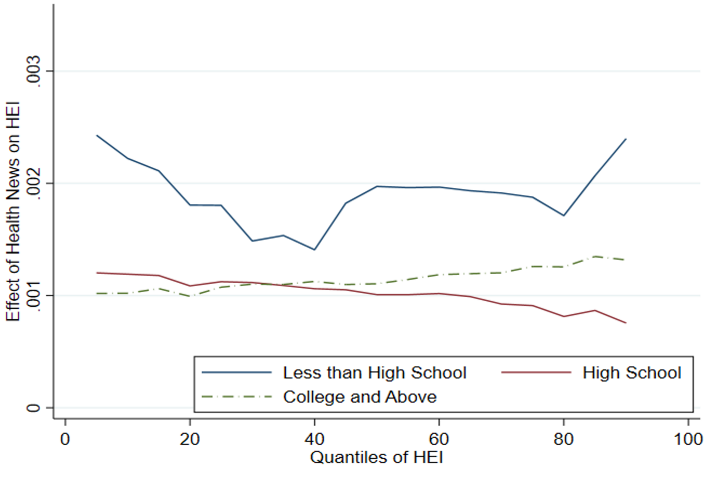

Figure 3. Estimated Relationship between Health News and Healthfulness of Retail Food Purchases by Education Levels
Source: Author estimates using data from NexisUni; the IRI Consumer Network, 2015–2018; USDA's Food and Nutrient Database for Dietary Studies, Food Pattern Equivalent Database, and the Purchase to Plate Crosswalk.

Specifically, we include the interactions of health news and these education-level dummy variables. The results are presented in Table 3. From the 2SLS results, the coefficients of the interaction terms are all negative and significant, suggesting the significant additional effect of health information among higher-educated households relative to lower-educated households. We further calculate the net effects of the health information across education levels. On average, one additional piece of health news is associated with an increase in the household's HEI of 0.0020 for households with heads not finishing high school, 0.0010 for high school graduates, and 0.0012 for college educated and above. Figure 3 plots the net relationship between health information and HEI across education levels. The relationship between health information and households whose heads have less than a high school education is significantly stronger compared to households with higher education levels. Further, the effect is higher at the highest and the lowest quantiles of the HEI distribution for households with low education levels. Between households with high school and college and above, there is no statistically significant difference in the effects of health information across almost all quantiles of diet qualities, except for the highest quantiles.

At first glance, these results are contradictory to the concept of health literacy, where we might expect that the highly educated groups would be more willing to adopt the health information and change their diet decisions. However, considering the increase in exposure to media in all forms and the vast amount of information consumers may receive, it is possible that some information might not be reliable. High education groups usually have a higher diet quality already and are more likely to think critically about the information they receive (Huber and Kuncel, 2016). Therefore, they are less likely to be affected by media information. However, consumers with lower levels of education may be more easily influenced by information from media. In addition, households with higher education levels are more likely to have more existing knowledge of a healthy diet and a greater understanding of dietary quality; therefore, they have less to gain from media stories than households with less education and the association between healthy food purchases and health information is not as strong as it is in households with lower education levels.

Conclusions and Policy Implications

We use a panel unconditional quantile regression model of the healthfulness of household retail food purchases to investigate the relationship between health information and household diet quality beyond the mean. We quantify the volume of health and diet-related information available to consumers using the number of media stories on newspapers, magazines, television, radio, and online sources covering healthy diets, which we collected from the NexisUni database. Using household-level retail food purchase data from 2015–2018, we estimate the HEI-2015 for each household by matching purchases to nutrient and food composition data. Results from this study shed light on related government policies aiming to improve the healthfulness of diet.

First, we find that the association between health information and healthfulness of retail food purchases is higher at the lowest quantiles of the HEI distribution, although we cannot reject equivalence with the FE estimate for most quantiles. For households with very unhealthy retail food purchases, providing more health information is associated with a slightly larger effect compared to households whose retail food choices are in the middle and high quantiles of healthfulness. One possible explanation could be that households with very unhealthy food choices might have a lower baseline awareness of nutritional information or the health implications of their food selections. Therefore, the introduction of health information could lead to more significant changes in behavior in these households. Further, households with unhealthy food habits might be more slightly motivated to make positive changes when provided with health information. This could imply that media stories, educational efforts, or initiatives focused on health information may have a more noticeable effect on households with less healthy food choices, potentially contributing to improved healthfulness of food purchases. To provide a more effective campaign, many healthcare professionals, organizations, and governments could use this information to allocate their resources more efficiently.

Regarding the interpretation of our results, several limitations need to be acknowledged. First, our calculation of HEI scores only covers households' retail food purchases but not food away from home or other sources. Although household food purchase data has been shown to be consistent with overall diet quality, it may differ on specific nutrient intake. Second, our HEI score estimates are lower than those reported by other studies based on a simple average of individual scores using a week of food acquisitions, most likely due to underreporting of some food categories (e.g., fruits and vegetables), and the fact that random-weight items (e.g., loose fruits and vegetables) are not included in the data. Third, due to data limitations, we focus on the general health news environment at the aggregate state level, which is the volume of available health news stories available to all consumers in a state in a month. Our measure of the information volume may not include all the information that a consumer could receive, and not all consumers are exposed to all health information. The individual exposure to available health news stories might depend on subscriptions to media sources, which may vary across household demographics.

Second, although the impact of one piece of health-related news on a household's monthly HEI score is relatively modest (0.0011 points), the average monthly impact of a constant flow of health news is meaningful. Health-related news is associated with an average 2.86-point increase in HEI in a month. This contribution aligns with the effects of other influential demographic variables; for instance, college education of the household head(s) is associated with a 2.59-point increase in HEI, compared to households headed by individual(s) without a high school degree (see Table Đą1 in the online supplement). Comparing this effect to other interventions influencing diet quality reveals notable findings. Hastings, Kessler, and Shapiro (2021) find that the effect of Supplemental Nutrition Assistance Program (SNAP) participation on HEI is small, ranging from −0.101 to 0.448 points. Feng, Fan, and Jaenicke (2024) find that although SNAP has no significant impact on households' dietary quality on average, for households with initially low-to-intermediate dietary quality, SNAP participation reduces their HEI scores by more than 7 points. Allcott et al. (2019) finds that entry of supermarkets will increase the health index for households living in food desert by 0.014 points. Scharadin and Jaenicke (2020) estimated that a 1-hour reduction in secondary childcare per day leads to a 2.35-point increase in household HEI, and 30 minutes of additional food-at-home time per day would increase HEI by 2.01 points. From a policy perspective, our results imply that a constant flow of accurate health-related news positively contributes to a household's diet quality. In contrast, the demographic variables are impossible, or difficult, to change in the short run. However, a successful media campaign typically stimulates extensive media coverage across various platforms, including television, radio, and online sources. Additionally, it may foster broader discussions related to healthy diets and nutrition in the media landscape. Our results suggests that the improve health news environment could be effective in encouraging the purchases of healthier food and beverages thus improving diet quality.

Third, considering the increase in exposure to media in all forms and the vast amount of information consumers may receive, it is possible that some information might not be reliable. Nutrition research is complex and is often oversimplified by the media. It can be difficult for readers to distinguish reliable research from weak studies and sensational headlines. Our results indicate that consumers with lower education may be more easily influenced by information from media than those in more highly educated groups. As a result, effort should continue to improve information accuracy, particularly over health-related news and information, where misinformation tends to proliferate.

Overall, our study sheds light on the relationship between health news environment and the healthfulness of household retail food purchases. Our findings underscore the potential of media campaigns to positively impact diet quality, highlighting potential benefits of targeted efforts to improve information accuracy and accessibility, particularly for vulnerable populations. By leveraging the influence of media, policy makers and healthcare professionals can play a vital role in promoting healthier food choices and improving public health outcomes.

[First submitted September 2023; accepted for publication April 2024.]

References

Alé-Chilet, J., and S. Moshary. 2022. "Beyond Consumer Switching: Supply Responses to Food Packaging and Advertising Regulations." *Marketing Science* 41(2):243–270. doi: 10.1287/mksc.2021.1315.

Allcott, H., R. Diamond, J.-P. Dubé, J. Handbury, I. Rahkovsky, and M. Schnell. 2019. "Food Deserts and the Causes of Nutritional Inequality." *Quarterly Journal of Economics* 134(4): 1793–1844. doi: 10.1093/qje/qjz015.

Andersen, J. A., L. E. Wylie, and E. M. Brank. 2017. "Public Health Framing and Attribution: Analysis of the First Lady's Remarks and News Coverage on Childhood Obesity." *Cogent Social Sciences* 3(1):1268748. doi: 10.1080/23311886.2016.1268748.

Beck, F., J.-B. Richard, V. Nguyen-Thanh, I. Montagni, I. Parizot, and E. Renahy. 2014. "Use of the Internet as a Health Information Resource Among French Young Adults: Results from a Nationally Representative Survey." *Journal of Medical Internet Research* 16(5):e128. doi: 10.2196/jmir.2934.

Bonanno, A., F. Bimbo, R. Cleary, and E. Castellari. 2018. "Food Labels and Adult BMI in Italy – An Unconditional Quantile Regression Approach." *Food Policy* 74:199–211. doi: 10.1016/j.foodpol.2017.12.008.

Borah, B. J., and A. Basu. 2013. "Highlighting Differences between Conditional and Unconditional Quantile Regression Approaches through an Application to Assess Medication Adherence." *Health Economics* 22(9):1052–1070. doi: 10.1002/hec.2927.

Bowman, S. A., J. Clemens, J. Friday, R. Thoerig, and A. Moshfegh. 2014. *Food Patterns Equivalents Database 2011-12: Methodology and User Guide*. Beltsville, MD: US Department of Agriculture, Agricultural Research Service, Beltsville Human Nutrition Research Center, Food Surveys Research Group. Available online at www.ars.usda.gov/Services/docs.htm?docid=23871.

Brown, D. J., and L. F. Schrader. 1990. "Cholesterol Information and Shell Egg Consumption." *American Journal of Agricultural Economics* 72(3):548–555. doi: 10.2307/1243023.

Browning, M., L. G. Hansen, and S. Smed. 2019. "Heterogeneous Consumer Reactions to Health News." *American Journal of Agricultural Economics* 101(2):579–599. doi: 10.1093/ajae/aay055.

Butteriss, C., and J. Bradley. 2019. "The World's Best Public Health Social Media Campaigns." Available online at https://web.archive.org/web/20190312171530/https://www.bangthetable.com/.

Buyuktuncer, Z., A. Ayaz, D. Dedebayraktar, E. Inan-Eroglu, B. Ellahi, and H. Besler. 2018. "Promoting a Healthy Diet in Young Adults: The Role of Nutrition Labelling." *Nutrients* 10(10): 1335. doi: 10.3390/nu10101335.

Campos, S., J. Doxey, and D. Hammond. 2011. "Nutrition Labels on Pre-Packaged Foods: A Systematic Review." *Public Health Nutrition* 14(8):1496–1506. doi: 10.1017/S1368980010003290.

Carlson, A., E. T. Page, T. P. Zimmerman, C. E. Tornow, and S. Hermansen. 2019. *Linking USDA Nutrition Databases to IRI Household-Based and Store-Based Scanner Data*. Technical Bulletin TB-1952. USDA Economic Research Service.

Carrieri, V., and A. M. Jones. 2017. "The Income–Health Relationship 'Beyond the Mean': New Evidence from Biomarkers." *Health Economics* 26(7):937–956. doi: 10.1002/hec.3372.

Chrisinger, B. W., M. J. Kallan, E. D. Whiteman, and A. Hillier. 2018. "Where Do U.S. Households Purchase Healthy Foods? An Analysis of Food-at-Home Purchases Across Different Types of Retailers in a Nationally Representative Dataset." *Preventive Medicine* 112:15–22. doi: 10.1016/j.ypmed.2018.03.015.

Christoph, M. J., and R. An. 2018. "Effect of Nutrition Labels on Dietary Quality Among College Students: A Systematic Review and Meta-Analysis." *Nutrition Reviews* 76(3):187–203. doi: 10.1093/nutrit/nux069.

Cleary, R., A. Bonanno, A. Ghazaryan, L. Bellows, and M. McCloskey. 2021. "School Meals and Quality of Household Food Acquisitions." *Applied Economic Perspectives and Policy* 43(4): 1385–1442. doi: 10.1002/aepp.13130.

Diviani, N., B. Van Den Putte, S. Giani, and J. C. Van Weert. 2015. "Low Health Literacy and Evaluation of Online Health Information: A Systematic Review of the Literature." *Journal of Medical Internet Research* 17(5):e112. doi: 10.2196/jmir.4018.

eMarketer. 2021. "US Time Spent with Media 2021." Available online at https://www.emarketer.com/content/us-time-spent-with-media-2021.

Feng, J., L. Fan, and E. C. Jaenicke. 2024. "The Distributional Impact of SNAP on Dietary Quality." *Agricultural Economics* 55(1):104–139. doi: 10.1111/agec.12808.

Firpo, S., N. M. Fortin, and T. Lemieux. 2009. "Unconditional Quantile Regressions." *Econometrica* 77(3):953–973. doi: 10.3982/ECTA6822.

Guenther, P. M., S. I. Kirkpatrick, J. Reedy, S. M. Krebs-Smith, D. W. Buckman, K. W. Dodd, K. O. Casavale, and R. J. Carroll. 2014. "The Healthy Eating Index-2010 Is a Valid and Reliable Measure of Diet Quality According to the 2010 Dietary Guidelines for Americans." *Journal of Nutrition* 144(3):399–407. doi: 10.3945/jn.113.183079.

Hastings, J., R. Kessler, and J. M. Shapiro. 2021. "The Effect of SNAP on the Composition of Purchased Foods: Evidence and Implications." *American Economic Journal: Economic Policy* 13(3):277–315. doi: 10.1257/pol.20190350.

Huang, L., and Y. Liu. 2017. "Health Information and Consumer Learning in the Bottled Water Market." *International Journal of Industrial Organization* 55:1–24. doi: 10.1016/j.ijindorg.2017.08.002.

Huber, C. R., and N. R. Kuncel. 2016. "Does College Teach Critical Thinking? A Meta-Analysis." *Review of Educational Research* 86(2):431–468. doi: 10.3102/0034654315605917.

Im, H., and J. Huh. 2017. "Does Health Information in Mass Media Help or Hurt Patients? Investigation of Potential Negative Influence of Mass Media Health Information on Patients' Beliefs and Medication Regimen Adherence." *Journal of Health Communication* 22(3): 214–222. doi: 10.1080/10810730.2016.1261970.

Katare, B., J. K. Binkley, and K. Chen. 2021. "Nutrition and Diet Quality of Food at Home by Supplemental Nutrition Assistance Program (SNAP) Status." *Food Policy* 105:102165. doi: 10.1016/j.foodpol.2021.102165.

Lee, S.-Y. D., T.-I. Tsai, Y.-W. Tsai, and K. N. Kuo. 2010. "Health Literacy, Health Status, and Healthcare Utilization of Taiwanese Adults: Results from a National Survey." *BMC Public Health* 10(1):614. doi: 10.1186/1471-2458-10-614.

Liu, P., K. Lien, and F. Asche. 2016. "The Impact of Media Coverage and Demographics on the Demand for Norwegian Salmon." *Aquaculture Economics & Management* 20(4):342–356. doi: 10.1080/13657305.2016.1212126.

Mancino, L., J. Guthrie, M. V. Ploeg, and B.-H. Lin. 2018. *Nutritional Quality of Foods Acquired by Americans: Findings from USDA's National Household Food Acquisition and Purchase Survey*. Economic Information Bulletin EIB-188. USDA Economic Research Service.

Martin, C. L., J. B. Montville, L. C. Steinfeldt, G. Omolewa-Tomobi, K. Y. Heendeniya, M. E. Adler, and A. J. Moshfegh. 2014. *USDA Food and Nutrient Database for Dietary Studies 2011-2012*. USDA Agricultural Research Service, Food Surveys Research Group. Available online at https://www.ars.usda.gov/northeast-area/beltsville-md-bhnrc/beltsville-human-nutrition-research-center/food-surveys-research-group/docs/fndds/.

Miller, P. E., J. Reedy, S. I. Kirkpatrick, and S. M. Krebs-Smith. 2015. "The United States Food Supply Is Not Consistent with Dietary Guidance: Evidence from an Evaluation Using the Healthy Eating Index-2010." *Journal of the Academy of Nutrition and Dietetics* 115(1):95–100. doi: 10.1016/j.jand.2014.08.030.

Nagler, R. H. 2014. "Adverse Outcomes Associated with Media Exposure to Contradictory Nutrition Messages." *Journal of Health Communication* 19(1):24–40. doi: 10.1080/10810730.2013.798384.

Rieger, J., C. Kuhlgatz, and S. Anders. 2016. "Food Scandals, Media Attention and Habit Persistence Among Desensitised Meat Consumers." *Food Policy* 64:82–92. doi: 10.1016/j.foodpol.2016.09.005.

Scharadin, B., and E. C. Jaenicke. 2020. "Time Spent on Childcare and the Household Healthy Eating Index." *Review of Economics of the Household* 18(2):357–386. doi: 10.1007/s11150-020-09482-2.

Smed, S. 2012. "Information and Consumer Perception of the 'Organic' Attribute in Fresh Fruits and Vegetables." *Agricultural Economics* 43(s1):33–48. doi: 10.1111/j.1574-0862.2012.00618.x.

Smith, T. A. 2017. "Do School Food Programs Improve Child Dietary Quality?" *American Journal of Agricultural Economics* 99(2):339–356. doi: 10.1093/ajae/aaw091.

Suenaga, H., and M. R. Vicente. 2022. "Online and Offline Health Information Seeking and the Demand for Physician Services." *European Journal of Health Economics* 23(3):337–356. doi: 10.1007/s10198-021-01352-7.

Sweitzer, M., D. Brown, S. A. Karns, M. K. Muth, P. Siegel, and C. Zhen. 2017. *Food-at-Home Expenditures: Comparing Commercial Household Scanner Data from IRI and Government Survey Data*. Technical Bulletin TB-1946. USDA Economic Research Service.

Tonsor, G. T., J. R. Mintert, and T. C. Schroeder. 2010. "U.S. Meat Demand: Household Dynamics and Media Information Impacts." *Journal of Agricultural and Resource Economics* 35(1):1–17. doi: 10.22004/ag.econ.61056.

Vepsäläinen, H., J. Nevalainen, S. Kinnunen, S. T. Itkonen, J. Meinilä, S. Männistö, L. Uusitalo, M. Fogelholm, and M. Erkkola. 2022. "Do We Eat What We Buy? Relative Validity of Grocery Purchase Data as an Indicator of Food Consumption in the LoCard Study." *British Journal of Nutrition* 128(9):1780–1788. doi: 10.1017/S0007114521004177.

Verbeke, W. 2008. "Impact of Communication on Consumers' Food Choices: Plenary Lecture." *Proceedings of the Nutrition Society* 67(3):281–288. doi: 10.1017/S0029665108007179.

Volpe, R., A. Okrent, and E. Leibtag. 2013. "The Effect of Supercenter-Format Stores on the Healthfulness of Consumers' Grocery Purchases." *American Journal of Agricultural Economics* 95(3):568–589. doi: 10.1093/ajae/aas132.

Yang, J., and E. Goddard. 2011. "Canadian Consumer Responses to BSE with Heterogeneous Risk Perceptions and Risk Attitudes." *Canadian Journal of Agricultural Economics* 59(4):493–518. doi: 10.1111/j.1744-7976.2011.01225.x.

Zhu, C., R. A. Lopez, and X. Liu. 2016. "Information Cost and Consumer Choices of Healthy Foods." *American Journal of Agricultural Economics* 98(1):41–53. doi: 10.1093/ajae/aav057.

Journal of Agricultural and Resource Economics 49(3):S1
ISSN: 1068-5502 (Print); 2327-8285 (Online)
doi: 10.22004/ag.econ.342182

Online Supplement: Health News Environment and the Distribution of Diet Quality

Yizao Liu, Rebecca Cleary, and Andrea Carlson

Table S1. Relationship between HEI and Health News

		RIF Regressions						
	2SLS	**Q05**	**Q10**	**Q25**	**Q50**	**Q75**	**Q90**	**Q95**
Variable	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Health News	0.0011***	0.0011***	0.0011***	0.0011***	0.0011***	0.0012***	0.0012***	0.0012***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)
Lag Health News	0.0008***	0.0008***	0.0008***	0.0008***	0.0007***	0.0008***	0.0008***	0.0008***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)
High School	0.2964**	1.5702***	1.1982***	0.7864***	0.3981***	-0.3576*	-0.6805***	-0.5605**
	(0.1379)	(0.3129)	(0.2479)	(0.1930)	(0.1708)	(0.1871)	(0.2292)	(0.2689)
College	2.5991***	2.5972***	2.5106***	2.6268***	2.8134***	2.5540***	2.5043***	2.5891***
	(0.1373)	(0.3118)	(0.2469)	(0.1922)	(0.1701)	(0.1865)	(0.2287)	(0.2684)
Children	-0.8481***	-0.6234***	-0.6903***	-0.8615***	-0.8995***	-0.8995***	-0.9383***	-0.9417***
	(0.0238)	(0.0436)*	(0.0367)*	(0.0311)*	(0.0297)*	(0.0342)*	(0.0433)*	(0.0521)*
Black	0.1343***	0.1894***	0.2574***	0.4299***	0.3187***	-0.0668	-0.4181***	-0.5484***
	(0.0400)	(0.0748)	(0.0615)	(0.0514)	(0.0503)	(0.0607)	(0.0806)	(0.0999)
White	0.0009	0.5580***	0.3375***	0.1854***	-0.0624	-0.2444***	-0.3778***	-0.4439***
	(0.0342)	(0.0641)	(0.0527)	(0.0440)	(0.0429)	(0.0516)	(0.0685)	(0.0849)
Asian	0.9117***	-0.3173***	-0.1483*	0.3620***	0.8525***	1.4479***	2.0775***	2.3635***
	(0.0500)	(0.0935)	(0.0761)	(0.0631)	(0.0627)	(0.0785)	(0.1096)	(0.1401)
Income	0.0259***	0.0144***	0.0175***	0.0225***	0.0278***	0.0322***	0.0321***	0.0300***
	(0.0002)	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0004)
Employed part-time	0.4408***	0.1718***	0.2646***	0.3731***	0.4964***	0.6006***	0.5763***	0.5412***
	(0.0173)	(0.0306)	(0.0258)	(0.0220)	(0.0217)	(0.0262)	(0.0350)	(0.0436)
Employed full-time	-0.6624***	-0.2475***	-0.2889***	-0.4733***	-0.6775***	-0.8793***	-0.9731***	-1.0540***
	(0.0164)	(0.0292)	(0.0246)	(0.0209)	(0.0205)	(0.0248)	(0.0334)	(0.0418)
Household Size	-0.6559***	0.0037	-0.1319***	-0.3601***	-0.6843***	-1.0045***	-1.1696***	-1.1934***
	(0.0079)	(0.0150)*	(0.0126)**	(0.0104)**	(0.0098)**	(0.0112)**	(0.0142)*	(0.0172)*
Hispanic	0.4122***	-0.1232**	0.0808*	0.3585***	0.5972***	0.6518***	0.3762***	0.2028***
	(0.0305)	(0.0554)	(0.0459)	(0.0387)	(0.0382)	(0.0464)	(0.0614)	(0.0757)
Q2 – April, May, June	-0.3797***	-0.2365***	-0.2484***	-0.2816***	-0.4033***	-0.4538***	-0.5355***	-0.5897***
	(0.0205)	(0.0340)**	(0.0291)**	(0.0254)**	(0.0257)**	(0.0320)**	(0.0436)**	(0.0551)*
Q3 – July, Aug, Sept	-0.7809***	-0.3861***	-0.4543***	-0.5859***	-0.7811***	-0.9892***	-1.1660***	-1.2733***
	(0.0212)	(0.0361)	(0.0307)	(0.0266)	(0.0266)	(0.0326)	(0.0440)	(0.0552)
Q4 – Oct, Nov, Dec	-2.8739***	-2.3515***	-2.4607***	-2.6509***	-2.9273***	-3.2352***	-3.3003***	-3.2699***
	(0.0211)	(0.0386)	(0.0323)	(0.0272)	(0.0264)	(0.0316)	(0.0419)	(0.0522)
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The market fixed effects were included in the regressions, however omitted here for brevity. HEI = Healthy Eating Index; 2SLS=Two Stage Least Squares; RIF = Recentered Influence Function. Source: Author estimates using data from NexisUni, the IRI Consumer Network, 2015-2018, USDA's Food and Nutrient Database for Dietary Studies, Food Pattern Equivalent Database, and the Purchase to Plate Crosswalk. The number of observations in each regression

The material contained herein is supplementary to the article named in the title and published in the *Journal of Agricultural and Resource Economics* (*JARE*).