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Health Information Availability and the Consumption of Eggs: Are Consumers Bayesians?

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This study uses a generalized Bayesian updating model to estimate the impact of health information appearing in the popular media on the consumption of eggs. The framework permits us to explore the possible effects of several known psychological biases in learning. Generalized Bayesian learning allows media publications to have a decaying effect on behavior. Our primary finding is that health information has a significant impact on U.S. egg consumption. Furthermore, the reaction to health information is found to be temporary. Health information will, on average, decay to a point of unimportance in a matter of a few weeks without a constant and consistent stream of confirming information.

Key words: generalized Bayesian model, health knowledge, information, psychological bias

Introduction

With a growing number of overweight individuals, and a prevalence of diet-related diseases, policy makers have made a concerted effort to better inform the American public. It is widely believed that health information awareness in consumers alters the pattern of food consumption. This belief has led to a rapidly multiplying number of public service messages and information campaigns, such as those described on websites like Nutrition.gov or MyPyramid.gov. While there is some evidence of the impact of health information on aggregate market behavior, little has been said of how these impacts may change over time. In this paper, we use a generalized Bayesian updating model to examine the rate of decay in impacts of health information appearing in popular media.

Recently, some applied economists have attempted to analyze the impact of health information on consumers' perceptions by utilizing several health publication indices describing the content of various health-related articles in both the United States and Europe. These studies provide some interesting, though slightly conflicting results regarding the importance of published health information. While the majority of studies find large and significant impacts of health information on behavior, a few have provided contrary evidence (see Chern and Rickertsen, 2003). The diverse conclusions may be due to one of several reasons. Among the possible reasons are the contrasting

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methodologies utilized by different authors. There are two primary methodological differences we can point to here. First, the information sources selected for measuring the quantity of health information are different among the various studies, including published medical journal articles from *Med-Line*, or the popular press (such as the *Washington Post*). Second, models of consumer perception of behavior differ, with some using static indices of media activity to measure health beliefs, and others using Bayesian models of learning. Economists' choices of consumer perception models have been somewhat arbitrary.

Meanwhile, the marketing literature has concluded that health information plays little to no role in food consumption decisions, and is far outweighed by concerns of price, taste, and ease of preparation (see, e.g., Asp, 1999). Only about half of consumers state they are very concerned with nutrition, as compared to 83% who are very concerned with finding low prices (Food Marketing Institute, 2003). Some of the disparity between the economics and marketing literatures might be due to the different types of information examined in the two sets of literature. While economists tend to look for the effect of any health information on aggregate consumption, marketing scientists have examined more individual effects of specific pieces of positive health information. Strict assumptions about the impact of information in economics may have led to a situation where general trends in consumption are falsely attributed to general trends in media coverage.

By eliminating the restricted structure imposed by both Bayesian and static index measures of consumer perceptions, the marketing studies consistently show little hope for simple health information policies. We propose that this disparity is due to behavioral problems with learning and the difficulty of changing one's habits for more than a short period of time. For example, Chern, Loehman, and Yen (1995) use survey data describing consumer beliefs to show that individuals behave very much like Bayesians. However, their panel is extremely short (three time periods), and, as the behavioral literature has highlighted, behavior may not follow belief. Further, pure Bayesian models only allow for once-and-for-all changes in belief. A Bayesian never forgets, but can only update based on new information. Behavioral studies suggest information decays very rapidly, leading to wild changes in behavior for very little new information, in a process called "representativeness bias" (Grether, 1980). Such a bias would have significant implications on the types and duration of health information campaigns that would be effective in changing consumers' long-term behavior and health.

This study seeks to illuminate some of the cognitive processes affecting behavior. We propose a generalized Bayesian model to analyze the impact of health information on consumer behavior. The generalized framework allows for both the possibility that old information will be discounted over time, and that new information may be disregarded. In using this flexible model, we are able to address the information-updating processes of consumers regarding health risks related to the cholesterol content of eggs.

Like much of the economics literature to date, we find that health information in the popular media can have large impacts on food consumption decisions. However, this impact appears to be short lived, unless followed by a steady stream of supporting articles. This result, which largely supports those found in the marketing literature, has many implications for the dissemination of health information and the use of information campaigns as a means to fight obesity. First and foremost, it appears that government education efforts must be continuous if they are to have substantial effects on individuals' health.

Health Information Indices, Beliefs, and Learning

There are many potential sources of information consumers may use in determining the health content of various foods, including physicians, neighbors, the popular media, and consumers' own observations, among others. It is impossible for researchers to find a comprehensive metric representing the total flow of information to consumers. Consequently, it is necessary for researchers to make several simplifying assumptions when selecting the proxy for health information. Measures of the flow of health information included in current research are derived from three primary sources: published medical journals, the popular press, and binary choice variables generated from surveys of individual health knowledge. Table 1 provides an abridged summary of many important articles using demand estimation to infer the impact of health information. By examining the impact on demand, the research focuses on how information is translated into aggregate behavior, which may or may not represent belief.

Brown and Schrader's (1990) seminal paper introduced the use of medical journal publication-based indices as a measure of the availability of health information. By searching *Med-Line* for articles with the word "cholesterol," the authors construct an index representing the number of published medical articles in each quarter having something to do with cholesterol. They provide two indices. The first is the net number of positive articles (those supporting a link between cholesterol and health problems minus those disputing a link). The second index measures total publicity by simply identifying the total number of articles mentioning cholesterol. Several other papers have used similar methodologies, employing various sets of key words to select articles and define new health information indices (e.g., Kinnucan et al., 1997; Rickertsen and Lothe, 2001).

In contrast, McGuirk et al. (1995) argue that consumers get more information from popular press periodicals, such as the *Washington Post* or *USA Today*, than from medical journals. Using a search of periodical literature, the authors address the relation between heart disease and cholesterol from 1960 to 1980. Similarly, Schmit and Kaiser (2003) develop a quarterly health index for the period 1975 to 2000 based on a periodical search, using their index to assess the importance of cholesterol information on consumer demand for shell eggs.[1] Their work provides the point of departure for our current study.

While it is important to use relevant sources of health information to construct a measure of health information, it is also important that the metric be flexible enough to admit realistic use of information. Various models have been proposed to describe the process of learning given new information. The most prominent approaches in the literature can be approximately categorized into two families: static and dynamic.

Initial attempts to capture the process of health information dissemination resulted in the inclusion of a simple time trend in the demand equation (Brorsen, Grant, and Rister, 1984). Brown and Schrader's (1990) approach (later continued by McGuirk et al., 1995; and Schmit and Kaiser, 1998, 2003), employing the accumulated number of published medical articles, supposes that learning is a rigid, well-defined, once-and-for-all

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[1] The health index formula used by McGuirk et al. (1995) and Schmit and Kaiser (2003) is expressed as:

$$CHOL_t = \sum_{s=1}^{t} WCOUNT_s,$$

where $WCOUNT_s$ is the article count in period s, weighted by periodical subscription levels.

Table 1. Summary of Health Index Measurements in the Literature

Authors (Year)	Market	Health Index	Primary Finding
Brown & Schrader (1990)	U.S. shell eggs	Accumulated difference in supporting and questioning articles	Cholesterol information reduces egg consumption by 19%.
Capps & Schmitz (1991)	U.S. meat products	Brown & Schrader (1990) index	Health information contributes negatively to the demand for beef and pork.
Chang & Kinnucan (1991)	Canada butter	Negative media index	Consumer awareness of health information in Canada has contributed to the decrease of butter consumption.
Kinnucan et al. (1997)	U.S. meat products	Negative media index	Health information negatively impacts the demand for beef and pork.
Schmit & Kaiser (2003)	U.S. shell eggs	Cumulative articles	Health knowledge is negatively associated with egg consumption.
Kim & Chern (1999)	Japan fats & oils	Brown & Schrader (1990) index; cubic weighting function; geometrical declining lag index	Increasing consumer health information appears to have reduced the consumption of hog grease, tallow, and palm oil, and increased the use of fish oil, but it has had no major impact on other vegetable oils yet.
Boetel & Liu (2003)	U.S. meat products	Index based on Kim & Chern (1999)	The demand for beef and pork is associated negatively with health knowledge.
Chern, Loehman & Yen (1995)	U.S. fats & oils	Bayesian model	The Bayesian model fits the health information process well.

activity. By using the cumulative count of articles, the model implies consumers will change their behavior by some specific amount after reading a single article, and, without another article refuting the first, will continue. Thus, consumers are not allowed to forget, fall back on old habits, or allow an article to diminish in value. Further, at any point in time, each article is given equal weight in behavior no matter when it appears (so long as it is in the past or present).

Unlike the static health index approaches introduced above, Chern, Loehman, and Yen (1995) argue that the change in consumer beliefs regarding health risks might depend on the consumer's current perception—a process which can be represented through Bayes' rule. They focus on the information relevant to food choices, especially the linkage between health risks and food consumption. Chern, Loehman, and Yen use the Health and Diet Survey (HDS) data collected by the Food and Drug Administration (FDA) to document consumers' knowledge of health concepts in the years 1982, 1986, and 1988. Additionally, they adopt a Brown-Schrader index as the basis for information input (likelihood information) for each period, calculating consumer beliefs. Beliefs regarding the negative health effects of consuming oils are represented as a beta distribution, allowing Bayesian updating using a simple conjugate prior. Initial year beliefs were assumed to match the 1982 HDS survey data, with subsequent years' beliefs predicted through Bayesian updating using the beta likelihood function. They report a 9% bias in their predictions for the year 1988. While the model tracks the survey reasonably, there are only two predicted periods. Their work provides some evidence that Bayesian models may be fruitful in predicting consumer beliefs. Still, Bayesian models imply optimally weighted information. New information can only replace old information if new information has more content (i.e., representing greater precision or greater numbers of observations). Thus, if individuals do not learn in a way that optimally preserves old information in the face of new information (or a lack of new information), Bayesian models will be insufficient.

The subsequent work of Kim and Chern (1999) yields evidence that this is the case. They test a Brown and Schrader type index against two other indices allowing for information decay in explaining Japanese consumption of fats and oils. Kim and Chern find the greatest explanatory power in using a geometrically declining weighting of articles, allowing an article's importance to decline by 20% each month. The authors select the decline rate arbitrarily, but argue successfully that the actual rate is unimportant in estimation because the general trend of the index is insensitive to the selected rate. Within the context of health policy, however, this rate may be important in and of itself. To permit the greatest flexibility in describing behavior, we propose to modify the Bayesian approach, allowing for behavioral responses to information.

Psychological Bias in Information Perception and Updating

There are several documented psychological biases which could be expected to play a role in health information updating, and its impact on behavior (Rabin, 2002; Kahneman and Tversky, 2000). We build on the Bayesian approach, allowing a flexible form that can represent several known information processing biases. Chief among these is the representativeness bias (Grether, 1980). In several settings, and in various applications, psychologists have found that new information is given special weight as compared to older information. If this is found to hold in the health information arena, new articles should be expected to unduly influence current consumption. But, after having influenced consumption, this information may be discarded for more recent information. Grether models this process as a generalized Bayesian process, where the prior and likelihood are given unequal weight.

Availability bias occurs when individuals assess the probability of events based on how prominent they are in one's mind. Media coverage of accidental deaths has been shown to lead to availability bias in individual assessments of the probability of accidental death versus death by disease (Slovic, Frischhoff, and Lichtenstein, 1982). Individuals perceive that accidental death is more prevalent than death by disease, when in fact the opposite is true. This may be primarily attributable to the high level of news coverage given accidental deaths relative to deaths caused by disease. Availability issues are closely related to the issue of exposure to information discussed in the previous section regarding the media coverage of health information. The types and quantity of media coverage may substantially bias our understanding of health issues.

Finally, not all beliefs are directly translated into actions. Individuals display cognitive dissonance when they behave in a way that contradicts their stated belief—a phenomenon often observed in dieting and nutrition. For this reason, it is important to examine the impact of information on *effective belief*, or the beliefs incorporated in decision making. For example, many smokers may believe smoking will eventually kill them, and openly profess they should stop. Yet, because of the difficulty of quitting, they continue to smoke. Thus, we make use of estimation techniques similar to those developed by Strand and Lipton (1985). They examined the impact of newspaper articles on the demand for possibly contaminated fish, using newspaper articles as a proxy for information. Employing the data and demand estimation methods of Schmit and Kaiser (2003), we use magazine articles as a proxy for information regarding the detrimental health effects of egg consumption.

Data and Empirical Strategy

The data used for this paper were originally obtained from various sources documented in Schmit and Kaiser (2003). A list of the sources for each of the variables can be found in table 2. The data consist of a monthly time series of several variables relevant to egg production and consumption from 1982 to 2000, and article count data from 1975 to 2000. In order to focus on the issue of information updating, we follow Schmit and Kaiser's approach by proposing a system of supply, demand, and retail markup equations. A similar and possibly more accessible approach can be found in Schmit and Kaiser (1998).

The supply of shell eggs is represented by:

$$(1)\qquad \ln(QSF_t) = \ln(\beta_0) + \beta_1 \ln(\overline{P}_t) + \sum_{i=1}^{3} \mu_i DUM_{i,t} + \alpha_1 \ln(QSF_{t-1}) + \alpha_2 TREND_t + \varepsilon_t,$$

where QSF_t is the quantity supplied of shell eggs, $\overline{P}_t$ is a simple average of the ratio of the farm price of eggs to feed costs over the previous two periods, DUM_i are quarterly dummy variables, and *TREND* is a linear trend term. Note that all right-hand-side variables are lagged or exogenous. The markup equation is written as:

$$(2)\qquad WP_t = \phi_0 + \phi_1 FP_t + \phi_2 WAGE_t + \sum_{i=1}^{3} \kappa_i DUM_{i,t} + \omega_t,$$

where *WP* is the wholesale price of eggs, *FP* is the farm price of eggs, and *WAGE* is the average hourly wage of a worker in poultry slaughter and processing.

We employ the demand equation:

$$(3)\qquad \ln(D_t) = \delta_0 + \delta_1 \ln(WP_t) + \delta_2 \ln(Y_t) + \delta_3 \ln(CBP_t) + \delta_4 \ln(TRK_t) + \delta_5 \ln(PRK_t) + \sum_{j=0}^{4} \gamma_i \ln(ADV_{t-j}) + \delta_6 CHOL_t + \nu_t,$$

where D_t is the per capita wholesale demand for eggs, Y_t is consumer per capita disposable income, *CBP* is the real price of cereal and bread products (which may be substitutes for eggs), *ADV* represents expenditures on generic advertising, and $\gamma_j = \lambda_0 + \lambda_1 j + \lambda_2 j^2$. In addition to cereals, which are used by Schmit and Kaiser (2003) as a demand substitute for eggs, we add two more potential substitutes: *TRK*, the real consumer price of turkey and other poultry products (excluding chicken); and *PRK*, the real consumer price of pork and pork products.

Table 2. Definition of Variables and Identification of Data Sources

Variable	Description	Sources
QSF	Farm egg production (million dozen)	*Poultry Yearbook*, USDA; *Chickens and Eggs*, USDA
FP	Producer price of market eggs divided by CPI (¢/dozen)	*Poultry Yearbook*, USDA; *Agricultural Prices*, USDA
WAGE	Average hourly earnings of production workers in poultry processing, normalized by CPI ($/hour)	U.S. Bureau of Labor Statistics
WP	Average wholesale egg price divided by CPI (¢/dozen)	*Poultry Yearbook*, USDA; *Agricultural Prices*, USDA
Y	U.S. disposable income per capita divided by CPI ($/capita)	U.S. Bureau of Labor Statistics
CBP	Real cereal and bakery products price index	U.S. Bureau of Labor Statistics
CHK	Real consumer price of chicken and chicken products	U.S. Bureau of Labor Statistics
TRK	Real consumer price of turkey and other poultry products (excluding chicken)	U.S. Bureau of Labor Statistics
PRK	Real consumer price of pork and pork products	U.S. Bureau of Labor Statistics
ADV	Advertising expenditures divided by media cost index	Grey Advertising, New York
x	Number of articles per month	Cholesterol article count in *Reader's Guide to Periodical Literature*

Note: With permission, this table mostly reproduces the information found in table 12.1 of Schmit and Kaiser (2003).

Close substitutes and complements of egg demand have not been clearly identified in the previous literature (Chavas and Johnson, 1981). However, a number of goods have been hypothesized to influence egg demand. Specifically, pork, beef, and turkey have all been used in the empirical literature (see Chavas and Johnson, 1981; Brown and Schrader, 1990). None of these substitutes have been found to be significantly related to egg demand. Nonetheless, we include pork and turkey for consistency with the literature. The real price of beef has been omitted because it is so closely related to the two included meats that it causes numerical errors in the nonlinear optimization routines used in subsequent sections. Results from estimation excluding these substitutes are similar in magnitude, size, and significance to the results we report below.

Schmit and Kaiser (2003) use three-stage least squares estimation and a simple cumulative number of articles,

$$CHOL = \sum_{i=1}^{t} x_i,$$

finding that health information has a significantly negative impact on demand. Such a form precludes any possibility that information would decay over time. Alternatively, estimating the generalized Bayesian updating process we propose later in the paper [see equation (11)] is empirically challenging due to the high degree of nonlinearity. In order to show the importance of how consumers weight old and new information, we first introduce the simplest generalization of the information index used throughout the literature, allowing different weights for the cumulative number of articles from previous periods and the number of new articles. The health index is specified as:

Table 3. Results of Demand Estimation Using Cumulative versus Current Articles

Variable	Coefficient	Standard Error[a]
Constant	2.3635	0.9609
Wholesale Egg Price (*WP*)	-0.0410	0.0204
Income (*Y*)	0.2465	0.1148
Cereal Price (*CBP*)	-0.3841	0.0703
Turkey Price (*TRK*)	0.0150	0.0553
Pork Price (*PRK*)	0.0842	0.1899
DUM_1	-0.0271	0.0073
DUM_2	-0.0398	0.0069
DUM_3	-0.0270	0.0069
Cumulative Number of Articles $\left(\sum_{i=1}^{t-1} x_i\right)$	0.0003	0.0000
Article Count in Current Period (x_t)	-0.0002	0.0011

Akaike Information Criterion (AIC) = -6.7074
Schwarz Information Criterion (SIC) = -6.3294

[a] Standard errors are based on the bootstrap method with 1,000 replications.

$$CHOL = \sum_{i=1}^{t-1} x_i + \eta x_t, \tag{4}$$

where x_t is the article count for period t, and η is a parameter to be estimated, which can be regarded as the relative weight of consumer perception between the cumulative information and the new information. If egg demand patterns display a rapid decay in information response, then behavioral anomalies must drive some egg consumption behavior—either because information is quickly forgotten, or because information is soon ignored. This finding would underscore the importance of understanding information processing when examining decision making under uncertainty.

The estimates of the demand-supply simultaneous system in equations (1)–(4) are given in table 3. In estimation, the terms of (4) were treated as separate linear regressors, as reported in the table. Thus, if an article has a once-and-for-all effect, we should observe identical signs and magnitudes for the coefficients on both media-related variables. The estimates of our model are substantially different from those found when imposing equal weights between current and previous periods. An article in the current period has a negative (though not significant) impact on the amount of eggs consumed. Alternatively, the cumulative number of articles about cholesterol from all previous periods appears to have a significant *positive* effect on consumption. Hence, a current month's article may decrease consumption as compared to the previous month's consumption. By the following month, the same article will actually increase consumption relative to the first month's consumption.

Notably, the estimates suggest that the marginal impact of a current period article is of nearly the same size as, though different sign than, an article from any previous period.

Ignoring the noise in the result, an article today will decrease consumption by nearly the same amount by which an article last month will increase egg consumption. In other words, articles have an impact on behavior that on average will cancel out within one month. If the same number of articles were published each month, the resulting index would not change from period to period. This is in stark contrast to the results of Schmit and Kaiser (2003) who find substantial significance when binding both cumulative and current articles to have the same coefficient. While not convincing evidence, this suggests cumulative article indices may either proxy for other time-varying effects, or there is a saturation point at which individuals cease to care about prior media attention and focus on current articles. In any case, it appears that more recent articles have a more negative impact on egg consumption, the ostensible objective of health information.

Theoretical Framework for an Information-Updating Process

While the previous section provides evidence of information decay, it is also important to understand the impact of such phenomena. Within this section, we propose a more general model of health information updating, and corresponding estimates, in an attempt to discern the magnitude of behavioral biases in learning.

Suppose a representative consumer maximizes the utility of consumption,

$$\max_{z} U\big(z, y, h(z)\big)$$

subject to:

$$p_z z + p_y y = W,$$

where z is the consumption of eggs, y is the consumption of other goods, h is health as a function of egg consumption, p_z, p_y are the respective prices of eggs and other goods, and W is income. The problem of information processing arises because of uncertainty regarding the nature of the function $h(z)$, and more particularly the slope of this function. Thus, the consumer problem may be better represented as the result of expected utility optimization,

$$\max_{z} (1 - p)U\big(z, y, h_g(z)\big) + pU\big(z, y, h_b(z)\big)$$

subject to:

$$p_z z + p_y y = W,$$

where p represents the subjective probability of eggs having a negative impact on health according to the function h_b, versus the possibility of eggs having a negligible impact on health according to h_g. The solution to this latter problem can be represented as:

$$(1 - p)\left[\frac{\partial U}{\partial z} + \frac{\partial U}{\partial h}\frac{\partial h_g}{\partial z}\right] + p\left[\frac{\partial U}{\partial z} + \frac{\partial U}{\partial h}\frac{\partial h_b}{\partial z}\right] - \lambda p_z = 0, \tag{5}$$

$$\frac{\partial U}{\partial y} - \lambda p_y = 0, \tag{6}$$

$$p_z z + p_y y = W. \tag{7}$$

If health in the good state has a negligible impact, then $\partial h_g/\partial z \approx 0$, and (5) can be rewritten as:

$$\text{(8)} \qquad \frac{\partial U}{\partial z} + p\left[\frac{\partial U}{\partial h}\frac{\partial h_b}{\partial z}\right] - \lambda p_z = 0.$$

Thus, using the price of other goods as a numeraire, demand can be represented as the function

$$\text{(9)} \qquad z = f(W, p_z, p).$$

In estimating (9), it is important to model the movement of the beliefs that eggs are harmful, p. One intuitive way to model these beliefs is by using a Bayesian process. For example, suppose the number of articles in a given time period was distributed Poisson, with probability density given by $f(x) = \mu_s^x e^{-\mu_s}/x!$, where x is a nonnegative integer representing the number of articles appearing in the media, and μ_s is the expected number of articles in state s. If eggs are truly harmful, then let the expected number of articles in a month be μ_b, while if eggs do not significantly affect health, let the mean be μ_g. If the prior belief that eggs are harmful in period $t = 0$ is p_0, then a perfect Bayesian would update according to

$$\text{(10)} \qquad p_t = \frac{p_0 \mu_b^{\sum_{i=1}^{t} x_i} e^{-t\mu_b}}{p_0 \mu_b^{\sum_{i=1}^{t} x_i} e^{-t\mu_b} + (1 - p_0)\mu_g^{\sum_{i=1}^{t} x_i} e^{-t\mu_g}},$$

where p_t is the perceived probability that eggs are harmful in period t. By introducing an explicit probability that media articles are in error, this model allows for some flexibility in learning.

Each term in equation (10) consists of an initial prior probability multiplied by several iterations of the Poisson distribution. If the mean number of articles connecting eggs to negative health effects given eggs are not harmful (μ_g) is high, it will take an even larger number of articles appearing before the representative consumer will believe in the health effects. A low number of articles published could be taken as a signal that there is no important health link if the average number of articles published is closer to μ_g than μ_b.

Alternatively, individuals may give greater weight to newer information. Grether (1980) has proposed the use of the generalized Bayes' rule to take account of the behavioral issues of updating. Bayes' rule can be written as $p_1(X = x \mid \theta) = p_0(X = x) l(\theta \mid X = x)/P(\theta)$, where p_t is the posterior probability distribution of the random variable X conditional on information θ, p_0 is the prior distribution of X, l is the likelihood of information θ conditioned on the value of X, and P is the marginal distribution of information. Zellner (1988) has shown that this is the optimal information-updating formula under a very general set of assumptions. The generalized Bayes' model gives exponential weights to the prior and/or the likelihood, and can be written as $p_1(X = x \mid \theta) = p_0(X = x)^{r_1} l(\theta \mid X = x)^{r_2} / P(\theta; r_1, r_2)$. The generalized Bayes' rule therefore allows for differences in learning effects where a larger value of r_1 will increase the variation of the prior, and thus increase its importance in the posterior. Likewise, increasing r_2 will make the posterior look more like the likelihood information which represents new information.

Just (2001, 2002) has shown that this model can capture many of the behavioral issues surrounding learning and decision making under uncertainty. In Just's version of the generalized Bayes' rule, designated the limited learning model (LLM), weights are a function of the properties of the likelihood and prior themselves. Hence, for example, diffuse and confusing information may be underemphasized and concise information overemphasized. If we suppose there is a static bias toward newer information, then the updating function becomes:

$$p_t = \frac{p_0 \mu_b^{\sum_{i=1}^{t} rx_i} e^{-\mu_b tr}}{p_0 \mu_b^{\sum_{i=1}^{t} rx_i} e^{-\mu_b tr} + (1 - p_0) \mu_g^{\sum_{i=1}^{t} rx_i} e^{-\mu_g tr}}, \tag{11}$$

where $r \in R_+$. This r is a geometric weight given to the likelihood, or new, information (where old information is given a weight of 1). While both forms are highly nonlinear, the perfect Bayesian model in (10) is a function generally of the number of time periods that have passed, the cumulative number of articles

$$\sum_{i=1}^{t} x_i,$$

and three unknown parameters,

$$p_t = f\left(\sum_{i=1}^{t} x_i, t; \mu_g, \mu_b, p_0 \right).$$

Alternatively, the LLM in (11) is the same function of the number of time periods multiplied by r, and a weighted cumulative sum of articles

$$\sum_{i=1}^{t} rx_i$$

and three unknown parameters,

$$p_t = f\left(\sum_{i=1}^{t} rx_i, tr; \mu_g, \mu_b, p_0 \right).$$

The main focus of our paper is in identifying the magnitude of r which determines the shelf life of new information. The smaller is r, the longer information persists, and the larger is r, the faster information decays.

The model in (11) allows for discounting of information because either the information in a period is not prominent enough to signal a true relationship between eggs and health or the information is forgotten or no longer acted upon as time passes. We replace the variable *CHOL* in (3) with the formula for current-period belief, p_t. In order to explore the overall behavior and potential explanations, three separate models are estimated here: model A, the full model appearing in equation (11); model B, the model in (11) with the additional restriction $r = 1$; and model C, the model in (11) restricting the expected number of articles appearing given no negative health effects from eggs (μ_g) to be a very low number.

Model B is the perfect Bayesian model, representing perfect, once-and-for-all learning. By estimating model B, we can examine whether disbelief resulting from sporadic media coverage alone may explain consumer behavior. Model C supposes that consumers have a high degree of faith in the media. Thus, estimating model C can allow us to determine if the decay of information alone may explain consumer behavior. In our estimation of model C, we restrict $\mu_g = 0.01$, which would imply an average of one article every 8.3 years. Estimates and the fit obtained from each model are compared in order to illuminate the drivers of consumer behavior relating to information.

The model is estimated using nonlinear three-stage least squares. The results of the demand function estimation are summarized in table 4. In order to ensure a reasonable prior, the prior is calculated in each iteration of optimization using the estimated Bayes' rule and the article data from 1975 to 1981—the year prior to egg consumption data.

In the estimation for models A, B, and C (table 4), we are interested primarily in the behavioral parameters r, μ_b, and μ_g. All other parameters are similar in sign, size, and significance to those found by Schmit and Kaiser (2003) using a conventional index of health knowledge. Advertising effects are omitted from table 4; however, the impacts are significantly positive, in contrast to the results found by Boetel and Liu (2003) when comparing the effects of advertising and health knowledge.

Examining the results for model A (table 4), we observe that newer information receives substantially more weight than older information. This is consistent not only with our hypothesis, but with the evidence found in the behavioral literature (e.g., Grether, 1980). In this case, newer information receives a geometric weight near 2.6, compared with older information which receives a weight of 1. This difference is significant at any reasonable level of confidence (only one of the bootstrapped draws had an estimate less than or equal to 1), and would suggest that old information has an effective shelf life of just a few weeks. This would lead to a geometric decline in information at a rate of about 60% per month, as compared with the 20% currently employed by Kim and Chern (1999).

Additionally, the estimates suggest individuals expect about three articles a month given that eggs truly have negative health effects, and about one article every four months if there is no link. This finding suggests a substantial disbelief in the media (or at least failure to act), particularly for those items not receiving much coverage. However, the parameter μ_g is not significantly different from zero, leaving open the possibility that this is just a poorly estimated relationship.

Estimates for model B (the perfect Bayesian model) imply individuals expect about 3.5 articles a month given that eggs truly have negative health effects and about one article every four months if no negative health effects. This model fails to estimate the expected number of articles in either state with any degree of precision. Neither of these estimates are significantly different from those estimated in the full model. Despite the lack of precision, the ability to explain behavior using the Bayesian model is similar to model A, as reflected in lower Akaike information criterion (AIC) and Schwarz information criterion (SIC) values.

Finally, estimates for model C (implying full faith in the media) suggest an even greater weight on new information than model A. Additionally, estimates suggest a slightly lower number of articles on average given that eggs truly have negative health effects. Neither of these differences are significant, however. Importantly, model C also has a similar ability to explain the consumption behavior, with the lowest AIC and SIC

Table 4. Results of Alternative Demand Specification

Variable	Model A (Full)	Model B (Bayesian)	Model C (Faith in Media)
Constant	-5.4445	-5.4475	-6.0314
	(1.2298)	(0.9922)	(1.1882)
Wholesale Egg Price (p_z)	-0.0474	-0.0473	-0.0037
	(0.0215)	(0.0204)	(0.0207)
Income (W)	1.0850	1.0853	1.0342
	(0.1151)	(0.1155)	(0.1146)
Cereal Price (CBP)	-0.4786	-0.4787	-0.2670
	(0.0716)	(0.0749)	(0.0729)
Turkey Price (TRK)	0.0242	0.0243	0.0323
	(0.0546)	(0.0567)	(0.0551)
Pork Price (PRK)	0.0741	0.0739	0.2223
	(0.1888)	(0.1854)	(0.1916)
DUM_1	-0.0269	-0.0269	-0.0252
	(0.0075)	(0.0074)	(0.0072)
DUM_2	-0.0401	-0.0401	-0.0365
	(0.0072)	(0.0072)	(0.0074)
DUM_3	-0.0262	-0.0262	-0.0257
	(0.0072)	(0.0070)	(0.0071)
Health (h)	-0.0079	-0.0079	-0.0164
	(0.0033)	(0.0031)	(0.0049)
Behavioral Variables:			
r	2.6655	1.0000	2.7695
	(0.1885)	(—)	(1.1195)
μ_g	0.2261	0.2432	0.0100
	(0.1299)	(0.3291)	(—)
μ_b	2.9160	3.4497	2.8230
	(0.6855)	(2.7771)	(1.0285)
AIC	-6.6502	-6.6623	-6.7535
SIC	-6.2344	-6.2654	-6.3566

Note: Values in parentheses are standard errors. Standard errors were obtained using 1,000 bootstrapped samples of the same size as the original sample.

criteria of the three models, revealing it may be more important to allow flexibility in weighting new information than to allow flexibility in the threshold of disbelief. This conclusion is, at best, tentative. While model C does perform better, the results from all three models are very similar in explanatory power. Notably, model C is the only model that performs better than our crude generalization of Schmit and Kaiser (2003) appearing in table 3. All models predict very nearly flat curves.

To better illustrate the results of this model, the predicted beliefs and article counts resulting from each model are plotted in figure 1. At first glance, this figure appears to show very dramatic swings in belief from probability of 0 to 1 and back. While the beliefs are primarily characterized by large swings at threshold points, there is substantial variation in beliefs even where the model appears to predict stable beliefs. For example, for the years 1982 to 1987, the standard deviation of belief is eight times as large as the average belief. Thus, the model predicts substantial variation in beliefs from period to period, with large shifts in average beliefs after critical amounts of media coverage (or

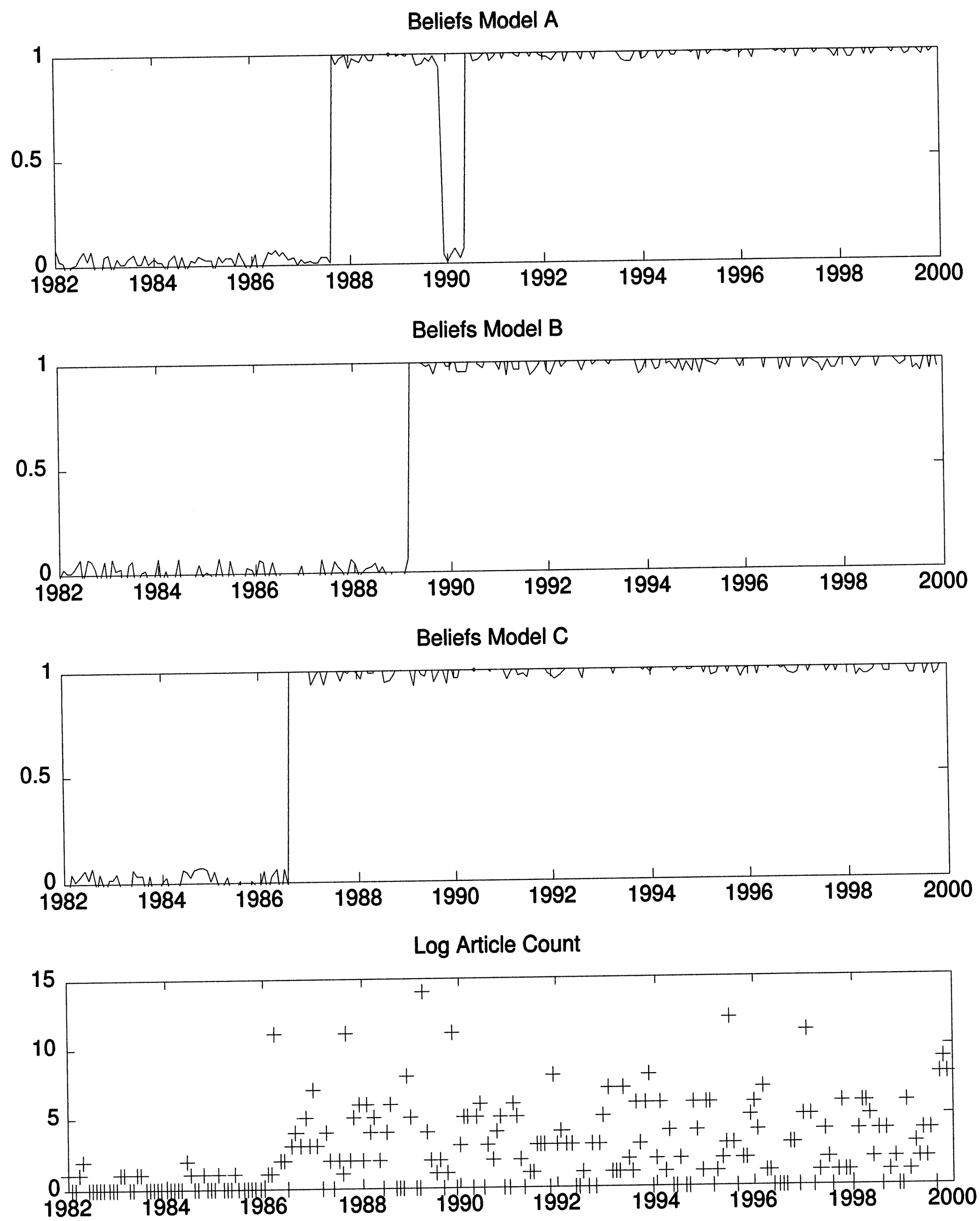

Figure 1. Predicted beliefs and article counts

lack of coverage). The large swings and stable areas are due to the use of the Poisson distribution. Bootstrapped draws resulting in estimates of μ_g and μ_b which are near one another produce plots that are smooth and beliefs that are much more stable. The indices used in prior works all suppose somewhat smooth shifts in belief. The estimates we produce here, however, suggest aggregate behavior is much lumpier. Even the plots for the perfect Bayesian model therefore appear to show a giant swing in response to the media around 1989.

Conclusions and Recommendations

In this paper we have attempted to estimate the rate at which information decays in decision making, and the general level of publication needed to overcome disbelief. Our best estimates differ significantly from the rational Bayesian model. Without constant and consistent information, our findings show that information decays to a point of unimportance in a matter of a few weeks. In the case of eggs and the negative effects of cholesterol, it appears media coverage has been constant enough to affect actions substantially. Other health issues may not be so easy to publicize. This has grave implications for health and nutrition information policy.

Additionally, our model appears to show that behavioral response to health issues occurs in large waves, rather than through slow and gradual change. The model we present supposes that large changes in behavior happen when sufficient media attention is received such that individuals no longer doubt the truthfulness of the reports. Of course, there may be several other explanations for this behavior. For example, it could be due to dietary fads or other social behavior. In any case, it is difficult to reconcile our results with either the standard health information indices or common models of belief updating currently employed in the literature.

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