NO NEWS IS GOOD NEWS: STOCHASTIC PARAMETERS VERSUS MEDIA COVERAGE INDICES IN DEMAND MODELS AFTER FOOD SCARES

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We develop a stochastic parameter approach to model the time-varying impacts of food scares on consumption, as an alternative to the inclusion of news coverage indices in the demand function. We empirically test the methodology on data from four food scares, the 1982 heptachlor milk contamination in Oahu, Hawaii and the bovine spongiform encephalopathy and two *Escherichia coli* scares on U.S. meat demand over the period 1993–9. Results show that the inclusion of time-varying parameters in demand models enables the capturing of the impact of food safety information and provides better short-term forecasts.

Key words: food safety information, forecasting, Kalman filter, time-varying parameters.

Media play a crucial role in determining market response to a food scare. In social sciences, news coverage is recognized as a key to explaining the evolution of consumer response in the aftermath of a food safety incident. This has generated a vast amount of empirical research, aimed at modeling consumer reaction over time as a function of some indicator of the prevalence of media reporting. Despite such studies offering a good approximation of the phenomenon, it is argued that the use of a news index is not strictly necessary and can be substituted by a stochastic, time-varying response parameter.

The objective of this research is to show that demand models with one or more stochastic parameters are a valid alternative to modeling demand-response to a food scare through the use of a media coverage index (MCI). Using empirical evidence, we claim that the proposed demand modeling strategy has the desirable properties of (*a*) improving the econometric accuracy of the results; (*b*) enabling detection of turning points, trend reversals, and nonlinear shapes of the scare pattern; (*c*) allowing for the resurgence of food scares with a change in the marginal impacts; and (*d*) improving the forecasting performance, especially in the short term. Furthermore, the article explores the relationships between the estimated impacts and news coverage indices, opening the way to the econometric evaluation of the dynamics of any media effect.

The rationale behind the extension of demand models to account for food scares is that the release of novel risk information alters the existing market equilibrium. Some time elapses before a new equilibrium is reached, and the length and shape of the consumer reaction pattern over this period of time is unknown. An accurate modeling of the disequilibrium path can provide key support to policy makers in monitoring a crisis, and obtaining a more accurate evaluation and prediction of its amplitude and welfare effects to calibrate compensation and countermeasures. Furthermore, collecting and processing adequate media coverage information is potentially a time-consuming and expensive operation that can only occur *ex post*, so that the proposed method might offer a more practical solution to short-term policy modeling needs.

The interaction between consumer reaction and media behavior is well described by sociologists, who acknowledge that food scares exhibit a fairly standard pattern. Beardsworth and Keil (1996) classify public reaction in five

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steps: (i) initial equilibrium characterized by a lack of concern about the potential food risk factor; (ii) news about a novel, potential risk factor, and public sensitization; (iii) public concern increases as the risk factor becomes a major element of interest in public debate and media coverage; (iv) public response begins, usually with avoidance of the suspect food item; (v) public concern gradually decreases as attention switches away 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. Even after a 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" (Beardsworth and Keil 1996).

In economics, the two equilibria correspond to changes in the utility function, as information on the new risk factor leads consumers to adjust their preferences (and hence their budget allocation, *ceteris paribus*). As in Basmann (1956), it is assumed that consumer preferences for a commodity vary as a function of its characteristics, including safety and quality. Information does not affect the level of these characteristics, but alters consumer perceptions of these attributes. Such framework has been popular in the literature investigating the effects of advertising on food demand (Chang and Kinnucan 1991; Brester and Schroeder 1995), and has been frequently exploited for information related to health and food scares, as in the highly cited article by Swartz and Strand (1981). In a recent article, Piggott and Marsh (2004) provide a thorough explanation of the use of news coverage indices to model U.S. meat demand-response to food safety information. In Europe, following the bovine spongiform encephalopathy (BSE) scare, several studies have modeled consumer reaction as a function of a media coverage index (Burton and Young 1996; Burton, Young, and Cromb 1999; Verbeke and Ward 2001). Although there is no question of the empirical performance of the above models, it can be alleged that they have some key limitations that may reduce their reliability in certain situations, not least the one of scare resurgence. This objection is founded on three main issues.

First, discrimination between positive and negative information, invoked in several articles (Smith, van Ravenswaay, and Thompson 1988; Liu, Huang, and Brown 1998; Verbeke and Ward 2001), can be highly subjective. For example, news about the incubation period of the Creutzfeldt-Jakob disease, which has been linked to BSE, suggests a possible latency period of up to twenty years. While this could be a source of anxiety for a younger consumer, the same information could lead to a lower hazard perception for an elderly one. Furthermore, Smith, van Ravenswaay, and Thompson (1988) noted an extremely high correlation between news classified as positive and news classified as negative. This is due to the fact that media interest drives the volume of news, and when coverage increases, both positive and negative news reports rise. A change in the balance between positive and negative news could only be triggered by the disclosure of novel scientific evidence, which rarely happens in the short term.

A second consideration concerns the depreciation of the information effect, not only because of memory discounting effects, but also due to the time-varying marginal effect of additional information. As noted in Beardsworth and Keil (1996), the acute phase of a scare is characterized by the social amplification phenomenon, which is generated by the initial "news spiral" and is recognized as a self-limiting process. Smith, van Ravenswaay, and Thompson (1988) address this issue by including lags of the media coverage variable, while Burton, Young, and Cromb (1999) correct their stock information index to account for decreasing lagged impacts. Both approaches require assumptions on the depreciation rate or the number of lags.

The third argument against modeling consumer reaction through a media index is related to the potential crisis resurgence. If the public is already aware of a specific food risk factor, the marginal effect of novel or confirmatory news is likely to be different than in the first instance. This outcome is consistent with the persistence of low-level anxiety.

As an alternative to the inclusion of the MCI in a demand model, this study shows that the food scare impact can be elicited by introducing a stochastic intervention variable (SIV) or by adopting a more general structural time series (STS) specification. We evaluate the performance of the latent variable approach using two data sets: (*a*) Piggott and Marsh (2004) data on U.S. meat consumption and (*b*) Smith, van Ravenswaay, and Thompson (1984, 1988) data on milk consumption in Hawaii. The first data set covers three different meat-related events: (i) the 1993 *Escherichia coli* outbreak in the state of Washington; (ii) the 1996 BSE news from Europe; and (iii) the 1997 *E. coli* outbreak in Midwest United States. The second data set allows us to analyze the 1982 heptachlor milk contamination incident in Hawaii.

The following section extends demand analysis to account for the effects of food safety information and introduces the stochastic parameter extension. Next, the estimation strategy for such models is discussed. Finally, the comparative results are presented and some concluding remarks are drawn.

The Model

As in Basmann (1956) and Swartz and Strand (1981), it is assumed that the consumer maximizes the utility function $U(x_1, \ldots, x_g, \theta(\mathbf{r}))$, where $x_1, \ldots, x_g$ are the quantities of the g goods consumed in each period of time, given an income level I and prices $p_1, \ldots, p_g$. The level of utility depends on consumer preferences. These preferences vary as a function θ of a set of characteristics of the goods (the vector $\mathbf{r}$), including physical attributes, and also any information or psychological variables altering the perception of such attributes (Nayga, Tepper, and Rosenzweig 1999). Hence, food safety information enters the utility function through the vector $\mathbf{r}$ and utility maximization yields a Marshallian demand function where the news coverage index appears as a demand shifter. As in Burton and Young (1996) or Verbeke and Ward (2001), it is possible to extend the almost ideal demand system (AIDS) specification with shifters linked to MCIs. A linear approximation of the dynamic (partial adjustment) AIDS with an intercept shift[1] is (Alessie and Kapteyn 1991):

$$(1) \qquad w_{it} = \alpha_{it}^* + \sum_{j=1}^{n} \gamma_{ij} \ln p_{jt} + \beta_i \ln\left(\frac{Y_t}{P_t^*}\right) + u_{it} \quad i = 1, 2, \ldots, n$$

$$(2) \quad \alpha_{it}^* = \alpha_i + \sum_{j=1}^{n} \rho_{ij} w_{i,t-1} + \sum_{s=1}^{3} \phi_{is}\delta_{st} + \lambda_i N_t$$

where w_{it} is the expenditure share for the ith good at time t, p_{jt} is the price of the jth good, Y_t is the total expenditure, P_t^* is the Stone index, and u_t is a white-noise normally distributed error. The intercept (2) is a function of the vector of lagged shares (to account for habit persistence), of the news coverage index N_t, typically represented by the number of articles about the food scare appearing in the media, and of (quarterly) seasonal factors, where δ_{ts} is a set of dummy variables equal to 1 when the time period t falls in quarter s and 0 elsewhere. System (1) fulfils the demand theory requirements when the usual constraints on the coefficients are met, namely

$$\sum_{i=1}^{n} \alpha_i = 1, \quad \sum_{i=1}^{n} \rho_{ij} = 0, \quad \sum_{i=1}^{n} \lambda_i = 0,$$

$$\sum_{i=1}^{n} \gamma_{ij} = 0, \quad \sum_{i=1}^{n} \beta_i = 0, \quad \sum_{i=1}^{n} \phi_{is} = 0$$

(adding-up $\forall j$), $\sum_{j=1}^{n} \gamma_{ij} = 0$ (homogeneity $\forall i$) and $\gamma_{ij} = \gamma_{ji}$ (symmetry $\forall i, j$) plus an additional constraint to ensure identification of the dynamic system, $\sum_{j=1}^{n} \rho_{ij} = 0 \ \forall i$.

We suggest two related approaches to approximate the time-varying impact of information through stochastic parameters. The first is based on the inclusion of a SIV, and presumes knowledge on the exact date of the first occurrence of the food scare. The second avoids this prior assumption and is based on the STS specification of the demand model (Harvey 1989; Fraser and Moosa 2002), where the intercept is specified as a local linear trend over the whole sample and seasonality is also stochastic.

The SIV method overcomes the difficulties in measuring and discounting N_t and the limits intrinsic to deterministic (albeit nonlinear) shifters as in Foster and Just (1989) or Mazzocchi, Stefani, and Henson (2004).[2] In the SIV models, the time-varying impact of information is approximated by a stochastic shifter, so that the intercept of (1) is reformulated with the following specification:

$$(3) \qquad \alpha_{it} = \alpha_{it-1} + \sum_{j=1}^{n} \rho_{ij} w_{i,t-1} + \sum_{s=1}^{3} \phi_{is}\delta_{st} + \psi_{it} h_t + \varepsilon_{\alpha it}$$

[1] A shortcoming of intercept shifters is that the AIDS model is not "closed under unit scaling" (see Alston, Chalfant, and Piggott 2001); hence the estimated elasticities are not invariant to the scaling of the data. This does not affect the time path of the stochastic shifters estimated in this article. We are grateful to anonymous referees for pointing this out.

[2] A recent article by Rucker, Thurman, and Yoder (2005) explores a similar problem in a financial event-study setting. In their model, the response pattern of futures markets to slowly evolving information events is constrained to follow the shape of a given probability distribution. This also allows them to estimate rather than assume the location and width of the event window. We are grateful to an anonymous referee who brought this article to our attention.

which differs from (2) as the news index is substituted by a dummy variable h_t where $h_t = 0$ before the first news release and $h_t = 1$ afterward and the stochastic coefficient ψ_{it} is defined by:

$$(4) \qquad \psi_{it} = \pi_0 + \pi_1 \psi_{i,t-1} + \varepsilon_{\psi it}$$

where $\varepsilon_{\alpha it}$ and $\varepsilon_{\psi it}$ are white-noise errors. To ensure adding-up, it is required that $\sum_{i=1}^{n} \psi_{it} = 0$. In most demand studies with time-varying parameters (see e.g., Leybourne 1993; Fraser and Moosa 2002), a random walk specification is adopted to capture smooth structural change. The unit root hypothesis can be tested on ψ_t using the augmented Dickey–Fuller (ADF) and Philips–Perron (PP) tests. In this study, the two alternative intercept specifications (2) and (3) are applied to the meat demand data used in the analysis of Piggott and Marsh (2004).

If there is no clear-cut information about the first occurrence of the scare, a viable alternative is to specify a STS demand system as in Fraser and Moosa (2002). As shown in this article, the STS approach is able to model consumer reaction to news when a food scare occurs, although outside the scare periods, the time-varying intercept is sensitive to any other factor-inducing structural change. The full STS–AIDS specification is obtained by omitting h_t and rewriting (3) as

$$(5) \qquad \alpha_{it} = \alpha_{it-1} + \psi_{t-1} + \sum_{j=1}^{n} \rho_{ij} w_{i,t-1} + \vartheta_{it} + \varepsilon_{\alpha it}$$

where $\vartheta_{it} = -\sum_{l=1}^{3} \vartheta_{i,t-l} + \varepsilon_{\vartheta it}$ allows quarterly stochastic seasonality to evolve over time as in Fraser and Moosa (2002), with $\sum_{i=1}^{n} \vartheta_{it} = 0$ to ensure adding-up. Again, if the unit root hypothesis is not rejected by the ADF and PP tests, a more parsimonious random walk specification $\psi_{it} = \psi_{i,t-1} + \varepsilon_{\psi it}$ can be adopted.

The second application discussed in this article is based on the single Marshallian milk demand function specified in Smith, van Ravenswaay, and Thompson (1988):

$$(6) \qquad Q_t = \alpha_0 + \sum_{j=1}^{11} \alpha_j S_j + \beta_1 \mathrm{DPM}_t + \beta_2 \mathrm{SUB}_t + \beta_3 \mathrm{INC}_t + \beta_4 \mathrm{TRND}_t + \beta_5 \mathrm{DV}_t + A(L)N_t + \varepsilon_t$$

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, and DV_t is the dummy variable designed to capture the impact of the food scare that is 0 before March 1982 and 1 thereafter. The negative MCI N_t enters the model through a second-order Almon polynomial distributed lag structure to take into account the discounting effect, $A(L)N = \sum_{l=0}^{3} \omega_l N_{t-l}$, where the coefficients ω_l are constrained to follow $\omega_l = \mu_0 + \mu_1 l + \mu_2 l^2$. Like the intercept in (3), the news effect can be substituted by a single stochastic shift, where the information variable is regarded as latent as follows:

$$(7) \qquad Q_t = \alpha_0 + \sum_{j=1}^{11} \alpha_j S_j + \beta_1 \mathrm{DPM}_t + \beta_2 \mathrm{SUB}_t + \beta_3 \mathrm{INC}_t + \beta_4 \mathrm{TRND}_t + \psi_{it} \mathrm{DV}_t + \varepsilon_t$$

where ψ_t is defined as in (4) and represents the shift in preferences due to the new perceived quality level. If the a priori information on the scare inception is ignored, the STS specification is adopted:

$$(8) \qquad Q_t = \alpha_t + \beta_1 \mathrm{DPM}_t + \beta_2 \mathrm{SUB}_t + \beta_3 \mathrm{INC}_t + \beta_4 \mathrm{TRND}_t + \varepsilon_t$$

with $\alpha_t = \alpha_{t-1} + \psi_{t-1} + \vartheta_t + \varepsilon_{\alpha t}$ and $\vartheta_t = -\sum_{l=1}^{11} \vartheta_{t-l} + \varepsilon_{\vartheta t}$ with ψ_t as previously defined.

State–Space Form and Estimation

System (1) with the time-varying intercepts (3) and (5) and equations (7) and (8) can be estimated by re-specifying the model in the state–space form and applying a maximum-likelihood algorithm (Harvey 1989, p. 125). The state–space form is given by defining a measurement equation and a transition equation as follows:

$$(9) \qquad \mathbf{y_t} = \mathbf{Z_t' a_t} + \mathbf{W_t' b} + \mathbf{e_t^M}$$

$$(10) \qquad \mathbf{a_t} = \mathbf{T a_{t-1}} + \mathbf{e_t^T}$$

where $\mathbf{y_t}$ is the dependent variable, respectively, the vector of expenditure shares $\mathbf{w_t}$ for (1) and milk consumption Q_t for (7) and (8). For each of the equations in system (1) with the SIV intercept (3), the state vector is $\mathbf{a_{it}} = [\alpha_{it}\ 1\ \psi_{it}]'$, the measurement vector is $\mathbf{z_{it}} = [1\ 0\ h_t]$, and the transition matrix is

$$\mathbf{T}_i = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & \pi_{i0} & \pi_{i1} \end{bmatrix}$$

with $\mathbf{e_{it}^T} = [e_{\alpha it}^T\ 0\ e_{\psi it}^T]'$. The multivariate specification simply requires writing the state vector as $\mathbf{a_t}=[\mathbf{a_{1t}}\ \mathbf{a_{2t}}]'$ and $\mathbf{Z_t}$, $\mathbf{T}$, and $\mathbf{e_t^T}$ as block-diagonal matrices from $\mathbf{z_{it}}$, $\mathbf{T_i}$, and $\mathbf{e_{it}^T}$. Considering the STS formulation of the intercept defined in (5), with stochastic seasonality and no dummy intervention, $\mathbf{a_{it}} = [\alpha_{it}\ 1\ \psi_{it}\ \vartheta_{it}\ \vartheta_{it-1}\ \vartheta_{it-2}\ \vartheta_{it-3}]'$, $\mathbf{z_{it}} = [1\ 0\ 1\ 1\ 0\ 0\ 0]$, and

$$\mathbf{T}_i = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & \pi_0 & \pi_1 & 0 & 0 & 0 \\ 0 & 0 & 0 & -1 & -1 & -1 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix}$$

with $\mathbf{e_{it}^T} = [\,e_{\alpha it}^T\ 0\ e_{\psi it}^T\ e_{\vartheta it}^T\ 0\ 0]'$. Again, the multivariate matrices are built using a block-diagonal structure. The specifications of the single-equation model (7) and (8) follow directly from the above. All other variables with constant coefficients are included in the block-diagonal matrix $\mathbf{W_t}$. The measurement equation is equivalent to the original models, apart from the dynamic specification of the time-varying parameters, which is defined through the transition matrix $\mathbf{T}$ within equation (10). The stochastic specification is completed by the disturbance terms $\mathbf{e_t^M}$ and $\mathbf{e_t^T}$, each with zero mean and covariance matrices equal to $\mathbf{\Sigma_M}$ and $\mathbf{\Sigma_T}$, respectively.

Once a model is expressed in the state–space form, a maximum-likelihood procedure based on the Kalman filter and Kalman smoother can be applied. An exhaustive technical discussion of the estimation procedures and the derivation of the log-likelihood function can be found in Harvey (1989). Maximum likelihood estimates can now be obtained using an optimization algorithm, such as the BHHH procedure by Berndt et al. (1974).

Data and Applications

The performance of the stochastic parameter model is evaluated on two data sets, one from Piggott and Marsh (2004) on U.S. meat consumption, the other from Smith, van Ravenswaay, and Thompson (1984, 1988) on Hawaii milk consumption. The benchmark models are those with a MCI and the assessment is based on residual diagnostics and forecasting performance. Besides the econometric performance, the relationship between the estimated scare effects and the news indices is explored and discussed.

The Piggott and Marsh data set consists of 71 quarterly observations from 1982(1) to 1999(1) and provides expenditure shares for beef, pork, and poultry, their prices, and food safety indices built through key-word searches on the top fifty English language newspapers indexed by the Lexis–Nexis search tool.[3] Over the sample period, three relevant food scares had occurred: an *E. coli* outbreak in the state of Washington in 1993(1), a BSE scare induced by news from Europe in 1996(1), and another *E. coli* scare in 1997(3) in the Midwest United States. Although Piggott and Marsh (2004) found a significant but minimal impact of information at the aggregate level for the above food scares, their data provides an application involving multiple incidents. This allows for an evaluation of the impact of multiple events and scare resurgence. For this analysis, we limit our examination to one food safety index (beef), while Piggott and Marsh (2004) exploited product-specific indices. As regards the SIV model (3), we assume that $h_t = 1$ after 1993(1), i.e., with the occurrence of the first *E. coli* scare.

The second data set covers the March 1982 heptachlor contamination incident in Oahu, Hawaii. This case study is especially interesting, as it deals with a prominent and isolated food scare. On March 18th, 1982, the U.S. Department of Health reported that milk on the island of Oahu had been found to be highly contaminated by a pesticide (heptachlor). Since no fluid milk was imported on the island, the entire population had been exposed. The crisis was followed by the media especially in the first two months, then press attention declined, but public concern remained high. In their two studies, Smith, van

[3] Further details on data and sources are provided in Piggott and Marsh (2004).

Table 1. Unit Root Tests on Stochastic Intervention Parameters

Equation	Augmented Dickey–Fuller	Philips–Perron	Critical Values 5%	1%
Model MEAT–SIV				
Beef	0.991	0.523	−1.945	−2.597
Pork	1.002	0.692	−1.945	−2.597
Poultry	−1.248	−1.922	−1.945	−2.597
Model MILK–SIV				
Milk	−0.484	−0.449	−1.945	−2.594

Note: Tests assume no intercept and 2 lags (ADF) and 3 truncation lags (PP).

Ravenswaay, and Thompson (1984, 1988) provide a thorough discussion of the issues related to classifying information as positive or negative. Their model, as specified in equation (6), accounts for, what they term as, the lagged effects of media coverage. Furthermore, this data set has become a classic case study, further exploited by Foster and Just (1989) for welfare evaluations and by Liu, Huang, and Brown (1998) for risk assessment. Their data consist of seventy-eight monthly observations from January 1977 to June 1986 for each of the variables needed to estimate the milk demand models described in the previous section, with $\mathrm{DV}_t = 1$ after the first information release, i.e., March 1982.

For each application, three alternative models are estimated: (a) the MCI model with the media index; (b) the SIV model with a stochastic intervention parameter and no MCI; and (c) the STS model based on the STS specification. The models including a media index are described by equations (1) and (2) for Piggott and Marsh data (model MEAT–MCI) and equation (6) for the heptachlor scare (model MILK–MCI). In the SIV models, the news index is substituted with a stochastic shifter; hence equations (1) and (3) define the meat demand system (model MEAT–SIV), and the milk demand function for the heptachlor scare (model MILK–SIV) is specified as in (7). The STS models are formed by equations (1) and (5) for the meat case study (MEAT–STS) and by equation (8) for the heptachlor case study (MILK–STS).

Results

Maximum likelihood estimates of the meat demand system MEAT–MCI were obtained by iterated seemingly unrelated equation (SUR), the model MILK–MCI was estimated by ordinary least squares (OLS), while the BHHH algorithm was applied for the SIV models MEAT–SIV and MILK–SIV, and the STS models MEAT–STS and MILK–STS.[4] The stochastic intervention parameters Ψ_t in MEAT–SIV and MILK–SIV were first estimated assuming an autoregressive specification as in (4), and the unit root hypothesis was tested on the estimated time series using the ADF and PP tests. As shown in table 1, the unit root hypothesis was not rejected at the 5% confidence level for any of the equations; hence a random walk specification was adopted for ψ_t in MEAT–SIV and MILK–SIV.

Table 2 reports the parameter estimates for the meat demand systems. The poultry equation was dropped from the systems to overcome the singularity problem and estimates were retrieved through the imposed constraints for adding-up, homogeneity, and symmetry. The basic goodness-of-fit ($\bar{R}^2$) and serial correlation diagnostics are shown. Given the dynamic structure of the models, the usual Durbin–Watson statistic is not applicable and the Ljung and Box Q-statistic is reported, instead. The Q-statistic is computed for different lags as $Q(k) = T(T+2)\sum_{j=1}^{k} r_j/(T-j)$, where k is the lag order, r_j is the jth autocorrelation, and T is the sample size. Under the null hypothesis of no serial correlation up to lag k, Q is distributed as a Chi-square with k degrees of freedom where a common rule-of-thumb suggests $k = \ln(T)$ (Ljung and Box 1978).

Models MEAT–MCI and MEAT–SIV are both satisfactory in terms of goodness-of-fit

[4] The models were estimated using Econometric Views$^{\mathrm{TM}}$ 4's state–space objects on an Intel Pentium 4 processor, 1.6 GHz. Convergence of the BHHH algorithm for models MEAT-SIV, MEAT-STS, MILK-SIV, and MILK-STS was achieved in 23, 31, 14, and 207 iterations, respectively. Estimation times were between two and twenty-eight seconds.

Table 2. Estimation Results for the MEAT Models

	MEAT–MCI			MEAT–SIV			MEAT–STS		
Equation	Parameter	Estimate	(S.E.)	Parameter	Estimate	(S.E.)	Parameter	Estimate	(S.E.)
Beef	α_1	0.365	(0.048)	α_{1t} (final)	0.566	(0.015)	α_{1t} (final)	0.492	(0.018)
	ρ_{11}	0.562	(0.028)	ρ_{11}	−0.143	(0.379)	ρ_{11}	−0.131	(0.079)
	ρ_{12}	−0.109	(0.070)	ρ_{12}	0.255	(0.435)	ρ_{12}	0.053	(0.105)
	ρ_{13}	−0.452	(0.077)	ρ_{13}	−0.112	(0.326)	ρ_{13}	0.079	(0.107)
	ϕ_1	0.051	(0.004)	ϕ_1	0.019	(0.013)	ϕ_1	0.015	(0.002)
	ϕ_2	0.038	(0.003)	ϕ_2	0.019	(0.026)	ϕ_2	0.010	(0.003)
	ϕ_3	0.027	(0.002)	ϕ_3	−0.013	(0.025)	ϕ_3	−0.022	(0.003)
	γ_{11}	0.042	(0.015)	γ_{11}	0.029	(0.071)	γ_{11}	0.119	(0.019)
	γ_{12}	−0.036	(0.010)	γ_{12}	0.019	(0.049)	γ_{12}	−0.049	(0.011)
	γ_{13}	−0.006	(0.010)	γ_{13}	−0.047	(0.071)	γ_{13}	−0.070	(0.026)
	β_1	0.050	(0.047)	β_1	0.092	(0.229)	β_1	0.062	(0.050)
	λ_1	0.2×10^{-5}	(0.4×10^{-5})	ψ_{1t} (final)	−0.002	(0.006)	ψ_{1t} (final)		
	$\bar{R}^2$	0.963		$\bar{R}^2$	0.938		$\bar{R}^2$	0.915	
	$Q(4)$	8.838		$Q(4)$	6.420		$Q(4)$	8.148	
Pork	α_2	0.300	(0.035)	α_{2t} (final)	0.156	(0.008)	α_{2t} (final)	0.258	(0.017)
	ρ_{21}	−0.193	(0.020)	ρ_{21}	0.038	(0.244)	ρ_{21}	0.290	(0.055)
	ρ_{22}	0.276	(0.053)	ρ_{22}	0.127	(0.282)	ρ_{22}	−0.278	(0.078)
	ρ_{23}	−0.083	(0.071)	ρ_{23}	−0.165	(0.205)	ρ_{23}	−0.011	(0.090)
	ϕ_1	−0.020	(0.003)	ϕ_1	−0.011	(0.012)	ϕ_1	−0.010	(0.001)
	ϕ_2	−0.028	(0.002)	ϕ_2	−0.003	(0.018)	ϕ_2	−0.015	(0.001)
	ϕ_3	−0.020	(0.002)	ϕ_3	0.021	(0.017)	ϕ_3	0.016	(0.003)
	γ_{21}	−0.036	(0.010)	γ_{21}	0.019	(0.049)	γ_{21}	−0.049	(0.011)
	γ_{22}	0.079	(0.011)	γ_{22}	0.064	(0.054)	γ_{22}	0.080	(0.011)
	γ_{23}	−0.043	(0.008)	γ_{23}	−0.083	(0.051)	γ_{23}	−0.031	(0.024)
	β_2	0.007	(0.033)	β_2	−0.135	(0.141)	β_2	0.016	(0.038)
	λ_2	0.7×10^{-5}	(0.3×10^{-5})	ψ_{2t} (final)	0.002	(0.003)			
	$\bar{R}^2$	0.883		$\bar{R}^2$	0.780		$\bar{R}^2$	0.495	
	$Q(4)$	8.980		$Q(4)$	9.392		$Q(4)$	11.637*	
Poultry	α_3	0.335	(0.035)	α_{3t} (final)	0.278	(0.017)	α_{3t} (final)	0.250	0.024
	ρ_{31}	−0.368	(0.021)	ρ_{31}	0.104	(0.472)	ρ_{31}	−0.158	0.096
	ρ_{32}	−0.167	(0.053)	ρ_{32}	−0.382	(0.596)	ρ_{32}	0.226	0.131
	ρ_{33}	0.535	(0.038)	ρ_{33}	0.278	(0.417)	ρ_{33}	−0.067	0.140
	ϕ_1	−0.031	(0.003)	ϕ_1	−0.008	(0.019)	ϕ_1	−0.006	0.021
	ϕ_2	−0.010	(0.002)	ϕ_2	−0.016	(0.035)	ϕ_2	0.005	0.017
	ϕ_3	−0.007	(0.002)	ϕ_3	−0.008	(0.032)	ϕ_3	0.006	0.003
	γ_{31}	−0.007	(0.010)	γ_{31}	−0.048	(0.071)	γ_{31}	−0.070	0.107
	γ_{32}	−0.043	(0.008)	γ_{32}	−0.082	(0.051)	γ_{32}	−0.031	0.024
	γ_{33}	0.049	(0.016)	γ_{33}	0.082	(0.100)	γ_{33}	0.101	0.037
	β_3	−0.057	(0.035)	β_3	0.042	(0.299)	β_3	−0.078	0.077
	λ_3	0.5×10^{-5}	(0.3×10^{-5})	ψ_{3t} (final)	0.001	(0.006)			
	$\bar{R}^2$	0.970		$\bar{R}^2$	0.893		$\bar{R}^2$	0.894	

Asterisk (*) denotes significance at the 5% level.

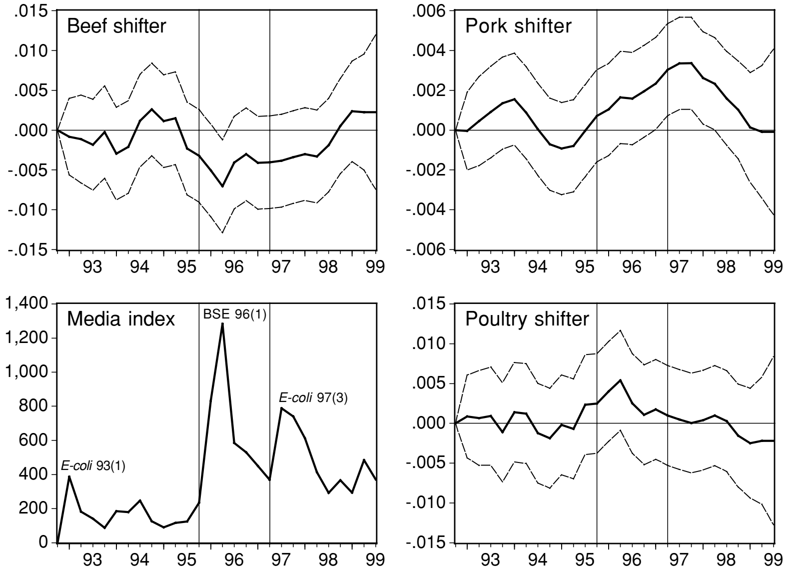
and lack of serial correlation in the residuals, while the STS specification of model MEAT–STS results in a lower $\bar{R}^2$ and evidence of serial correlation for the pork equation. There are some differences in the parameter estimates, also reflected in the Marshallian conditional elasticities reported in table 3. The coefficients of the media index are statistically insignificant in MEAT–MCI, and the ψ_{it} parameter in MEAT–SIV is also nonsignificant throughout the sample (see also the intervention plots in figure 1). The time-varying intercepts of MEAT–STS shown in figure 2 only register very small departures from the long-term trend. This confirms the results of Piggott and Marsh (2004), which show that these meat scares had little impact on aggregate consumption. However, it is interesting to look at the patterns of the stochastic intervention parameters ψ_{it} and compare them to the media index N_t (figure 1). The graph starts with the 1993(1) *E. coli* scare, which has

Table 3. MEAT Models, Conditional Uncompensated Elasticities

	Price Elasticity			Expenditure
Model	Beef	Pork	Poultry	Elasticity
MEAT–MCI		Short-run elasticity (s.e.)		
Beef	−0.96	−0.08	0.01	1.11
	(0.05)	(0.04)	(0.02)	(0.10)
Pork	−0.13	−0.74	−0.15	1.02
	(0.06)	(0.04)	(0.04)	(0.11)
Poultry	0.09	−0.11	−0.73	0.75
	(0.08)	(0.06)	(0.08)	(0.15)
		Long-run elasticity (s.e.)		
Beef	−1.01	−0.04	0.01	1.05
	(0.10)	(0.07)	(0.04)	(0.19)
Pork	−0.09	−0.82	−0.11	1.02
	(0.08)	(0.06)	(0.05)	(0.16)
Poultry	0.04	−0.05	−0.84	0.89
	(0.11)	(0.08)	(0.11)	(0.20)
MEAT–SIV		Short-run elasticity (s.e.)		
Beef	−1.03	−0.02	−0.12	1.20
	(0.25)	(0.17)	(0.15)	(0.49)
Pork	0.27	−0.65	−0.17	0.55
	(0.29)	(0.19)	(0.20)	(0.47)
Poultry	−0.29	−0.41	−0.69	1.18
	(0.68)	(0.45)	(0.69)	(1.29)
		Long-run elasticity (s.e.)		
Beef	−1.02	−0.02	−0.14	1.22
	(0.47)	(0.32)	(0.28)	(0.92)
Pork	0.10	−0.68	−0.01	0.61
	(0.41)	(0.28)	(0.29)	(0.67)
Poultry	−0.08	−0.38	−0.72	1.17
	(0.89)	(0.58)	(0.90)	(1.68)
MEAT–STS		Short-run elasticity (s.e.)		
Beef	−0.81	−0.14	−0.18	1.13
	(0.09)	(0.06)	(0.05)	(0.13)
Pork	−0.19	−0.75	−0.11	0.55
	(0.10)	(0.11)	(0.09)	(0.15)
Poultry	−0.14	−0.03	−0.49	0.66
	(0.19)	(0.15)	(0.20)	(0.33)
		Long-run elasticity (s.e.)		
Beef	−0.83	−0.13	−0.16	1.12
	(0.17)	(0.11)	(0.10)	(0.25)
Pork	−0.15	−0.75	−0.11	1.05
	(0.14)	(0.16)	(0.13)	(0.22)
Poultry	−0.12	−0.03	−0.48	0.66
	(0.25)	(0.19)	(0.26)	(0.43)

a very small effect, negative on beef and positive on pork and poultry. The 1996 BSE scare (shown by the corresponding vertical line) is the most prominent event, and interventions reach a minimum for beef, a maximum for poultry, and a smaller positive effect emerges for pork. The 1997 *E. coli* scare is also negligible, but the beef intervention remains negative and the pork intervention reaches its peak. Despite the small scale of the scares, the stochastic patterns are able to capture the relevant turning points and patterns.

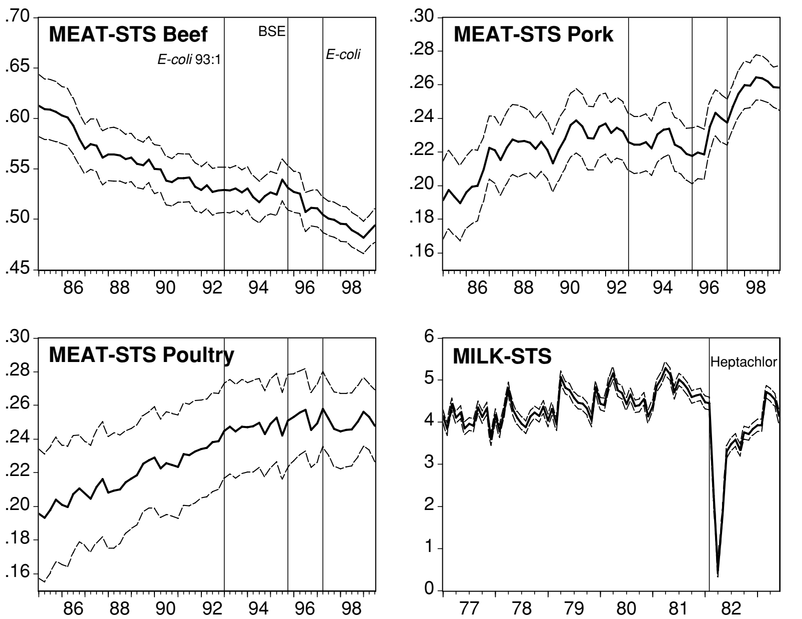
The heptachlor scare is more prominent and its effect is adequately captured by all models. Table 4 reports parameter estimates and the Marshallian elasticities. While there are only relatively small differences in the parameters, diagnostics show that the SIV specification of



Note: Dotted lines show smoothed estimates of standard errors

Figure 1. Smoothed estimates of the time-varying impact of food scares on aggregated U.S. meat consumption: shifters from the MEAT–SIV model and Piggott and Marsh (2004) beef safety index

model MILK–SIV leads to more efficient estimates. Furthermore, evidence of higher order serial correlation from the MILK–MCI model disappears in models MILK–SIV and MILK–STS. This is a relevant result, as Piggott and Marsh (2004) conclude that autocorrelation disappears when food safety information is adequately taken into account.



Note: Dotted lines show smoothed estimates of standard errors.

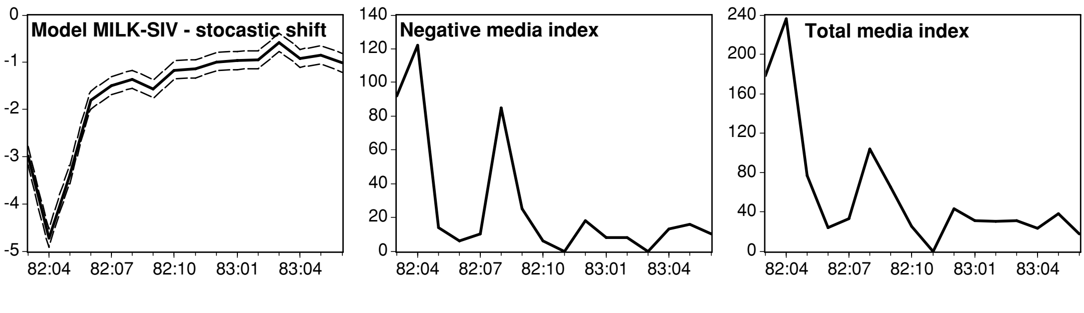
Figure 2. Smoothed estimates of the time-varying intercepts from MEAT–STS and MILK–STS models

Table 4. Estimation Results and Elasticities for the MILK Models

	MILK–MCI		MILK–SIV			MILK–STS		
Variable	Parameter	Estimates (S.E.)	Parameter	Estimates	(S.E.)	Parameter	Estimates	(S.E.)
CONSTANT	5.813	(1.774)		5.831	(0.549)	α_t (final)	4.144	(0.513)
JAN	0.270	(0.169)		0.333	(0.117)		0.316	(0.334)
FEB	0.309	(0.168)		0.326	(0.118)		0.326	(0.474)
MAR	0.171	(0.170)		0.247	(0.104)		−0.078	(0.533)
APR	0.518	(0.165)		0.557	(0.110)		−0.088	(0.599)
MAY	0.544	(0.168)		0.541	(0.181)		0.152	(0.703)
JUN	−0.238	(0.165)		−0.269	(0.119)		−0.462	(0.764)
JUL	−0.331	(0.171)		−0.311	(0.146)		−0.452	(0.847)
AUG	−0.025	(0.169)		−0.249	(0.134)		−0.380	(0.756)
SEP	0.665	(0.169)		0.520	(0.166)		0.399	(0.723)
OCT	0.460	(0.169)		0.392	(0.180)		0.322	(0.627)
NOV	0.239	(0.168)		0.246	(0.107)		0.216	(0.248)
DPM	−4.404	(2.179)		−3.882	(1.440)		−3.140	(8.676)
SUB	3.841	(2.637)		3.067	(1.252)		7.414	(8.812)
INC	0.00031[a]			0.00031[a]			0.00031[a]	
TRND	−0.005	(0.002)		−0.006	(0.002)		−0.021	(0.128)
DV	−0.388	(0.218)	ψ_t (final)	−1.622	(0.192)			
N_t	−0.023	(0.002)						
N_{t-1}	−0.014	(0.001)						
N_{t-2}	−0.008	(0.001)						
N_{t-3}	−0.004	(0.002)						
				Diagnostics				
R^2	0.91			0.99			0.63	
Ljung-Box Q(4)	9.86*			7.50			6.71	
				Unconditional Marshallian elasticities (s.e.)				
Own-price	−0.503	(0.249)		−0.443	(0.164)		−0.359	(0.991)
Substitution	0.251	(0.172)		0.201	(0.082)		0.485	(0.576)
Income	0.249			0.249			0.249	

[a] Estimates conditional on income, as in Smith, van Ravenswaay, and Thompson (1988).
Asterisk (*) denotes significance at the 5% level. Double asterisk (**) denotes significance at the 1% level.

Figure 3 shows estimates of the time-varying shifter from model MILK–SIV, and the negative and total media indices from Smith, van Ravenswaay, and Thompson (1988). The pattern of the estimated stochastic shift (ψ_t) is consistent with the events occurring during the 1982 contamination period (Smith, van Ravenswaay, and Thompson 1984). The impact of the food safety news is smaller in the first month, because only the last two weeks were affected as information first appeared in the media on March 18. Model MILK–SIV captures a peak impact in April 1982, in correspondence with the highest level of media



Note: Dotted lines show smoothed estimates of standard errors.

Figure 3. Smoothed estimates of the time-varying effect of the heptachlor crisis: shifter from the MILK–SIV model and Smith, van Ravenswaay, and Thompson media coverage indices

Table 5. Model Selection Test for Nonnested Specifications: Media Coverage Index versus Stochastic Intervention

Event Specification	Nested Variable (Equation 11)	Parameters Subject to Wald Test	t-Value
	MEAT–MCI versus MEAT–SIV		
	Beef equation		
MCI	X_{1t}	$\alpha_1 + \lambda_1 N_t$	−1.85
SIV	X_{2t}	$\alpha_{1t} + \psi_{1t} h_t$	16.14**
	Pork Equation		
MCI	X_{1t}	$\alpha_2 + \lambda_2 N_t$	1.28
SIV	X_{2t}	$\alpha_{2t} + \lambda_{2t} h_t$	16.68**
	MILK–MCI versus MILK–SIV		
MCI	X_{1t}	$\beta_5 \mathrm{DV}_t + \omega_0 N_t + \omega_1 N_{t-1} + \omega_2 N_{t-2} + \omega_3 N_{t-3}$	0.11
SIV	X_{2t}	$\psi_{it} \mathrm{DV}_t$	7.31**

Double asterisk (**) denotes significance at the 1% level.

coverage, then a relatively quick recovery by June 1982, and a slower one thereafter. In September 1982, this trend shows a small but visible turning point, possibly linked to the reopening of schools and the concerns expressed by Environmental Protection Agency 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.[5] Model MILK–STS also captures the scare pattern (see figure 2). However, when information on the scare onset is ignored, there is an efficiency loss as reflected in larger standard errors and a lower $\bar{R}^2$ index.

The random walk shift models MEAT–SIV and MILK–SIV seem to maintain the descriptive power of their media index counterparts, but a statistical evaluation of their comparative performance requires some selection test for non-nested models. A straightforward method for model selection is based on the estimation of a comprehensive model nesting for both specifications:

$$(11) \quad y_t = X_{0t}\varphi_0 + X_{1t}\varphi_1 + X_{2t}\varphi_2 + \varepsilon_t$$

where the dependent variable y_t is expressed as a function of the explanatory variables common to both models (X_{0t}), of the explanatory variables specific to the first model (X_{1t}), and of the variables which only appear in the second one. Hence, Wald t-tests on the coefficients φ_1 and φ_2 allow the assessment of whether the corresponding variables explain the variability in y_t. Model (11) is estimated by iterated SUR to assess model MEAT–MCI versus MEAT–SIV and by OLS for MILK–MCI versus MILK–SIV. The components specific to models MEAT–SIV and MILK–SIV are significant, while the coefficients of the variables specific to MEAT–MCI and MILK–MCI are not significantly different from 0 (table 5).

The out-of-sample forecasting performance of the models is shown in table 6, which reports the values of the Theil's U-statistic for different estimation periods and forecast windows (Greene, 2003, p. 113).[6] Models MEAT–MCI and MILK–MCI require actual observations of the news coverage index for the forecast period, while predictions from models MEAT–SIV, MEAT–STS, MILK–SIV, and MILK–STS do not entail the news coverage index or any other out-of-sample observation except for prices and total expenditures. The SIV specification yields more precise out-of-sample forecasts, especially in the short term. On average, model MEAT–SIV doubles the forecast precision of MEAT–MCI within a one-year forecasting period. In a three-month

[5] 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.

[6] The Theil U-statistic is the ratio of the root-mean-squared error (RMSE) to the RMSE of a model, assuming no change in the dependent variable. A value > 1 means the model performance was worse than when assuming a constant dependent variable, while the 0 lower bound reflects perfect predictions. The U-statistic is especially useful to compare the predictive performance of models with different dependent variables.

Table 6. Out-of-Sample Forecasting Performances: Theil's *U*-Statistic

	MEAT Models						MILK Models			
	Estimation Period 1982:2–1993:4			Estimation Period 1982:2–1996:4				Estimation Period January 77–June 82		
	Forecast Window			Forecast Window				Forecast Window		
Equation	2 Quarters	1 Year	2 Years	2 Quarters	1 Year	2 Years	Model	3 Months	6 Months	1 Year
	Model MEAT–MCI			Model MEAT–MCI			MILK–MCI	0.40	0.27	0.17
Beef	0.010	0.011	0.013	0.009	0.010	0.013	MILK–SIV	0.11	0.17	0.22
Pork	0.021	0.018	0.019	0.026	0.023	0.027	MILK–STS	0.29	0.21	0.19
Poultry	0.078	0.088	0.083	0.021	0.037	0.028				
Average	0.036	0.039	0.038	0.019	0.023	0.023				
								Estimation Period		
	Model MEAT–SIV			Model MEAT–SIV				January 77–December 82		
Beef	0.011	0.015	0.013	0.001	0.006	0.014	MILK–MCI	0.13	0.15	
Pork	0.023	0.020	0.015	0.015	0.020	0.030	MILK–SIV	0.08	0.06	
Poultry	0.007	0.019	0.021	0.017	0.017	0.016	MILK–STS	0.17	0.20	
Average	0.014	0.018	0.017	0.011	0.014	0.020				
	Model MEAT–STS			Model MEAT–STS						
Beef	0.014	0.012	0.023	0.009	0.010	0.010				
Pork	0.019	0.014	0.019	0.003	0.012	0.022				
Poultry	0.022	0.028	0.034	0.019	0.020	0.030				
Average	0.019	0.018	0.025	0.010	0.014	0.021				

Table 7. Correlations and Lagged and Leading Cross-Correlations between Stochastic Parameters and Media Coverage Indices

Parameter Equation	Simultaneous	Cross-Correlation Lags −1	−2	Leads 1	2
	Piggot and Marsh beef safety index				
SIV Ψ_i	MEAT—SIV				
Beef	−0.64	−0.46	−0.28	−0.55	−0.47
Pork	0.56	0.54	0.51	0.45	0.33
Poultry	0.51	0.27	0.05	0.45	0.43
	MEAT–STS				
STS $\Delta(\Psi_i)$	All sample				
Beef	−0.19	−0.05	0.04	−0.07	−0.17
Pork	0.31	0.24	0.04	0.19	0.17
Poultry	−0.16	−0.23	−0.10	−0.15	−0.01
	Sample 1993:1–1999:3				
Beef	−0.42	−0.18	−0.01	−0.21	−0.35
Pork	0.59	0.46	0.05	0.35	0.26
Poultry	−0.11	−0.26	−0.05	−0.11	0.15
	Sample 1996:1–1999:3				
Beef	−0.58	−0.15	−0.04	0.05	−0.02
Pork	0.63	0.47	−0.08	0.17	0.07
Poultry	−0.06	−0.35	0.13	−0.24	−0.05
	MILK–SIV				
SIV Ψ_i	Negative media coverage				
Milk	−0.72	−0.75	−0.34	−0.22	0.03
	Total media coverage				
Milk	−0.85	−0.81	−0.37	−0.37	−0.02
	MILK–STS				
STS $\Delta(\Psi_i)$	Negative media coverage				
Milk	−0.71	−0.75	−0.35	−0.20	0.05
	Total media coverage				
Milk	−0.83	−0.79	−0.37	−0.35	0.00

forecast window, and an estimation period including only three observations within the scare period, model MILK–SIV is almost four times more precise than model MILK–MCI. Models MEAT–STS and MILK–STS also predict better than their media index counterparts in the short term, but the precision gain is much smaller. On balance, the SIV specifications exploiting information regarding the onset of the scare lead to more efficient estimates and better forecasting performances.

Finally, it may be interesting to see how the latent information variables and the time-varying intercepts relate to the MCIs computed and explored in Piggott and Marsh (2004) and Smith, van Ravenswaay, and Thompson (1988). A simple but powerful insight is gained by examining the correlations and cross-correlations between the stochastic intervention estimated in MEAT–SIV and MILK–SIV and the MCIs, as reported in table 7. Within the STS specification of MEAT–STS and MILK–STS, cross-correlation between the first-differenced intercept and the news coverage index is shown to eliminate the trend effect. Cross-correlations measure the correlation between the shifter time series and the MCI time series, the latter for different lags and leads. The examination of cross-correlations allows evaluation of the lagged and leading effects of the food scare, providing additional information besides the degree of co-movement of the two series, which is captured by simultaneous correlations. Such information could be useful, as it may allow an effective and less subjective discounting of available media indices.

The relatively high correlations for models MEAT–SIV and MILK–SIV confirm the close link between the estimated time-varying impact of the food scares and the MCIs, including the substitution effect emerging from the positive correlations between the beef safety index and the pork and poultry stochastic shifters in MEAT–SIV. An intriguing interpretation of cross-correlations could be surmised by assuming that lagged correlations measure the carry-over effects, contemporaneous correlations capture the immediate impact, and lead cross-correlations explore the social amplification, or news spiral effect, discussed in Beardsworth and Keil (1996). In this perspective, results show evidence of a carry-over and leading effect for both the meat and milk demand models. These effects are smaller for meat demand, but they seem to last longer (at least six months for beef and pork) than those of the heptachlor incident, where the carry-over effect disappears within two monthly lags and social amplification becomes negligible within a single lead. This result can be explained by the different nature of the food scares. Crises like BSE bring persistent uncertainty about the extent and outcomes of the safety issue, and hence more attention for novel information, while the Oahu contamination incident is isolated in both time and space. Cross-correlations from model MILK–SIV are shown for the two types of media indices built by Smith, van Ravenswaay, and Thompson (1988), one accounting for negative reports only, and the other including any type of article on the contamination incident. Interestingly, correlations are stronger with the total media index, suggesting that the distinction between positive and negative information might be redundant.

While model MILK–STS returns cross-correlations that are very similar to those of MILK–SIV, those from model MEAT–STS are less informative when the whole sample is considered. However, when computing cross-correlations in restricted subsamples around one or more food safety incidents, correlation values improve and become more similar to those in MEAT–SIV. Again, this suggests that the timing of the first occurrence of a food scare improves the reliability of the model, and the performance of stochastic specifications discussed in this article is dependent on the prominence of the food safety incident.

Concluding Remarks

This article contributes to the literature on demand response to food scares by evaluating the potential of stochastic parameters demand models as compared to the customary inclusion of MCIs. We show that a stochastic approach to modeling the impact of a food scare over time should be considered as a valid alternative to methods based on MCIs, especially when dealing with a prominent and sudden food safety incident. Demand models with a SIV (or a simple time-varying intercept) result in a better econometric and forecasting performance, and enable the detection of turning points in the aftermath of a food scare. Furthermore, when a news coverage index is available, the stochastic models can be exploited to evaluate the presence of carry-over and discounting effects in consumer processing of food safety information.

The empirical comparison of alternative model specifications also indicates a major improvement in their performance when information about the timing of the scare onset is explicitly taken into account. However, a more general STS specification is also able to capture the effects of the scare without requiring any timing information. The random walk specification can also be replaced by an autoregressive specification, although empirical tests corroborated the unit root hypothesis.

The substitution of the news coverage index with a random walk intervention variable avoids the need for subjective assumptions on the accumulated impact of information and the difficult distinction between positive and negative information. Furthermore, it provides a more reliable and flexible specification to account for resurgent or multiple food scares affecting the same products. Finally, it indirectly takes into account the possible spiraling impact of media coverage, often observed at the early stages of a food scare, with results showing evidence of carry-over and social amplification effects. This also supports the view that the distinction between positive and negative media coverage is not necessary when evaluating the impact of news on a food safety incident.

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