Journal of Consumer Policy
https://doi.org/10.1007/s10603-018-9396-x

ORIGINAL PAPER

Evidence from Retail Food Markets That Consumers Are Confused by *Natural* and *Organic* Food Labels

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Received: 15 June 2018 / Accepted: 22 October 2018/Published online: 23 November 2018

Abstract

In the USA, food producers can label their products as *organic* only if they are certified by the United States Department of Agriculture (USDA) as having met comprehensive regulatory standards for environmental stewardship. In contrast, the Federal Government has not defined the term *natural* for most food products. Survey and experimental studies suggest that consumers are confused by the meanings of *natural* and *USDA Organic* on food labels, and often believe that these two label claims have similar meanings. In this paper, we examine whether this confusion influences aggregate retail food expenditures. High-frequency Google Trends data on the volume of web searches for "organic food" and for "natural food" are used as indicators of consumer interest in those food attributes. Results from a vector autoregression model show that web searches for both terms are correlated with retail purchases of organic food. Web searches for both help predict retail purchases. If consumers were aware of differences implied by the two label claims, searches for natural food would be uncorrelated with decisions to purchase organic products. These results are therefore evidence that consumers view the two claims as related, or even view the two claims as identical.

Keywords Food labels · Natural food · Organic food · Vector autoregression

Worldwide, consumer protection organizations, food policy analysts, and food policy advocates have argued that many green claims on food labels are nothing more than marketing ploys designed to confuse consumers so that consumers pay a price premium for attributes that are not meaningful or that products do not possess (e.g., Federal Trade Commission 2012;

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Terrachoice 2010). Their arguments raise an economic issue: Do consumers understand which claims are meaningful and which are not? If they do understand, the credible label claims might help consumers choose foods that embody the environmental stewardship attributes they want and the claims that are not credible would be ignored – no consumer protection policy questions would be raised.

Here, we examine two green label claims – *natural* and *USDA Organic* — that are widely used in the United States of America (USA), but receive markedly different Federal treatment. All farmers and food manufacturers who want to make an organic claim in the USA must adhere to Federal regulatory standards that govern all aspects of organic crop and livestock production, food processing, product labeling, and enforcement. In contrast, the Federal Government does not even provide an official definition for the natural claim or regulate its use on most food products. In this paper, we provide statistical evidence that both label claims influence retail purchases of organic food, evidence for consumer confusion.

The Origin of Consumers' Confusion About Organic and Natural Food Labels

A new generation of consumers emerged in the 1960s demanding food produced without pesticides, artificial colours, and other synthetic chemicals (Mergantime 1994). Although retailers responded quickly to meet to this demand, there was little clarity about what the natural, organic, and other new food labels meant (Price and Brown 1984).

By 1990, nearly half the States had established legislation to set organic standards, and over half had established legislation on organic labeling, with many linking the terms organic and natural food. However, treatment varied across these States. The California Organic Foods Act of 1990 required food labelled or advertised as organic – or using similar terms – to meet the law's legal production and processing standards and labeling requirements. California defined "organically grown," "naturally grown," "ecologically grown," and "biologically grown," along with grammatical variations of those terms, as synonymous with "organic" (Anton 1992). Other State legislation defined the two terms in tandem. For example, the 1978 Massachusetts law, "Food, Natural and Organic Labeling," defined "organically grown food" as "natural food which has not been subjected to pesticides or artificial fertilizers, hormones, or antibiotics" (Anton 1992). However, other States established legislation on organic labeling or set organic standards with no reference to the term natural.

In 1990, Congress supplanted these varying State laws with Federal legislation to establish a national organic regulatory program with standards for organic production, processing, labeling, and enforcement. After a relatively long rule-making process, USDA published U.S. organic standards and implemented a national organic regulatory program in 2000. In order to label or advertise food as organic, all farmers, food processors, and manufacturers must comply with USDA organic standards – and those earning over $5000 in annual organic sales must be certified by a USDA-accredited certifier.

Use of the USDA Organic claim is controlled through an extensive set of regulations. USDA defines organic production as practices that "foster cycling of resources, promote ecological balance, and conserve biodiversity" (U.S, Department of Agriculture, Agricultural Marketing Service 2000). USDA regulatory standards require crop producers to use practices to maintain and enhance healthy soil, and to avoid the use of synthetic pesticides and fertilizers, sewage sludge, and genetic engineering. Livestock producers must use organically grown feed, meet minimum pasture requirements, and must avoid use of hormones and antibiotics. Food handlers must not use volatile synthetic solvents and other synthetic processing aids during food processing or add artificial flavourings, colouring, preservatives, and other synthetic ingredients. Before conventional farmers can be certified organic and obtain organic price premiums, they must avoid the use of synthetic pesticides, genetically modified organisms, and other prohibited substances for three years.

Federal treatment of the natural claim has been entirely different from the treatment of the USDA Organic claim. The U.S. Food and Drug Administration (FDA) regulates food labeling for most food products except meat, and has not established a regulatory definition or standards to use the natural claim (U.S. Food and Drug Administration 2018). Informally, FDA considers natural to mean that nothing artificial or synthetic has been added to a food product. USDA regulates labeling on meat products and allows a natural claim if no artificial ingredients or colours are added during processing, and the processing method does not fundamentally alter the product (U.S. Department of Agriculture, Food Safety, and Inspection Service 2008). Neither of these definitions addresses the use of synthetic pesticides, genetically modified organisms, hormones, and antibiotics in crop and livestock production.

Survey evidence suggests that most retail consumers are unable to discriminate between organic and natural claims (Consumer Reports 2015).[1] Results of a 2015 survey show, for example, that 64% of respondents believed that natural meant that no artificial growth hormones were used, 59% believed that it meant that animals were fed feed that did not contain genetically modified organisms (GMOs), and 57% believed that it meant that no antibiotics or other drugs were used. A food supplier making a natural claim is not required to meet any of these conditions, but if they were making a USDA Organic claim, they would be. Presumably, the majority of consumers who incorrectly associate a natural claim on a meat product with the idea that animals were raised without antibiotics would be surprised to find that the product is composed of meat from animals that could have been fed antibiotics.

Survey and experimental research on natural and USDA Organic labels has consistently confirmed that many consumers are confused. In focus groups, Abrams et al. (2010) found evidence that consumers are skeptical and distrustful of natural claims, but nonetheless many believed that labeling meat products as “all natural” meant that no antibiotics and no hormones were used to raise animals (which it does not). Some believed that it meant animals were raised outside (also not related to natural claims). Gifford and Bernard (2011) used surveys and experimental auctions to estimate consumer willingness to pay (WTP) for USDA Organic and natural chicken. They found that, before receiving additional information, about two thirds of participants in their study equated the attributes of USDA Organic products with those of natural products. Onken et al. (2011) also documented generally higher WTP for natural relative to organic label claims in an experiment in five Mid-Atlantic States, and Butler and Vossler (2018) found that consumers were willing to pay 20% more, on average, for natural products. McFadden and Huffman (2017) tested the impact of information treatments on WTP for organic, natural, and conventional foods. One finding of their work was that providing consumers with industry information about natural foods increased consumer WTP for organic foods – a type of information externality. Together, these studies suggest that consumer confusion about the meaning of organic and natural claims is widespread.

[1] Consumer Reports® described its survey as a nationally representative sample of 1005 adult U.S. residents selected by means of random-digit dialing, weighted so that respondents were demographically and geographically representative of the US population.

Economic Impacts of Uneven Regulatory Treatment

Organic production reduces some of the externalities associated with agriculture, such as those associated with on-farm pesticide use (Reganold and Wachter 2016). There is no reason to suspect that food labelled natural augments environmental stewardship. Organic standards are also associated with higher on-farm costs to produce food (McBride et al. 2015). Many foods labelled natural could not be otherwise, so the major cost of producing food labelled natural often is adding the word natural to packaging. By themselves, these conditions suggest that if consumers were well-informed about product attributes, consumers would not consider organic and natural food as similar to one another. As such, the survey research and experimental studies that point to the existence of consumer confusion imply that consumers often pay for food product attributes they do not receive and sellers often receive a price premium for attributes for which they neither incurred a production cost nor produced. Although the Federal Trade Commission and FDA made several attempts to define natural for all food products, none of these efforts have been successful (Price and Brown 1984; Kuchler et al. 2017). In sum, if the results of survey and experimental studies are correct and consumers are confused about what each label says about product attributes, and Federal efforts to help markets differentiate products have not informed consumers, impacts of consumer confusion on both industries will persist.

In a competitive marketplace, this confusion could persist because suppliers of foods labelled natural or USDA Organic have little incentive to correct consumers' misperception (Darby and Karni 1973; Baksi et al. 2017). Firms using the natural claim are unlikely to give up a price premium that requires no off-setting cost. Oberholtzer et al. (2006) argued that organic meat faces direct competition from meats labelled natural, which developed a market before meat was allowed to carry the USDA Organic claim and is now required to meet the production standards that USDA set for organic products. Suppliers of foods labelled USDA organic could mount a public information campaign to explain the difference in label claims, but doing so would be costly and if contributing to the campaign were voluntary, a successful campaign would benefit all organic food suppliers (not just the firms incurring the cost of the campaign).[2] Either way, if consumers are confused, voluntary actions of food suppliers are not sufficient to remedy the information issues at play.

Foods bearing the natural or USDA Organic labels are no longer niche markets, so any degree of confusion cannot be considered trivial. Organic food sales in the USA have exhibited double-digit growth during most years since the 1990s (Greene et al. 2017). Although the growth rate has begun to slow in the last few years, the Organic Trade Association estimated organic food reached a record $45.2 billion in retail sales in 2017 – a 5.5% share of U.S. retail food sales. Along with specialty food stores, restaurants, and direct marketers, most major U.S. food retailers – including Costco, Walmart, and Target—have expanded their organic food offerings in recent years.

After Congress passed the Organic Foods Production Act of 1990, industry analysts expected the natural foods industry to revise production practices and become the organic foods industry (Gilbert 1991). This metamorphosis did not occur. U.S. food sales of products

[2] The Federal Government has been involved in commodity research and promotion campaigns for conventional commodities for many decades. In 2014, Congress authorized a potential organic commodity promotion order, which would enable industry-funded organic research and promotion. The Organic Trade Association subsequently submitted an organic research and promotion proposal to USDA with a goal of helping clear up confusion among consumers regarding what it means for food to be labelled USDA Organic. USDA terminated rule-making efforts on this proposal in May 2018.

with a natural label have also shown double-digit growth during most years since the 1990s, and natural sales were still higher than organic in 2016 (Nutrition Business Journal 2017).

Objectives and Methods

In recognition of the growing use of computers and influence of the internet on consumer behaviour by the late 1990s, Klein (1998) proposed a new model of consumer information search that integrated the principles of information economics with the product classification model based on credence and experience characteristics. Computers and internet are now widely available in U.S. households, and the emergence of Google and other internet search engines has made the internet an important source of external information influencing consumers during their purchasing decision process (Zgodka 2011).

For the purposes of this study, we assume that search behaviour for certain types of food products is an indication of consumer interest in purchasing those products, such as in the case where a consumer searches for “organic food” and later purchases organic food products. This search behaviour could reflect non-negative search costs or incomplete information about label meanings or food product attributes. In this context, because “natural” is essentially a meaningless attribute with respect to food products – as we established in the introduction of this paper – we hypothesize that searches for “natural food” should have no relationship to the consumer decision to purchase organic foods if consumers were fully informed about the meaning of the word natural in the context of food labeling. If searches for natural food were found to be related to consumer purchase decision about organic food, this might be consistent with the existence of consumer confusion with respect to natural and organic food labels, as has been demonstrated in survey and experimental research (Abrams et al. 2010; Gifford and Bernard 2011; Onken et al. 2011; Butler and Vossler 2018).

To test our (null) hypothesis that consumers have full information about the meanings of natural and organic foods (and are not confused about their meaning), we follow the research path initiated by Choi and Varian (2009), using time series data on the volume of internet searches to identify consumers’ relative interest in products and product attributes along with their likely purchase behaviour. Google Trends indices of internet search volume for organic food and for natural food were combined with retail scanner data on organic food purchases from the market research firm Information Resources, Inc. (IRI). The data allow us to investigate the temporal relationship between consumers’ interest in organic and natural foods and the food they purchase. Searches for organic food should mirror consumers’ intentions to purchase organic food. On the other hand, if consumers understood the difference between organic claims and natural claims, the natural food search volume ought to be unrelated to organic sales.

As our goal is to describe and characterize co-movements of these variables, we estimate a vector autoregression (VAR) model. A VAR model will involve current and lagged values of multiple time series, and thus capture co-movements that could not be detected in univariate or bivariate models. The tools we use include Granger-causality tests, impulse response functions, and variance decomposition.

Using Internet Search Activity to Understand Consumer Behaviour

Google Trends, a public web facility of Google Inc., provides market researchers and other users with an index of the volume of specific internet searches on Google. Use of Google

Trends in business decision making now appears to be commonplace. Businesses have emerged that use Google Trends to help firms monitor consumer interests, understand consumers' behaviours, and monitor brand health. As a business tool, Google Trends can be informative as it allows users to assemble high-frequency information on consumers' interest in products and product attributes. Trends observed in Google Trends data are often used to forecast sales, develop marketing campaigns, make business decisions about products, and design web sites (Spiegel 2015; Kuenn 2013).

In economics, use of Google Trends has found a practical use in predicting the present. That is, many government statistics are released monthly, and those statistics can be informative regarding the current state of markets the statistics reflect. If there were no publication lag, the statistics would allow policy analysts and investors to identify where an industry stands within a business cycle, recognizing changes as they occur. But publication of all such statistics lags the activity being described, and they are sometimes revised after publication. Choi and Varian (2009, 2012) explored the idea that Google Trends data may be correlated with the current level of activity in an industry, and as it is released without a lag, at high frequency, and never revised, may predict the government statistics of interest almost in real time and well before those statistics are published. Choi and Varian (2012) examined automobile sales, travel destination planning, and consumer confidence. They found that internet searches provide a meaningful forecasting lead as they help predict, for example, the end-of-month report on motor vehicles and parts that is not released until two weeks later.

A wide variety of economic research has also investigated whether internet search data contain signals about searchers' concerns or subsequent behaviour. Askitas and Zimmerman (2009) were the first to show strong correlations between particular Google Trends keyword searches and German unemployment rates. As such, they could provide immediate, high-frequency information on unemployment during the Great Recession when economic conditions were changing rapidly. Also focusing on the recession, Chen et al. (2015) used Google Trends to construct indicators of concern, based on keywords "foreclosure help," "layoff," and "recession" to identify recession turning points in the USA five months faster than NBER. Troelstra et al. (2016) used Google data (Dutch equivalent to "quit smoking" as keyword) to estimate how interest in smoking cessation might respond (magnitude and duration) to Dutch restaurant smoking bans and to programs that support smoking cessation. They found that impacts of support for smoking cessation lasted longer than those of bans.

The common element linking use of Google Trends across research projects is the assumption that internet searches reflect what is on people's minds. People who are considering the purchase of a specific product search for it by name. In this paper, we maintain the common assumption that internet searches reflect what is on consumers' minds, and is an indicator of their purchase intentions. The implication of the assumption is that it reveals where and when consumers are confused about product attributes. Namely, product attribute confusion is indicated by behaviour in which thinking about one attribute influences subsequent purchases of an entirely different attribute.

Here, Google Trends data include weekly search volume indices specified by the keywords natural food and organic food, for the 5-year period between 2010 and 2014. Tabulations were requested for web searches made within the USA and in English. Each data point is a normalized share – a search term's search volume relative to total search volume each week. Google Trends normalizes shares so that the maximum share is set to 100 and all other shares are relative to that maximum. Internet search volume in total is large[3] but shares for any specific search are likely to be very small numbers. Instead of reporting very small numbers, Google Trends normalizes shares to vary between 100 and (potentially) 0 when it judges search volume too low to report.

Figure 1 shows the two time series. The two series were requested in combination so the weekly search shares would be comparable. Note that the two series frequently cross. That is, the two search share series are often equal – equal shares of total web searches. The natural food series mean is 60.4 and the organic food series mean is 55.9. However, the organic food series shows greater variability. Standard deviation of organic food is 8.3, compared to 5.3 for natural food. The organic food series varies over 33–100 (it includes the largest and the smallest share), while the natural food series ranges from 44 to 88.

Retail Market Data

A time series on weekly organic food purchases was constructed from IRI retail scanner data, denoted InfoScan.[4] We use aggregate consumer expenditures on organic fruit, vegetables, milk, yogurt, and eggs between 2010 and 2014 to represent organic food sales. Products from these five categories accounted for about half of all organic food sales in 2014 (Nutrition Business Journal 2017).

A selection of retail establishments across the USA and Puerto Rico provide IRI with records of transactions collected through store scanners. These records include revenue and quantity data for each unique item sold by the retailer. The data are aggregated to a weekly level such that each record contains the weekly revenue and quantity sold for each universal product code (UPC) or item by store. The stores reporting food sales include grocery stores, mass merchandisers, convenience stores, drug stores, dollar stores, and liquor stores. Some retailers provide data at the store level, i.e., sales data for a particular brick-and-mortar location, while others provide data for stores within a market area.

Over the period 2010–2014, the organic food retail sales data were derived from scanner records that varied annually from 18,168 to 27,148 individual stores and 101 to 103 aggregate retailer market areas representing 17,022 to 18,647 additional stores. We used the sum of weekly sales from stores and from market areas to identify total US weekly consumer expenditures from these establishments. Data from January 2010 through December 2014 yielded 260 weekly observations that were used in analysis.

The IRI data contain separate data series for packaged (UPC-labelled) products and perishable products. Perishable products are random-weight and uniform-weight fresh produce, meat, deli, and bakery items.[5] Expenditures for organic fresh fruits and vegetables are from the perishables data series, and expenditures for organic milk, yogurt, and eggs are from the packaged product data series. Not all stores report sales data for perishable products, but the vast majority of stores that provide UPC-level data also provide data for these fresh foods (Muth et al. 2016). To provide a consistent sample of stores across series, we only include UPC-level sales from stores that also report perishable product sales.

[3] In the USA, Google searches number approximately 11 billion monthly (Statista 2018).

[4] As the IRI InfoScan data are proprietary, this portion of the source data is available from the authors for verification purposes only.

[5] Random-weight products are variable-weight fresh produce, meat, deli, and bakery products without a UPC sold by the pound or the count. Fixed weight perishable products may be labelled with a UPC, such as fresh produce enclosed in a bag or clamshell container.

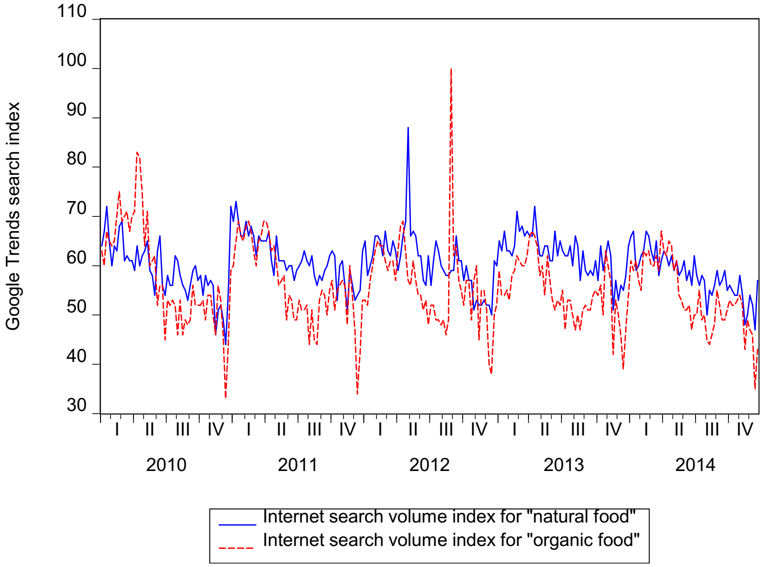

Fig. 1 Weekly internet searches in the USA for "organic food" and "natural food". Source: Google Trends. Index numbers represent relative search volume – searches relative to all web searches. Numbers are scaled relative to the maximum, set at 100

IRI provides dictionaries of product information to describe each item in the sales data, and these files contain product characteristics such as category, description, size, brand, and package claims. Product information is collected and coded by IRI using a variety of retailer, client, and industry sources; package information; brand; and produce PLU (price look-up) codes, and these product attributes allow us to identify organic products in the data.

Figure 2 shows a time plot of weekly purchases of organic food. The upward trend and an annual seasonal pattern is apparent.

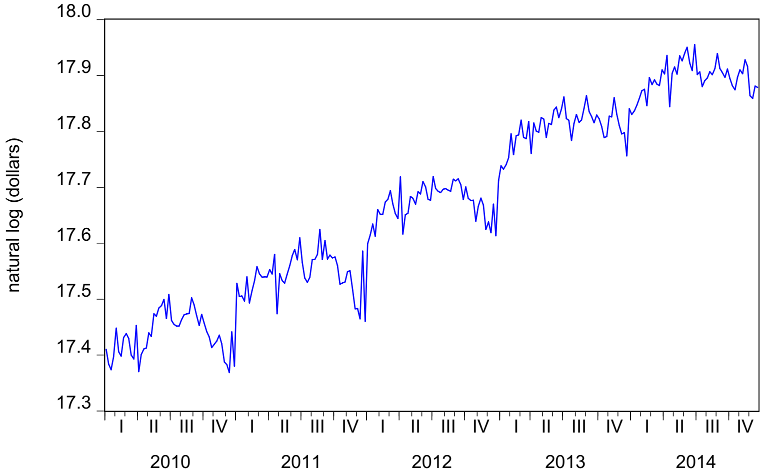

Fig. 2 Weekly U.S. expenditures on major categories of organic food: fruit, vegetables, milk, yogurt, and eggs. Source: IRI InfoScan data

Results

Statistical Evidence That Web Search Volume Is Related to Purchases of Organic Food

Estimating a VAR allows us to describe co-movements among the data series: the causal relations among variables along with short-term dynamics. In a VAR, each variable is allowed to be endogenous. VAR allows for cross-variable dynamics as each variable is related to its own past and all the other variables in the system.

Here, a VAR consists of three equations. Three left-hand-side variables are expenditures on organic food (natural log), web searches for organic food, and web searches for natural food. On the right-hand side are lags of each variable, where lag length is to be determined, and a set of exogenous variables. Right-hand-side variables are the same for each equation.

Describing co-movements among the series consists of three components. First, Granger-causality tests reveal whether one variable contains useful information for predicting another (in the linear least squares sense), over and above the past histories of the other variables in the system. That is, if one variable Granger-causes another, then at least one of the lags of first variable that appear on the right side of the other variable's equation must have a non-zero coefficient. It is also useful to consider the opposite situation, in which one variable does not Granger-cause another. In that case, all of the lags of the first variable that appear on the right side of the other equation must have zero coefficients. We use F tests to assess whether all coefficients on lags of a variable are jointly zero (our null hypothesis in testing for Granger causality).

Second, impulse response functions are calculated, showing the ways a shock to each variable moves through the system. Impulse response functions trace out the response of current and future values of each of the variables to a 1-unit increase in the current value of one of the VAR errors (an unexpected change), assuming that this error returns to zero in subsequent periods and that all other errors are equal to zero. Impulse responses are constructed by inverting the VAR system, yielding the moving average representation.

Third, the forecast error decomposition measures the amount of information each variable contributes to the other variables in the autoregression. It is the share of the forecast error variance explained by exogenous shocks to each of the variables in the system, calculated at a given horizon (say, for example, two weeks). When a large share of a variable's forecast errors is attributable to another variable, that second variable can be considered important for predicting or explaining the first variable. Thus, the forecast error decomposition is like a partial R^2 for the forecast error, by forecast horizon (Stock and Watson 2001).

Granger-causality testing, using a Wald test to test some zero restrictions on the parameters of a VAR, can be compromised by the presence of unit roots in the variables of a VAR. If any of the variables are non-stationary (whether or not they are cointegrated), test statistics for the model parameters will have a non-standard distribution (Sims et al. 1990). In effect, regression coefficients could be incorrectly judged to be statistically significant if the possibility of non-stationarity is ignored.[6] Impulse response functions and variance decompositions that are calculated from VARs with roots near unity are inconsistent, especially at long forecast horizons (Phillips 1998).

As the unit root tests are not very powerful, each of the three series was tested two ways: under the null hypothesis that the series has a unit root (Augmented Dickey-Fuller test (ADF))

[6] There are modifications to VARs that will allow Granger-causality tests to be valid even when data are non-stationary. Additional lags of variables must be added to a VAR as exogenous variables (Toda and Yamamoto 1995). But, to do so requires knowing the order of integration of variables.

and under the null hypothesis that the series is stationary (Kwiatowski-Philips-Schmidt-Shin test (KPSS)). That is, rejection of the unit root null under the ADF suggests stationarity. Simultaneously failing to reject the null of stationarity under KPSS would confirm the stationarity conclusion.

ADF tests were done in the most general form – including a constant and a linear trend.[7] On that basis, all three series appear to be stationary. Under ADF, the organic food expenditure series rejected the null at the 5% level ($p = 0.0180$). Under KPSS, the series failed to reject the stationarity null hypothesis even at 10% (when it is relatively easy to reject). That is, both tests indicated that the series is stationary.

Over a long time horizon, the web search series are likely to be stationary: They are bounded by the 0–100 interval and must fall when they reach 100. Nevertheless, these series were tested for unit roots to check for short-run non-stationarity. The organic food web search series and the natural food web search series both rejected the ADF null hypothesis that the series has a unit root at the 1% level (when it relatively difficult to reject). Testing the reverse null hypothesis that the series are stationary, KPSS test statistics gave similarly decisive answers. The tests failed to reject the null even at the 10% level for the both series. Both tests indicated that the two web search series are stationary.

Exogenous variables in the VAR included a constant and a linear trend in each equation, along with variables designed to account for the regular, seasonal movements of the three endogenous variables. A set of 52 weekly dummy variables could have been used to account for seasonality, but a more parsimonious approach is to take advantage of the fact that the seasonality displays continuous wave-like up and down movements throughout each year (with the organic expenditures also trending upward). As such, generalized sinusoidal waveforms might capture a share of the seasonality (Waugh and Miller 1970). We allowed for an annual cycle in each equation, $Rcos\left(\frac{2\pi}{52}t-\phi\right)$. R is the amplitude – height of the series peak relative to the mean, $\frac{2\pi}{52}$ converts time to radians where there are 52 weeks per year, $t = 0, 1, 2, \ldots$, and ϕ is the phase angle – the time difference between the first peak of the cycle and the origin. Using the cosine rule for addition/subtraction of angles, each sinusoid can be expressed as a linear function of a sine and a cosine function and those two terms were added to each equation.

The Akaike information criterion (AIC) and Schwartz information criterion (SC) were used to identify lag length. AIC and SC are estimators of the relative quality of statistical models for a given set of data–model selection criterion. Both reward goodness of fit (as assessed by the likelihood function), but include a penalty that is an increasing function of the number of estimated parameters. Overfitting is less likely when following SC guidance as the SC penalty for parameters is larger than the AIC penalty. AIC was minimized at three lags and SC at one.

Residual serial correlation was examined with the autocorrelation Lagrange multiplier (LM) test, which reports the multivariate LM test statistics for residual serial correlation up to a specified order. Tests were conducted up to order 15. With fewer than three lags, lower-order statistics rejected the null of no serial correlation. With three lags in the VAR, there was no evidence of serial correlation so the selected model was identified as having three lags.

Further diagnostics showed that inverse roots of AR characteristic polynomial were all within the unit circle: The system satisfies dynamic stability conditions. Estimation results are shown in Table 1.

[7] Estimates were made using the EViews 9.5 software.

Table 1 Vector autoregression estimates (and t-statistics)

	Endogenous variables		
	Natural food web searches	Organic food web searches	*ln*(purchases of organic food)
Lagged endogenous variables			
Natural food web searches (− 1)	0.4346 (6.5793)	0.0606 (0.6134)	0.0016 (3.5454)
Natural food web searches (− 2)	0.0265 (0.3602)	0.0024 (0.0216)	0.0007 (1.4458)
Natural food web searches (− 3)	0.0904 (1.3014)	− 0.0143 (− 0.1374)	0.0003 (0.5562)
Organic food web searches (− 1)	0.0401 (0.8909)	0.4356 (6.4734)	− 0.0002 (− 0.7047)
Organic food web searches (− 2)	0.0055 (0.1125)	0.0784 (1.0781)	0.0006 (1.8076)
Organic food web searches (− 3)	− 0.1263 (− 2.8391)	0.0104 (0.1557)	− 0.0011 (− 3.5717)
ln (purchases of organic food (− 1))	17.8806 (1.9243)	28.7780 (2.0714)	0.2462 (3.9387)
ln (purchases of organic food (− 2))	− 1.9033 (− 0.2085)	18.0188 (1.3199)	0.3002 (4.8889)
ln (purchases of organic food (− 3))	− 6.2580 (− 0.6993)	− 6.4955 (− 0.4854)	− 0.0157 (− 0.2605)
Exogenous variables			
Constant	− 134.5067 (− 0.7437)	− 664.6752 (− 2.4579)	7.9337 (6.5219)
Trend	− 0.0244 (− 0.9952)	− 0.1015 (− 2.7672)	0.0010 (6.3369)
Cos ($2\pi t/52$)	0.1079 (0.2264)	2.1180 (2.9716)	− 0.0115 (− 3.5806)
Sin ($2\pi t/52$)	2.0693 (4.4763)	2.0121 (2.9111)	0.0089 (2.8552)
R^2	0.5185	0.5712	0.9789

Results of Granger-causality tests are in Table 2, part A. The entries show the p values for F tests on the joint significance of all coefficients of lags of a particular variable. The null hypothesis—non-causality—is that lags of the variable in the row labelled *Regressor* do not enter the reduced form equation for the column variable labelled *Dependent variable in regression*. Reported p values less than 0.05 indicate rejection of the null hypothesis at the 5% level of significance, leading to the conclusion that one variable does help predict another.

The tests show that lags of the natural food searches variable help predict expenditures on organic food. The null of non-causality was rejected ($p < 0.001$). Similarly, the tests show that lags of organic food searches help predict expenditures on organic food. The null of non-causality was rejected for this variable as well ($p = 0.0030$). Despite the fact that the two attributes are entirely different from a legal and regulatory perspective, web searches for both can be said to Granger-cause organic expenditures.

It is plausible that consumers learn from the information they acquire. Their web searches may substantially contribute to their knowledge about foods labelled natural and differences from foods labelled organic. Conceivably, consumers search for information about natural food, discover what natural really means on a food label, and ultimately make informed choices. That is, some websites that provide credible and persuasive information about the difference between labels could be discovered by web searches for natural food.

If true, the hypothesis that consumers are learning from their web searches would mean that confusion and market failure are temporary, and of no consequence to economic efficiency in the long run. In this case, the path to becoming fully informed is likely two steps: searching for either natural food or organic food and discovering that the searched attribute is not what was first imagined, then searching for the other. This two-step hypothesis about the process of becoming informed and influencing organic purchases can be evaluated with the results of the causality tests.

On this question, the Granger-causality test results yield mixed results. Web searches for organic food Granger cause natural food web searches ($p = 0.0247$) but web searches for natural food do not Granger cause web searches for organic food ($p = 0.9280$). That is, web

Table 2 VAR descriptive statistics

A. Granger-Causality Tests[1]			
	Dependent variable in regression		
Regressor	*ln*(purchases of organic food)	Web searches for "organic food" keyword	Web searches for "natural food" keyword
ln(purchases of organic food)		0.0357	0.2879
Web searches for "organic food" keyword	0.0030		0.0247
Web searches for "natural food" keyword	<0.0010	0.9280	
All	<0.0010	0.0497	0.0424

B. Variance decompositions from the recursive VAR *Ordered as web searches for natural food, web searches for organic food, and organic food purchases*				
Forecast horizon	Forecast standard error	Variance decomposition of web searches for "natural food" keyword (Percentage of forecast error)		
		ln(purchases of organic food)	Web searches for "organic food" keyword	Web searches for "natural food" keyword
1 week	3.7315	0.00	0.00	100.00
5 weeks	4.4165	1.67	2.73	95.60
10 weeks	4.4882	1.78	5.14	93.08
15 weeks	4.4945	1.89	5.21	92.90
		Variance decomposition of web searches for "organic food" keyword (Percentage of forecast error)		
		ln(purchases of organic food)	Web searches for "organic food" keyword	Web searches for "natural food" keyword
1 week	5.5793	0.00	90.22	9.78
5 weeks	6.6831	5.46	80.95	13.59
10 weeks	6.8034	6.34	78.49	15.17
15 weeks	6.8165	6.33	78.50	15.17
		Variance decomposition of organic food purchases (Percentage of forecast error)		
		ln(purchases of organic food)	Web searches for "organic food" keyword	Web searches for "natural food" keyword
1 week	0.0251	99.68	0.11	0.21
5 weeks	0.0315	80.51	3.10	16.39
10 weeks	0.0329	74.50	7.80	17.70
15 weeks	0.0330	74.10	8.28	17.62

[a] Entries in part A show the p values for F tests (rejection of null hypothesis) that lags of the variable in the row labelled *Regressor* do not enter the reduced form equation for the column variable labelled *Dependent variable in regression*. Results were computed from a VAR with three lags. Exogenous variables included a constant term and time trend

searches for organic food may lead to searchers acquiring additional product information, but searches for natural food appear to stop there.

The multivariate nature of the model makes it difficult to interpret coefficients independently of one another and to discern the short-run dynamics. Instead, impulse response functions reveal how impacts of a shock to one variable might feed through the model and affect future values of the shocked variable or other variables.

However, without imposing some structure on the VAR, the estimated model may allow for a shock to simultaneously affect two or more variables in the model, and impulse response functions will be impossible to calculate. Here, residuals of the VAR were orthogonalized by a Cholesky decomposition using the following ordering: natural food web searches, organic food web searches, and organic food purchases. The point of doing so was to isolate the initial impact of a shock to one variable as it moves through each of the variables in the system. This ordering maintains the focus on the importance in natural food web searches in organic food purchases. Here, impulse response functions measure the effect of a one-standard-deviation innovation of a single variable on current and future values of each of the variables in the system of equations.

Figure 3 shows the nine calculated impulse response functions (solid lines) along with the 2 standard error bands (95% confidence interval around each response estimate). Panels along the diagonal show the responses of a variable to its own shocks. Off-diagonal panels show the responses of the variables to shocks in other variables. Points at which the lower confidence limit is positive indicate that an estimated response would be positive more than 95% of the time.

The lower left and lower center panels show responses of purchases of organic food to web searches. The response to natural food web searches shows that for weeks 2 through 7, confidence intervals are entirely positive.[8] For those weeks, *t* tests (at 5%) indicate that response estimates (using analytic standard errors) are positive, confirming the Granger-causality results that natural food web searches help predict organic food expenditures. Also, for weeks 4 and 6–11, confidence intervals about responses to organic food web searches are entirely negative. And *t* tests indicate that responses are negative for those weeks, again confirming the Granger-causality results.

The impulse response functions add new details to the picture of consumer confusion. The Granger-causality results suggest confusion by showing that organic food web searches help predict purchases of organic food, but so too do natural food web searches. The impulse response functions offer information about direction. The response of organic food purchases to organic food web searches is negative. Namely, searches yield a reduction in purchases of organic food. The response of organic food purchases to natural food web searches is positive, yielding an increase in purchases of organic food.

While the directions of these responses suggest consumer confusion, impulse response functions also point to the possibility that learning is occurring, partially conflicting with Granger-causality results. Conceivably, purchasing organic food may induce further interest in organic food, and reduce interest in natural food. Granger-causality tests suggest feedback from purchases to web searches for organic food ($p = 0.0357$) but not to web searches for

[8] Results appear to be robust to the Cholesky decomposition. Reversing the order in which variables entered the model (purchases of organic food entered first, followed by web searches for "organic food" and then by web searches for "natural food") yielded a pattern of impulse responses that is qualitatively quite similar to the pattern shown in Figure 3. Using the reverse ordering, statistically significant responses of organic food purchases to "natural food" web searches occurred at periods 2 through 8. And statistically significant responses of expenditures to "organic food" web searches were found at periods 3, and 8 through 11. That is, under either ordering, qualitative conclusions drawn from impulse response functions are unchanged.

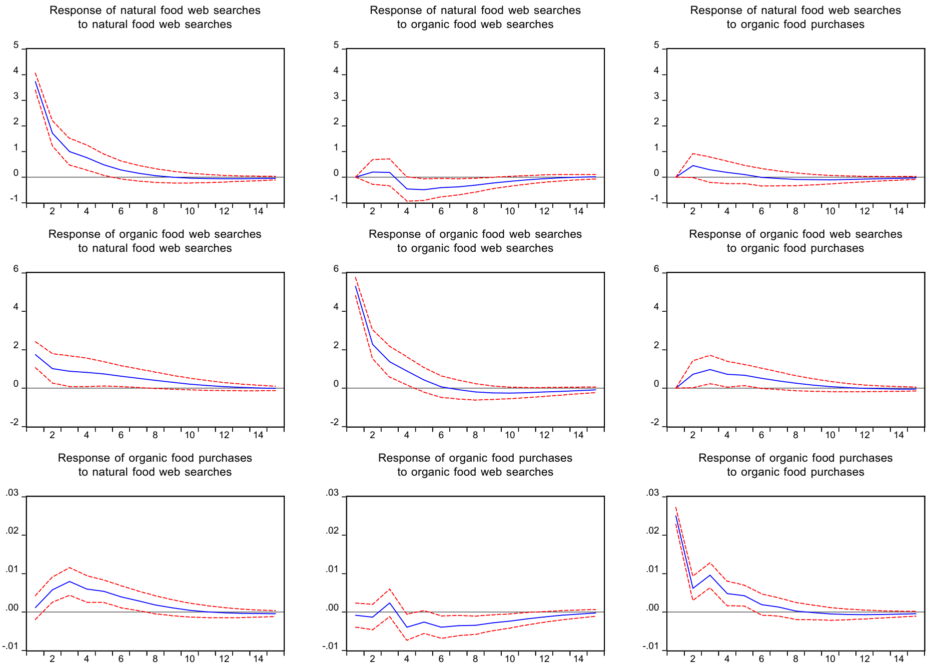

Fig. 3 Impulse response functions: Response to Cholesky One S.D. Innovations ± 2 S.E.

natural food ($p = 0.2879$). The impulse response functions show that the response of organic food web searches to purchases of organic food is largely positive. However, the response of natural food web searches to organic food web searches is largely negative.

The variance decomposition results (Table 2, part B) are consistent with the results from impulse response functions demonstrating confusion. Variance decomposition shows that after 15 weeks, searches for natural food explain more than twice as much (17.62%) of the forecast error variance for organic food expenditures as do searches for organic food. The latter is not significantly different from zero.

In sum, Granger-causality tests reveal that web searches for natural food and web searches for organic food both help predict organic food purchases. Impulse response functions confirm these results and add that the two operate in opposing directions. At relatively long forecast horizons, variance decomposition points to natural food web searches having a larger impact on organic purchases than web searches for organic food. So, the idea that consumers are well-informed and natural food web searches are irrelevant to organic food purchases can be rejected. The best explanation would then be that consumers really are confused.

Our findings suggest the existence of systematic confusion. What the finding does not say is whether the confusion is uniform across consumers or lodged in some particular sub-sets of consumers. Additional research will be needed to assess the magnitude of the problem.

Discussion and Conclusions

This paper explores the relationship between consumer demand for information about product attributes and their retail purchases. Results from a vector autoregression model show that web searches for both natural food and organic food are correlated with retail purchases of organic food. If consumers were aware of differences implied by the two label claims, searches for natural food would be uncorrelated with decisions to purchase organic products. These results therefore suggest that consumers view the two claims as related, or even view the two claims as identical.

Our analysis offers a revealed preference approach to analyzing what consumers actually did, using their own resources and time. Here, we statistically link consumer searches for product attributes with what consumers purchase immediately afterward. This finding builds on surveys and experimental work that find consumers are confused by *natural* and *USDA Organic* claims. While this analysis is not proof of consumer confusion or market failure, it contributes to a growing body of work that points in that direction. The analysis addresses the possibility of market failure from a quantitative perspective, relying on market data. That is, the analysis shows that it is sometimes possible that analysts can systematically and empirically examine whether information markets have failed.

A likely contributing factor to this confusion is the fact that Federal regulatory agencies consider *natural* to have a very limited meaning, while consumers believe it embodies many attributes that overlap with the standards required for *USDA Organic*. In response to stakeholder concern about the meaning of natural on food labels, both FDA and USDA have solicited public comments on the definition of natural during the last decade (U.S. Food and Drug Administration 2018; U.S. Department of Agriculture, Food Safety, and Inspection Service 2009). In both processes, outcomes are still pending. Regardless of its cause, the key issue here is the persistence of misleading information on food labels and the inability of competition among food suppliers to counter the misinformation. The confusion likely increases the profitability of the foods labelled as natural at the expense of the organic industry and reduces the provision of public health benefits from the reduced pesticide or antibiotic use in organic production systems.

Acknowledgements The findings and conclusions in this preliminary publication have not been formally disseminated by the U.S. Department of Agriculture and should not be construed to represent any agency determination or policy. This research was supported by the intramural research program of the U.S. Department of Agriculture, Economic Research Service. The analysis, findings, and conclusions expressed in this paper also should not be attributed to Information Resources, Inc. (IRI).

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