Modeling the Impact of Food Safety Information with No Information

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Abstract

This paper aims to propose a stochastic approach to measure the time pattern of a food scare, which does not require the inclusion of additional explanatory variables such as a news index. The application is based on the 1982 Heptachlor milk contamination in Oahu, Hawaii.

Keywords: food scare, food safety information, media coverage, demand.

JEL classification: D120, Q110

Introduction

The measurement of consumer response to food scares has been the subject of many empirical investigations. It is a policy relevant task, as it provides the basis for calibrating countermeasures and establishing potential compensations. This paper aims to propose a flexible stochastic approach to measure the time pattern of a food scare, which does not require the inclusion of additional explanatory variables such as a media index and easily accommodates the reoccurrence of the same or different scares.

Sociological studies acknowledge that food scares exhibit a fairly standard pattern. Beardsworth and Keil (1996) classify public reaction in five steps: (i) initial equilibrium characterized by unawareness or lack of concern about the potential food risk factor; (ii) news about a novel potential risk factor and public sensitization; (iii) public concern is raised as the risk factor becomes a major element of interest and concern in public debate

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and media; (iv) public response begins, usually with avoidance of the suspect food item; (v) public concern gradually decreases as attention switches from the issue, leading to the establishment of a new equilibrium. The same study highlights that public response in stage (iv) is often exaggerated and unrelated to the objective risk and even after the new equilibrium is reached in stage (v) a "chronic low-level anxiety may persist and can give rise to a resurgence of the issue at a later date".

Despite this general framework can be applied to most of food scare events, the duration of the single steps and the potential reoccurrence of the same scare remains a relevant econometric issue. Previous studies have followed different approaches to measure demand response. One direction is based on the assumption that consumer reaction is directly related to the amount of news released. Smith et al. (1988) and Liu et al. (2001) estimated the impact of the 1982 heptachlor contamination of milk in the Hawaiian island of Oahu by including a variable related to media coverage in a demand function. On the same case study, Foster and Just (1989) discard the media variable and substitute it with a nonlinear shift on the intercept which allows for an exponential decrease in the food scare effects and also some long-term persistence. Burton and Young (1996), Verbeke and Ward (2001) and Piggott and Marsh (2004) extend the Almost Ideal Demand System (AIDS) to account for a media index specifically built for distinguishing the impact on meat demand of positive and negative news about Bovine Spongiform Encephalopathy (BSE). Even though the empirical performance of the above models is generally acceptable, we argue that they have some key limitations that reduce their reliability in many situations, not least the one of scare resurgence. Our objection is founded on three main considerations.

The first is that discrimination between positive and negative information is a highly subjective operation. For example, news about the incubation period of the Creutzfeldt-Jakob disease (CJD), which has been linked to BSE, informed the public about a possible latency period of up to 20 years. While this could be a source of anxiety for younger consumer, the same information could lead to a lower hazard perception for the elderly one. Furthermore, Smith et al. (1988) noted the extremely high correlation between news classified as positive and negative, as their amount is related to the media interest rather than scientific evidence, which usually takes too long to be advertised and rarely influence behavior in the short term.

A second consideration concerns the way information is discounted over time in consumer perception, as it is recognized that within the same food scare event the marginal effect of additional information is decreasing. Also, the acute phase of a scare is characterized by the social amplification phenomenon (Beardsworth and Keil, 1996) which is generated by the initial 'news spiral', but is recognized as a self-limiting process. Some researchers (Smith et al., 1998) address this issue by including lags of the media variable, others (Verbeke and Ward, 2001) correct their index in order to account for decreasing lagged impacts, but both approaches require some subjective and undesirable assumptions.

The third argument against the modeling of consumer reaction through a media index or the nonlinear shift by Foster and Just is related to the crisis reoccurrence. It is clear that the marginal effect of novel or confirmatory news about a food risk factor already known to the public is likely to be different than in the period of the first occurrence. This

outcome which is consistent with the persisting low-level anxiety discussed by Beardsworth and Keil.

The approach proposed in this paper is based on the inclusion of a stochastic shift related to the food scare within the demand equation. The model allows a direct estimate of the time-varying pattern of consumer response based on actual data. Thus, the subjective and often difficult and expensive operation of retrieving media coverage data becomes unnecessary. We assess the performance of the stochastic shift approach as compared to the use of a media index using the data from Smith et al. (1988)[1] about the heptachlor milk contamination incident in Hawaii, March 1982.

This paper is structured as follows. Next section introduces the single-equation demand model employed by Smith et al. (1988) and extends it to account for the scare related stochastic shift. In the following section we briefly discuss the estimation strategy for such model. We then present the comparative results and some concluding remarks are drawn in the final section.

The model

The starting point of Smith et al. is to assume that consumers maximizes an utility function which includes their perception of the quality of a good, which is expressed as a function of available information. A change in information induces a modification in perceived quality and a re-allocation of consumer expenditure. Using the same notation as in Smith et al., the demand function is expressed as follows:

$$X_1 = X_1(P_1, P_2, I, N) \tag{1}$$

where X_1 is the demand for the good concerned by the food scare, P_1 is its price, P_2 is the price of substitute goods, I is the income level and N is the information variable influencing perceived quality. The specification of an econometric model based on (1) with time series data requires a number of assumption on how information is processed over time. With reference to Smith et al. application on the 1982 Heptachlor incident in Hawaii, the lagged effect of information is approximated by a second-degree Almond lag structure. They estimate the following equation:

$$Q_t = \alpha_0 + \sum_{j=1}^{11} \alpha_i S_j + \beta_1 DPM_t + \beta_2 SUB_t + \beta_3 INC_t + \beta_4 TRND_t + \beta_5 DV_t + A(L)N_t + \varepsilon_t \quad (2)$$

where Q_t is the quantity of fluid milk sales, S_j is a set of monthly dummies to capture seasonal effects, DPM_t is the deflated retail price of whole milk, SUB_t is the price of a fruit drink identified as the main substitute for milk, INC_t is the deflated per capita income, $TRND_t$ is a trend variable, DV_t is the dummy variable designed to capture the impact of the food scare that is 0 before March 1982 and 1 thereafter, N_t is a vector of variables which measure negative media coverage, $A(L)$ is a polynomial lag structure for the media variable and ε_t is the random error.

In our study we consider two alternative specifications to equation (2). The first model is based on the assumption that no media coverage index is available, hence the information variable is regarded as latent. This can be specified as follows:

$$Q_t = \alpha_0 + \sum_{j=1}^{11} \alpha_i S_j + \beta_1 DPM_t + \beta_2 SUB_t + \beta_3 INC_t + \beta_4 TRND_t + \eta_t DV_t + \varepsilon_t \quad (3)$$

where the stochastic shift η_t is assumed to follow a random walk, $\eta_t = \eta_{t-1} + u_t$, which models the shift in preferences due to the new perceived quality.

The second model assumes again a stochastic shift for the food scare and also a stochastic coefficient for the media coverage variable, expected to measure the time-varying impact of additional information.

$$Q_t = \alpha_0 + \sum_{j=1}^{11} \alpha_i S_j + \beta_1 DPM_t + \beta_2 SUB_t + \beta_3 INC_t + \beta_4 TRND_t + \eta_t DV_t + \gamma_t N_t + \varepsilon_t \qquad (4)$$

where also $\gamma_t = \gamma_{t-1} + v_t$ is a random walk and both u_t and v_t are random errors.

Estimation

Equations (3) and (4) can be estimated by rewriting the model in the state-space form and applying a maximum-likelihood algorithm. The state-space form of the system is given by defining a measurement equation and a transition equation as follows:

$$Q_t = Z_t' a_t + W_t' b + e_t^M \qquad (5)$$

$$a_t = T a_{t-1} + e_t^T \qquad (6)$$

where the state vector a_t includes the time-varying parameters of the model, i.e. η_t for equation (3) and (η_t, γ_t) for equation (4), the vector Z_t contains the explanatory variables whose coefficients are time-varying, i.e. DV_t for equation (3) and (DV_t, N_t) for equation (4). All other variables whose coefficients are constant are included in the vector W_t. The measurement equation is perfectly equivalent to the original model, apart from the stochastic specification of the time-varying parameters, which is defined through the transition matrix T within equation (6). The stochastic specification of the model is completed by the disturbance terms e_t^M and e_t^T, each with mean zero and with covariances equal to h and K respectively.. A detailed discussion about the state-space specification of a time-varying demand model is provided in Mazzocchi (2003).

Once a model is expressed in the state-space form[2], the Kalman filter (KF) can be applied. The Kalman filter is a recursive procedure producing the optimal estimates of the state vector at time t conditional upon the available information in the same time period. The optimal filtered estimator at time t is defined as

$$a_{t|t-1} = T a_{t-1} \tag{7a}$$

and its covariance matrix is

$$P_{t|t-1} = T P_{t-1} T' + K \tag{7b}$$

where $Var(a_t) = P_t$ is the covariance matrix for the state vector. Equations (7a) and (7b) are the prediction equations of the Kalman filter. Once the actual observation Q_t becomes available, the optimal estimator is updated according to the previous prediction error. This happens through the following updating equations:

$$a_t = a_{t|t-1} + P_{t|t-1} Z_t' F_t^{-1} \left(Q_t - Z_t' a_{t|t-1} \right) \tag{7c}$$

$$P_t = P_{t|t-1} - P_{t|t-1} Z_t' F_t^{-1} Z_t P_{t|t-1} \quad \text{where } F_t = Z_t P_{t|t-1} Z_t' + H \tag{7d}$$

The equations described in (7) constitute the Kalman filter.

Once the full set of filtered estimates $a_{t|t-1}$ and a_t are computed through the Kalman filter, it becomes possible to smooth the estimates of the state vector by exploiting all the information available in the data set. In other words, the Kalman smoother allows the computation of the least square estimates of the state vector at time t, conditional to the whole set of τ observations $\mathfrak{J}_\tau$, i.e. $a_{t|\tau} = E\left(\alpha_t | \mathfrak{J}_\tau \right)$. The fixed interval smoothing algorithm is a backward recursive procedure, described by the following equations:

$$a_{t|\tau} = a_t + P_t^* \left(a_{t+1|\tau} - T a_t \right) \tag{8a}$$

$$P_{t|\tau} = P_t + P_t^* \left(P_{t+1|\tau} - P_{t+1|\tau} \right) P_t^* \, ' \tag{8b}$$

where $P_t^* = P_t T' P_{t+1|t}^{-1}$. The smoother runs from $t=\tau$-1 to $t=1$, with $a_{\tau|\tau} = a_\tau$ and $P_{\tau|\tau} = P_\tau$ as

starting values. Estimates obtained through the Kalman smoother show mean square error inferior

or equal to those obtained through the Kalman filter, as they are based on a larger set of

observations. Given the assumption of a normal distribution for the disturbances in the

model and the initial state vector, the distribution of the vector of observation Q_t

conditional on the set of observation up to time t-1 is itself normal, where the mean and

covariance for such distribution can be derived through the Kalman filter. Hence, it

becomes possible to write explicitly the log-likelihood function for a multivariate normal

model:

$$\log L(Q, \Psi) = -\frac{\tau}{2}\log 2\pi - \frac{1}{2}\sum_{t=1}^{\tau}\log|F_t| - \frac{1}{2}\sum_{t=1}^{\tau}(Q_t - Z_t a_{t|t-1})' F_t^{-1}(Q_t - Z_t a_{t|t-1}) \tag{9}$$

where Ψ represents all unknown parameters of the model. Maximum likelihood

estimates can now be obtained using an optimization algorithm, as the BHHH procedure

by Berndt, Hall, Hall and Hausman (1974).

Application

The March 1982 Heptachlor contamination incident in Oahu, Hawaii provides a valuable

setting for evaluating the models performance. This data set is especially interesting for

various reasons. First, in their original study (Smith et al., 1984), the authors explore in

great details the events following the food scare and provide a thorough discussion of the

issues related to classifying information as positive or negative. Second, in a subsequent

article (Smith et al., 1988), the same authors extend the analysis to account for what they

terms as the lagged effects of media coverage. As discussed, time dynamics need to be taken into account when measuring the impact of food safety information, both for the discounting (memory) effect and the possibly changing marginal impact of information. As these effects can have different directions, the overall pattern is difficult to be anticipated. Third, this data set has become a sort of classic example, as Foster and Just (1989) used the same data set for welfare evaluations and Liu et al. (1998) for risk assessment.

Table 1 reports the parameters estimates and some diagnostics for 3 models: (a) the original Smith (1988) et al. model as described in equation (2)[3]; (b) the model with no information variable and a time-varying shift following the scare as in equation (3); (c) the model where the negative information variable is included, but with a random-walk coefficient as in equation (4).

While there are only relatively small differences in the parameters estimates, it is clear from the models' diagnostics that the stochastic approach leads to more efficient estimates. Also, evidence of higher order serial correlation from Smith's model disappears when the model allows for a random-walk intervention. The most relevant difference lies in the shift parameter linked to the scare, which is -0.39 according to the original model and is significantly larger in the alternative models.

The smoothed estimates of the state vectors, portraying the time-varying patterns of the random-walk parameters in (2) and (3), are represented in Figure 1.

Table 1. Parameters estimates

	Smith Model (a)		Model (b)		Model (c)
CONSTANT	5.81^{**}		5.83^{**}		5.74^{**}
JAN	0.27		0.33^{**}		0.32^{**}
FEB	0.31		0.33^{**}		0.31^{*}
MAR	0.17		0.25^{*}		0.19
APR	0.52^{**}		0.56^{**}		0.58^{**}
MAY	0.54^{**}		0.54^{**}		0.49^{*}
JUN	-0.24		-0.27^{*}		-0.27^{*}
JUL	-0.33		-0.31^{*}		-0.33^{*}
AUG	-0.02		-0.25		-0.27
SEP	0.66^{**}		0.52^{**}		0.51^{**}
OCT	0.46^{**}		0.39^{*}		0.36^{*}
NOV	0.24		0.25^{*}		0.23^{*}
DPM	-4.40^{*}		-3.88^{**}		-3.48
SUB	3.84		3.07^{*}		2.67
INC	$0.00031^{(a)}$		0.00031^{a}		0.00031^{a}
TRND	-0.0051^{*}		-0.0064^{**}		-0.0064^{**}
DV	-0.39	$\eta^{(b)}$	-1.62^{**}	$\eta^{(b)}$	-1.39^{**}
N_t	-0.023^{**}	h	0.042^{**}	$\gamma^{(b)}$	-0.0073
N_{t-1}	-0.014^{**}	k	0.536^{*}	h	0.043
N_{t-2}	-0.008^{**}			k_1	0.328
N_{t-2}	-0.004^{**}			k_2	0.0001
R^2	0.91		0.99		0.99
Ljung-Box Q (4)	9.86^{*}		7.50		6.93

Notes: * Significant at the 95% confidence level; ** Significant at the 99% confidence level

    (a) Estimates conditional on income, as in Smith et al. (1988)

    (b) Smoothed estimate, average for the period after the contamination event

The patterns of the stochastic shift are consistent with the events occurring during the 1982 contamination period (Smith et al., 1984). The effect of the news is slightly smaller in the first month, as the information appeared on the media only on March 18. Model (b) capture a peak effect in April 1982, then a relatively quick recovery by June 1982 and a slower one thereafter. In September 1982, the pattern shows a small but visible turning point, possibly linked to reopening of schools and the concerns expressed by EPA representatives on risks for infants. Another turning point emerges in April 1983, most

likely due to the renewed interest of media following the Safeway controversy[4]. Model (c) distinguishes between the overall impact of the event and the changing marginal impact of news. There are no major differences between the outputs of models (b) and (c), but the coefficient of the negative media index shows how the marginal impact of news varies significantly over time.

Figure 1. Smoothed estimates of time-varying parameters
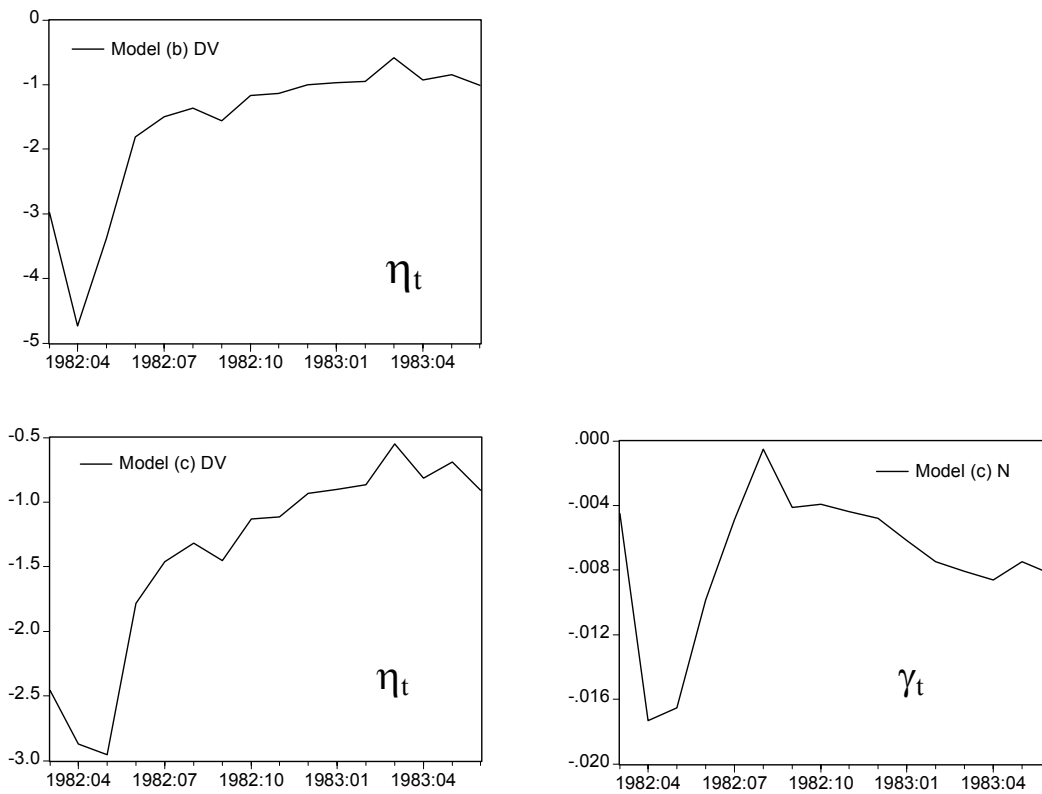
Finally, it might be interesting to see how the latent information variable in (2) relates to the various media coverage indices explored in Smith et al. A simple but powerful insight is provided by examining the cross-correlogram between the smoothed state vector and

the media coverage variables, as in Table 2. This allows to evaluate the degree of simultaneous co-movement, but also lagged and leading effects.

Table 2. Correlations and cross-correlations between estimated parameters and media coverage indices

	Simultaneous	Lags		Leads	
		-1	-2	1	2
		Negative media coverage			
Model (3)	-0.72	-0.75	-0.34	-0.22	0.03
Model (4)	-0.61	-0.76	-0.48	-0.28	-0.01
		Total media coverage			
Model (3)	-0.85	-0.81	-0.37	-0.37	-0.02
Model (4)	-0.75	-0.83	-0.52	-0.39	-0.06

Very high simultaneous correlations confirm the close link between the time-varying impact of the contamination incident and the media coverage indices. Interestingly, correlations are stronger with the total media index, suggesting that the distinction between positive and negative information might be redundant and when information is about a food safety incident, there is no such thing as positive news.

An intriguing interpretation of cross-correlations could be derived by assuming that lagged correlations measure the carry-over effects, contemporaneous correlation capture the immediate impact and lead correlations explore the social amplification effect described in Beardsworth et al. (1996). In this perspective, results show a carry-over effect lasting from two months, confirm the high immediate impact of (negative) food safety news and also present evidence of social amplification, even if to a smaller extent and for a shorter time span as compared to the carry-over effect, since no correlation emerges after the first lead.

Concluding remarks

We suggest that a stochastic approach to model the impact of a food scare over time should be preferred to the methods based on simple dummy shifts or media coverage indices, as it is otherwise difficult to give an objective evaluation of carry-over and discounting effects in food safety information. This method, based on a random walk specification of the intervention variable, avoids the need for subjective assumptions on the cumulated impact of information and the difficult distinction between positive and negative information. Furthermore it takes indirectly into account the possible spiraling impact of media coverage, often observed at the early stages of food scares.

Results show that how models without media coverage indices or allowing for a time-varying effect of news perform very well and support the view that the distinction between positive and negative media coverage is rather unnecessary when evaluating the impact of news on a food safety incident.

Footnotes

[1] We are grateful to Ju-Ching Huang and Eileen van Ravenswaay for kindly providing the data and further information about the case study.

[2] In the rest of the discussion we assume that all the unknown parameters, including the constant ones, are included in the state vector. This is easily done by assuming in the transition equation that in each time period their values is equal to the previous period's one and the variance of the error term is 0.

[3] The final model with a negative media coverage variable resulted from a specification search against other models where positive and neutral news were also considered. Our estimates slightly differ from those by Smith et al., probably due to rounding effects.

[4] Safeway had applied for a milk distributor's license to import milk from outside Hawaii, but the license was denied by the Board of Agriculture in April 1982. This raised a controversy between Safeway (and consumers) on one side and the milk industry on the other.

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