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

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Abstract

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We use a generalized Bayesian updating model to estimate the impact of health information appearing in the popular media on the consumption of eggs. Our model allows media publications with differing circulation numbers to have differing effects. Further, we explore the possible effects of several known psychological biases in learning.

Subject code: 9

Selected Paper prepared for presentation at the American Agricultural Economics Association Annual Meeting, Denver, Colorado, July 1-4, 2004

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

It is widely believed that health information awareness in consumers alters the pattern of food consumption. Health information changes the consumers' beliefs, causing the change of food purchase decision. With growing numbers of overweight individuals, at increased risk for diabetes, heart disease and other health problems, policy makers are highly interested in getting accurate and convincing information to consumers. While there is some evidence of impact of health information on aggregate market behavior, it is difficult to quantify the impact of beliefs, because there is no general rule to measure information and the unobserved process of consumer information perception.

There is some disagreement between the economics and marketing literatures regarding the impact of health information on consumption. The economics literature has supposed health information is a significant determinant of consumption, and, thus, policymakers can significantly improve the health of individuals by publicizing clear and accurate information regarding health. Recently, some applied economists attempted to analyze the impact of health information on consumers' perception by utilizing different health resources and health information sources in United States and European countries. Although they provide some interesting results of health impact on consumers' decision, the conclusions they reach are still diverse. For example, researchers focusing on US studies find that health information is a significant and large factors to consumers, but EU data shows that this factor is negligible (Chern and Rickersen 2003).

The diverse conclusion may be due to one or several reasons. Among the possible reasons, the different methodologies utilized by different authors might be the most important one. There

are two significant differences we can point to here. First, the information sources they select for measuring the health information is different among different researchers, including published medical journal articles from Med-Line, the popular press, such as the Washington Post. Second, their definition of the consumer perception process or the impacts on consumer health concern by these sources is different, including static process approaches, and Bayesian approaches. Basically, the models adopted for consumers' perception process is somewhat arbitrary (Chern and Rickertsen 2003).

Meanwhile, the marketing literature has concluded that health information plays little to no role in food consumption decisions, far outweighed by concerns of price, taste and ease of preparation (Asp, 1999; Food Marketing Institute, 1998).. Some of this disparity might be due to the different types of information examined in the two literatures. While economists tend to look for the effect of any health information, marketing scientists have examined more specifically the effect of specific pieces of positive health information. Certainly some consumers are affected by the information, but in very different ways. By eliminating the restricted structure imposed by economists, the marketing studies consistently show little hope for simple health information policies. We propose that some of this disparity may be due to behavioral problems with learning. Chern, Loehman, and Yen (1995) use survey responses on consumer beliefs to show that individuals behave very much like Bayesians. However, their panel was extremely short (three time periods), as the behavioral literature has highlighted, behavior may not follow belief. Behavioral studies suggest that information decays very rapidly, leading to wild changes in behavior for very little new information (Grether 1980), in a process called representativeness bias. Such a bias would have significant implications on the types and duration of health information campaigns that should be used to affect consumers' long term health.

In this paper we hope to illuminate some of the cognitive processes effecting behavior. We first review the existing methodology for quantitative the health information, and their potential drawbacks. We propose a generalized Bayesian model to analyze the health information impact on consumers. In so doing, we are able to discuss the information updating process of consumers' belief about cholesterol risk of egg consumption. More particularly we assess the importance of new information in changing behavior. Employing generalized Bayes theories, and some results from the behavioral economics literature, we find that health information in the popular media can have great impact on food consumption decisions. However, this impact appears to be short in duration unless followed by a steady stream of supporting articles. This result has many implications for the dissemination of health information. First and foremost, it appears that government education efforts must be continuous if they are to have substantial effects on individual health.

Literature Review

Health information sources

Consumers might receive health information from many sources including physicians, neighbors, and the popular media, and their own observations. It is an impossibility for researchers to find a complete index representing all of the possible sources. As a result, it is necessary for researchers to make several assumptions for selecting the proxy for defining health information sources. The possible indices of health information in current research includes four different kinds: published medical journals, popular press, and binary choice variables from surveys of individual beliefs.

The first information source of health concern appearing in the literature was from the medical index, Med-Line. Brown and Schrader's (1990) seminal paper introduced the use of

journal indices as a measure of health information. By searching the articles of Med-Line connected to cholesterol, they construct a cholesterol information index based on the numbers of published medical articles. In their paper, they provide two indices. The first index is the "net number" of positive group articles, supporting the linkage between heart disease and cholesterol, and the negative group articles, questioning the linkage. The second index is the "total publicity" in which the two groups of articles are simply added together. Following Brown and Schrader (1990), a lot of researchers use the same data set, but employing different key word searches for selecting the articles as the health information index. Some of these results are summarized in the next section. Although medical articles contain information on health, some researchers argue that the general public doesn't usually read these kinds of articles. Instead, they propose that the popular press, such as the Washington Post and USA Today, might be a better measure of the information disseminated to the general public. This is the method used by Schmit and Kaiser (2002) in assessing the importance of cholesterol information on consumer demand for shell eggs. Their work provides the point of departure for our current study.

Process of information perception

The second issue of importance in assessing the impact of health information, and primary focus of our paper, is how information is processed into consumers' perceptions. Various models have been proposed to implicitly define the processing of information. Here, we roughly summarize several kinds of different approach as following.

Type I Index: Simple time trend variable:

Originally, the impact of health information on consumption behavior was modeled by including simple time trend variables, in linear or quadratic form, into the demand function in order to capture the structural change of consumer behavior (Brorsen et al, 1984). Although this

is an easy and intuitive way for measuring the pattern of change in econometric studies, this kind of simple approach may not truly reflect the context of information change of consumers' behavior. Most important of all, simple times trend can't really reflect the pattern change of information over time, or the process by which this information is absorbed into behavior.

Type II index: Net publicity or total publicity index

Brown & Schrader (1990) (BS), the seminal article of health information indices, define a cholesterol information index as the accumulated number of published medical articles supporting a link between cholesterol and arterial disease minus the sum of articles questioning the link from Med-Line database. The main reason the authors used this index was based on the epidemiological evidence of populations with high fat diets and a low incidence of heart disease. As a result, they collected approximately 1000 medical articles from Medline with key words related to "diet cholesterol", "serum cholesterol", and "heart disease" or "arteriosclerosis". They also separated total articles into two groups, supporting and questioning groups, and calculated the difference between these two groups. Based on assumptions regarding information lags, they accumulated the net difference of each quarter to represent the "net health index". Some important assumptions of BS index should be noted. BS assume the diffusion of information was solely from medical articles. The second important assumption is that of equal weight given to all articles, regardless of time, or thesis.

Similar to BS index, Rickertsen et al. (2001) adopted two kinds of indexes by counting the number of articles found in Med-line with different kinds of keyword searches. They used "fat or cholesterol and heart disease or arteriosclerosis and diet" to search articles in order to construct their global index (GI). The Nordic index (NI), only included articles with an explicit reference to one of the Nordic countries. The NI index is based on the keywords "fat or

cholesterol" and "heart disease or arteriosclerosis", and "Denmark or Finland or Iceland or Norway or Sweden or Danish or Finnish or Icelandic or Norwegian or Swedish". Because less than 6% of the articles they search in any period questioned the relationship, they only select the articles with negative impact to health information.

McGuirk (1995) argued that consumers get more information from popular press periodicals than medical journals. So they used Periodical Literature (RGPL) to address the relation between heart disease and cholesterol from 1960-1980. Similar to McGuirk (1995), Schmit & Kaiser (2002) developed quarterly health index from 1975-2000 based on RGPL with the following formulas:

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

where $WCOUNT_s$ is the quarterly article count, weighted by periodical subscription levels. They find very significant negative effects on consumption over the time period 1975 to 1996. Over the period from 1997 to 2000 the effects differ significantly, they suppose, because the press became less negative over this period. This highlights one problem with the use of such a measure. While count of articles gives some link to the information that is disseminated, it can be difficult to delineate which articles are positive and which are negative. Each article in each different period could potentially have a different impact effect. Without delineating positive and negative groups, it may be difficult to determine what impact articles have in general. With respect to eggs, there has been very little positive written on eggs in the entire time period. Thus despite this weakness, we find Schmit and Kaiser to be a good starting point to examine behavioral models of learning in the consumption of eggs.

Type III index: weighted negative publicity index:

Kinnucan et al. (1997) try to determine a separate weighting scheme for positive and negative articles, amending the approach of Brown and Schrader (1990) by including all information from positive and negative groups of information. They collected medical articles from Canada and then separated them into two groups, negative and positive groups. They use a hybrid index of the two groups, they call "effective negative publicity". They suppose

$$INFO_t = \sum_{\tau=1}^{t} K_\tau \ NEG_\tau$$

Where K is the weighting factor computed as the ratio of negative information to the sum of negative and positive information. ie, $K = NEG/(NEG + POS)$. The variable NEG is the negative information datum in BS index, POS is the positive information datum in BS index. Each of these indices imposes severe structure on the updating process, and in particular a structure that gives equal weight to new and old information. Hence, in this structure, an article in 1975 should have the same impact on consumption in 2000 as an article published in 1999.

Type IV index: lag variable index:

A series of studies involving Chern (Chern and Zuo 1995; Kim Chern, and Jones, 1998; Feng and Chern 2000) attempted to construct an index to capture a more complete measure of Japanese consumers' fat and cholesterol information. They argue that, although the BS index has come to be recognized as problematic, such an index may yield high explanatory power while not truly reflecting changing consumer perception in an empirical demand analysis. As a result, Chern's articles adopted three different indices.

Kim and Chem (1997) constructed and compared three alternative measures of Japanese consumers' fat and cholesterol information. The first index was designed to extend the method developed by B&S (1990), using more keywords of diet and fat in addition to cholesterol and

heart disease. This index is a cumulative number of the published medical journal articles and is simply denoted as CNO.

The second index is based on a cubic weighting function developed by Chem and Zuo (1995) under the assumption that an article published in a specific time period has both carry over and decay effects. In this method, one has to specify the duration of the article's perceived impact (n) and the time period (m) for the maximum impact to occur after its publication. Kim and Chern (1997) showed that the choices of n and m, though arbitrary, are not very sensitive in depicting the general trends of the index. In this study, the second index is based on the assumptions of n = 24 (months) and m = I (first month), and it is denoted as C241.

The third index of Chern is based on the assumption that the impact of a published article will last indefinitely according to a geometrically declining lag structure developed by Kim and Chern (1997). In this study, we assume a monthly decay rate of 20 percent in this distributed lag scheme, and the index is denoted as G20. A different assumption of 10 percent decay rate yielded a very similar trend of the index. These indexes were first constructed as monthly series and then converted to annual series for this study. Specifically the annual indices are constructed by taking the mean value of the monthly indexes within the year. While improving over the previous studies, Chern's procedures highlight the difficulty in determining the process by which information is processed, and how long it may be active in consumer choice.

Type V index: Bayesian updating approach

Chern et al (1995) focused on the information relevant to food choices, especially the linkage between health risk and food consumption. Unlike other approaches for defining the health variables we mention above, they argue that consumer belief of health risk might change over time based on the information consumer's perception, which can be represented as a

Bayesian process. They used HDS data on consumers' belief about health in the year 1982, 1986 and1988, and a BS index as the basis information input of each period to calculate consumer beliefs. Beliefs are assumed to follow a beta distribution, as the linear function of mean and variance. The parameter of initial year of this Bayesian model is set up in order to match the 1982 survey of HDS. They find a 9% bias in the predictions of their model for the year 1988. While the model tracks the survey fairly closely, there are only two periods predicted. This provides some evidence that Bayesian models may be fruitful in predicting consumer beliefs. Still the question looms as to how fast information decays.

In the following sections 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, we should expect new articles 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 prior and likelihood are given inefficient weights. We build on this approach in the following section.

Psychological Bias in Information Perception and Updating

There are several documented psychological effects that could be expected to play a role in health information updating, and its impact on behavior (Rabin 2002; Kahneman and Tversky 2000). Availability bias occurs when individuals assess the probability of events based on how prominent they are in ones 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. This issue is highly related to the exposure issue in the health information literature.

Confirmation bias leads individuals to seek information that confirms their current beliefs and discount or discredit information that may contradict those beliefs. Several studies have shown individuals confidence in their beliefs to increase with new information whether the information confirms those beliefs or not. For this reason, we might expect articles relating a particular viewpoint to have a muted effect, or a polarizing effect leading individuals to harden their prior beliefs. While we have little ability to examine this issue in the current study, this effect seems a plausible explanation for the muted effect of health information found in the marketing literature.

Finally, not all beliefs are directly translated into actions. Individuals display cognitive dissonance when they behave in a way that contradicts their stated beliefs, 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. Thus, we make use of estimation techniques similar to those developed by Strand and Lipton. 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, we will use magazine articles as a proxy for information regarding the detrimental health effects of egg consumption.

A Model of the Information Updating Process

Suppose a representative consumer maximizes the utility of consumption

$$\max_{x} U\left(x, y, h\left(x\right)\right)$$

subject to

$$p_x x + p_y y = W ,$$

where x is the consumption of eggs, y is the consumption of other goods, h is health as a function of egg consumption, p_x, p_y are the 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 $h(x)$, and more particularly the slope of this function. Thus the consumer problem may be better represented as the result of expected utility optimization

$$\max_x (1-p)U\left(x, y, h_g(x)\right) + pU\left(x, y, h_b(x)\right)$$

subject to

$$p_x x + p_y y = W ,$$

where p represents the subjective probability of eggs having a negative impact on health according to 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

$$(1-p)\left[\frac{\partial U}{\partial x} + \frac{\partial U}{\partial h}\frac{\partial h_g}{\partial x}\right] + p\left[\frac{\partial U}{\partial x} + \frac{\partial U}{\partial h}\frac{\partial h_b}{\partial x}\right] - \lambda p_x = 0 \qquad (1)$$

$$\frac{\partial U}{\partial y} - \lambda p_y = 0 \qquad (2)$$

$$p_x x + p_y y = W . \qquad (3)$$

If health in the good state has a negligible impact, then $\frac{\partial h_g}{\partial x} \approx 0$, and (1) can be rewritten as

$$\frac{\partial U}{\partial x} + p\left[\frac{\partial U}{\partial h}\frac{\partial h_b}{\partial x}\right] - \lambda p_x = 0 . \qquad (4)$$

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

$$x = f\left(W, p_x, p\right). \tag{5}$$

In estimating (5) it is important to model the movement of the beliefs that eggs are harmful, p. One intuitive way to model these beliefs is using a Bayesian process. For example, suppose the number of articles in a given time period was distributed Poisson. If eggs are truly harmful, then the expected number of articles in a month is μ_b, while if eggs do not significantly affect health, the mean is 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

$$p_t = \frac{p_0 \left(t\mu_b\right)^{\sum_{i=1}^{t} x_i} e^{-t\mu_b}}{p_0 \left(t\mu_b\right)^{\sum_{i=1}^{t} x_i} e^{-t\mu_b} + \left(1 - p_0\right)\left(t\mu_g\right)^{\sum_{i=1}^{t} x_i} e^{-t\mu_g}}. \tag{6}$$

Alternatively, individuals may give greater weight to newer information. Grether (1980) has proposed the use of generalized Bayes rule to take account of the behavioral issues of updating. This model gives exponential weights to prior and likelihood. 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, called the limited learning model (LLM), weights are a function of the properties of the likelihood and prior themselves. Thus, 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

$$p_t = \frac{p_0 \left(\mu_b \sum_{i=1}^{t} r^{t-i+1}\right)^{\sum_{i=1}^{t} r^{t-i+1} x_i} e^{-\mu_b \sum_{i=1}^{t} r^{t-i+1}}}{p_0 \left(\mu_b \sum_{i=1}^{t} r^{t-i+1}\right)^{\sum_{i=1}^{t} r^{t-i+1} x_i} e^{-\mu_b \sum_{i=1}^{t} r^{t-i+1}} + \left(1 - p_0\right)\left(\mu_g \sum_{i=1}^{t} r^{t-i+1}\right)^{\sum_{i=1}^{t} r^{t-i+1} x_i} e^{-\mu_g \sum_{i=1}^{t} r^{t-i+1}}}, \tag{7}$$

where r falls within the unit interval. While both forms are highly non-linear, the perfect Bayesian belief is a function generally of the number of time periods that have passed, and the cumulative number of articles $\sum_{i=1}^{t} x_i$. Alternatively, the LLM will be a function of a discounted number of time periods $\sum_{i=1}^{t} r^{t-i+1}$, and a weighted cumulative sum of articles $\sum_{i=1}^{t} r^{t-i+1} x_i$. Note that the weighted sum of time periods is a geometric series, with a minimum value of r^t and a maximum value of $\frac{r}{1-r}$. The main focus of our paper will be in determining which is a closer model of the behavior represented in the demand for eggs. If the LLM model more closely follows egg demand patterns, then behavioral anomalies must drive some egg consumption behavior. This finding would underscore the importance of understanding processes of information processing when examining decision making under uncertainty.

Data, Methods and Empirical Model

In order to focus on the issue of updating, we employ the same dataset used in Schmit and Kaiser (2002). In addition, we will follow their assumptions about the structure and influence of demand factors not related to health beliefs. They propose a system of supply, demand and markup equations. The supply of shell eggs is represented by

$$\ln QSF_t = \ln(\beta_0) + \beta_1 \ln(\bar{P}_t) + \sum_{i=1}^{3} \mu_i DUM_{i,t} + \alpha_1 \ln QSF_{t-1} + \alpha_2 TREND_t + \varepsilon_t, \qquad (8)$$

where QSF_t is the quantity supplied of shell eggs, $\bar{P}_t$ 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 mark-up equation is written as

$$WP_t = \phi_0 + \phi_1 FP_t + \phi_2 WAGE_t + \sum_{i=1}^{3} \kappa_i DUM_{i,t} + \omega_t \,, \tag{9}$$

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

$$\ln(D_t) = \delta_0 + \delta_1 \ln(WP_t) + \delta_2 \ln(Y_t) + \delta_3 \ln(CBP_t) + \sum_{j=0}^{4} \gamma_i \ln ADV_{t-j} + \delta_4 CHOL_t + \upsilon_t \,, \tag{10}$$

where D_t is the per capita wholesale demand for eggs, Y_t is consumer per capita disposable income, CBP is the price of cereal and bread products (which may be substitutes for eggs), ADV is expenditures on generic advertising, and $\gamma_j = \lambda_0 + \lambda_1 j + \lambda_2 j^2$. We will employ four different definitions for $CHOL$ based on the updating model presented earlier. Model 1 will include

$$CHOL_t = \sum_{i=1}^{t} r^{t-i+1} x_i \left(\eta + \ln \sum_{i=1}^{t} r^{t-i+1} \right) - e^{\eta} \sum_{i=1}^{t} r^{t-i+1} \,, \tag{11}$$

where η is a parameter to be estimated. This is a generic representation of the primary term involved in the natural log of (7) above. Model 2 will involve

$$CHOL_t = \eta \ln \sum_{i=1}^{t} r^{t-i+1} + \sum_{i=1}^{t} r^{t-i+1} x_i \,, \tag{12}$$

which is consistent with a first order approach. The third model involves estimating the full non-linear Bayesian term in (7). In each of these versions we are looking for evidence that the weight is significantly different from 1. Finally, Model 4 defines

$$CHOL = \sum_{i=1}^{t-1} x_i + \eta x_t \,. \tag{13}$$

This will allow us to compare the relative influence of the cumulative number of articles versus the current period's articles. Since this model can be represented linearly, we will estimate the linear representation.

Data was originally obtained from various sources documented in Schmit and Kaiser (2002). See their Table 12.1 for a complete description of the data and sources. We use non-linear three stage least squares to estimate models 1, 2, and 3. In order to restrict r to the unit interval, we translate it through a standard normal cdf. Thus our results for r will be measured in inverse cumulative density on the standard normal scale. The results of estimation for variables other than those representing beliefs, are similar to those reported in Schmit and Kaiser (2002). Hence we present only the demand estimates not related to advertising expenditures in Table 1. All standard errors were obtained using a 1000 bootstrapped samples of the same size as the original sample.

Table 1. Results of Demand Estimation

Variables	Model 1	Model 2	Model 3	Model 4
Constant	-6.6294	-6.6292	-6.6194	2.8557
	(0.9305)	(0.8991)	(1.6802)	(2.7250)
Wholesale Price	-0.0336	-0.0336	-0.0343	-0.0503
	(0.0200)	(0.0210)	(0.1058)	(0.1814)
Income	1.2266	1.2266	1.2288	0.2107
	(0.1166)	(0.1163)	(0.1903)	(0.2960)
Cereal Price	-0.5108	-0.5108	-0.5173	-0.4003
	(0.0534)	(0.0607)	(0.0568)	(0.0594)
DUM1	-0.0254	-0.0254	-0.0259	-0.0280
	(0.0070)	(0.0072)	(0.0087)	(0.0103)
DUM2	-0.0363	-0.0363	-0.0367	-0.0406
	(0.0069)	(0.0070)	(0.0101)	(0.0117)
DUM3	-0.0235	-0.0235	-0.0235	-0.0266
	(0.0063)	(0.0066)	(0.0080)	(0.0089)
Health	-0.0005	-0.0002	-0.0029	
	(0.0001)	(0.0062)	(0.0171)	
η	-0.0023	-0.0252		
	(0.1171)	(0.0070)		
r	-0.3663	-0.3661	-0.7069	
	(0.8751)	(0.7089)	(0.5806)	
μ_g			0.0007	
			(0.0329)	
μ_b			16.4244	
			(19.9617)	
$\sum_{i=1}^{t-1} x_i$				0.0003
				(0.0000)
x_t				-0.0003
				(0.0015)
AIC	-6.6453	-6.6453	-6.6932	-6.6988
SIC	-6.3239	-6.3239	-6.3718	-6.3586

Of greatest interest in this estimation is the parameter r. In the first two models, those least susceptible to multicolinear effects, prior information decays quickly with a previous period's observation receiving around 0.3571 the weight of information published this period. The astounding part of this is that time is measured in months. Thus, information published today will have some impact on behavior that will decrease in importance by more than half each

month. With such a non-linear model, it is not surprising that the standard errors are large. Still, there is strong evidence that behavior is not consistent with Bayesian learning. For example, with model 1, a test that $r > .77$ rejects are the 90% level of significance. For model 2, the same test will reject $r > .71$. Certainly there is a steep decay of information, even within a few weeks time.

Figure 1 plots the belief index and the article count for each month of data. This plot shows how quickly beliefs decay. Particularly around 1997, it appears there is a spike in the fear of health effects from eggs, but this fear is followed by forgetfulness. Only six months later, the fear of eggs has subsided substantially. In our model this appears to be due to the sudden drop in media attention, reducing the availability of the health information. In Figure 2, the results for Model 2 are very similar, up to a scale effect. Both of these models suggest that in order to achieve prolonged behavioral change, it is necessary to hit consumers with a constant barrage of information. Short lived media campaigns will have effects only as long as they survive.

The extreme non-linearity of Model 3 prevents us making very accurate statements about the estimated parameters. However, two things are of interest. First, the estimate for r places the decay of information at near immediate. Last periods information is given a weight of 0.2398. With this model we reject $r > .52$ at the 90% level. Secondly, this model suggests that individuals do not believe everything they read. This estimate allows individuals a belief that a certain number of articles claiming eggs are damaging will be published each month, even if there is no link between eggs and health. To our knowledge, no current model includes an explicitly stated belief in false information. The estimates, are suggestive that individuals need to see a lot of press on an issue before they believe the result. According these estimates, if there is no important link between health and eggs, a representative consumer would expect to see an article about once every 1000 months (83 years) discussing such a link. Alternatively, if the link

exists, the consumer would expect 17 articles a month. Thus there is a threshold level of publicity before individuals truly believe the scientific discoveries that are reported, and this threshold is very low. However, the information is not regarded for very long. Figure 3 shows this complete model predicts about the same variation in beliefs month to month, but with much greater variation in extremes. This could be due to the scaling factor common in all three estimations. You will note the probability measure is a much smaller scale than the measures used in either of the previous two models. The Schwartz and Akaike information criteria both suggest that there are gains to be made by using the whole model to predict. This, despite the extra parameter and resulting problems with multicolinearity.

The estimates in Model 4 are substantially different and counterintuitive. The accumulated number of articles about cholesterol appears to have a positive and significant effect on consumption. While the effect of current articles is of the same size, yet negative, it is insignificant. If taken at face value, ignoring significance, an article today will decrease consumption by the same amount an article last month will increase consumption. In other words, articles have an impact on behavior that lasts approximately one month. One might suggest a law of information would read, “any action due to an article published this month will produce an equal and opposite reaction next month.” While not convincing evidence, this suggests that cumulative article indices may either proxy for other effects, or that 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 consumption, the action the majority of articles were promoting.

Conclusions and Recommendations

In this paper we have attempted to estimate the rate at which information decays in decision-making. Far from the rational Bayesian model, we find that information decays to a point of unimportance in a matter of a few weeks without constant and consistent information. This has grave implications for health and nutrition information policy. While we have known for some time that only a minority respond to health information, our work suggests that those who do respond, only respond for a short time. In order to affect lasting changes in diet, constant expenditures must be made to publicize health risks such as those resulting from egg consumption. This provides a clear alternative explanation for consumer behavior following 1997. Schmit and Kaiser suggest that subtle message changes caused a different reaction. Our model suggests the increase in consumption could have been due solely to the steep decline in articles published on the topic.

While our results are representative of actions, we admit several heroic assumptions must be made before one can suggest that our model represents beliefs. First and foremost, not all individuals act according to their beliefs regarding health. Further research could attempt to link surveyed beliefs with purchasing behavior in a more concrete way. In addition, other factors affecting the speed of learning, and the possibility of heterogeneous reactions need to be accounted for.

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Figure 1. Predicted Belief and Article Counts for Model 1.

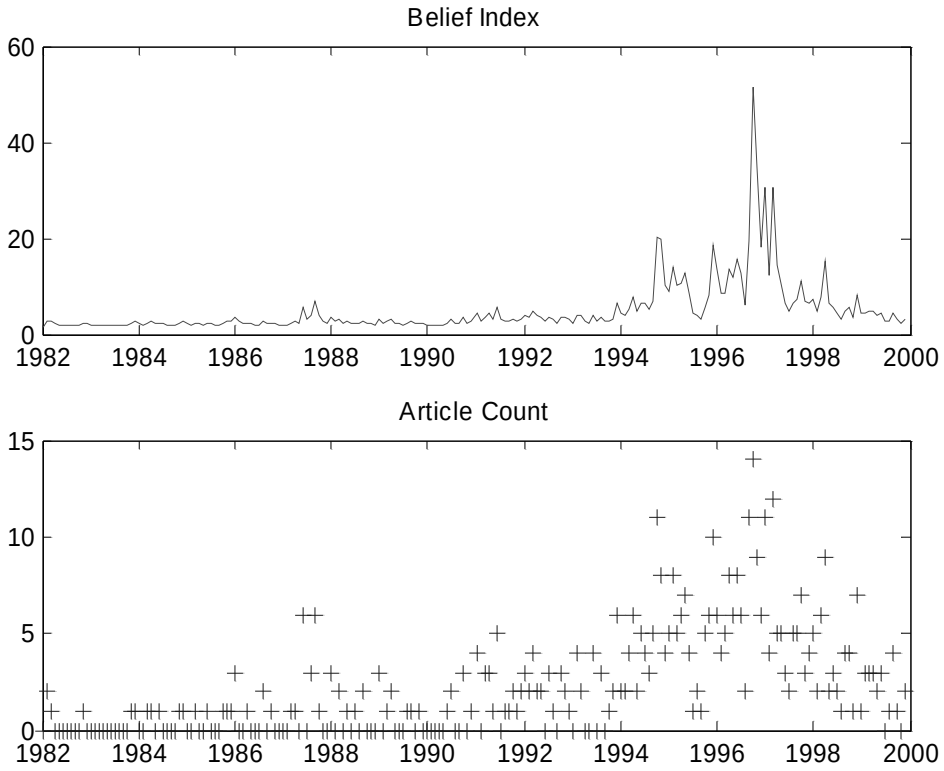

Figure 2. Predicted Belief and Article Counts for Model 2.

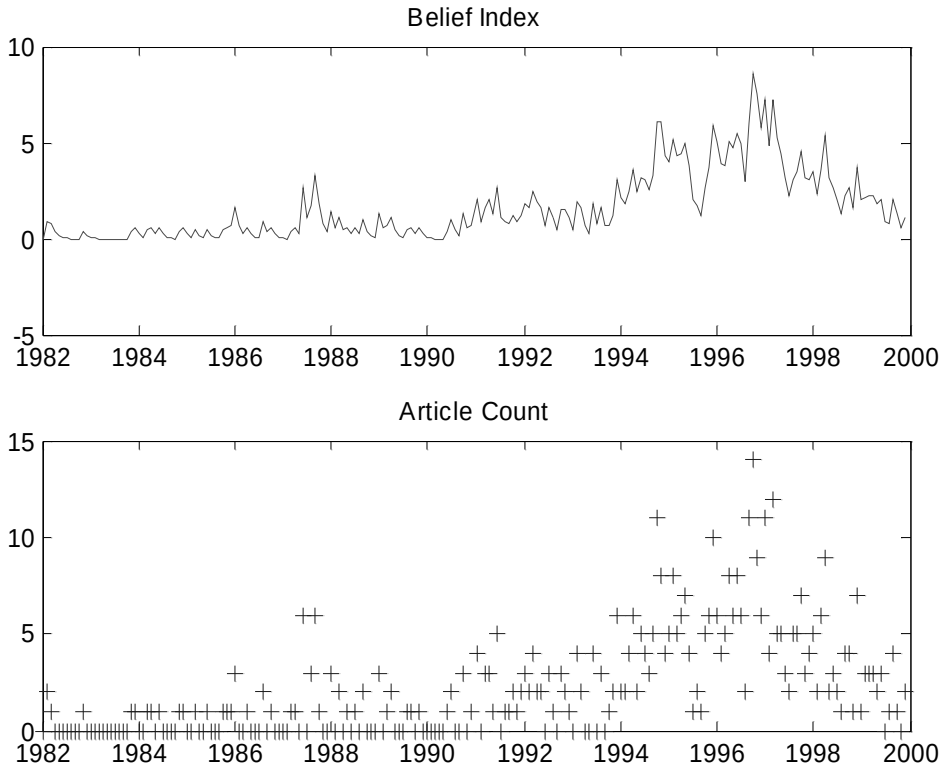

Figure 3. Predicted Belief and Article Counts for Model 3.