A LATENT-VARIABLE APPROACH TO MODELLING MULTIPLE AND RESURGENT MEAT SCARES IN ITALY

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Abstract

This paper aims to measure the time pattern of multiple and resurgent food scares and their direct and cross-product impacts on consumer response. The Almost Ideal Demand System (AIDS) is augmented by a flexible stochastic framework which has no need for additional explanatory variables such as a media index. Italian aggregate household data on meat demand is used to assess the time-varying impact of a resurgent BSE crisis (1996 and 2000) and the 1999 Dioxin crisis. The impact of the first BSE crisis on preferences seems to be reabsorbed after a few months. The second wave of the scare at the end of 2000 had a much stronger effect on preferences and the positive shift in chicken demand continued to persist after the onset of the crisis. Empirical results show little relevance of the Dioxin crisis in terms of preference shift, whilst not excluding the more relevant price effect.

Keywords: Meat Demand, BSE shock, Almost Ideal Demand System, Kalman filter

JEL Classification: D12, I12

Introduction

Consumers' response to food scares has been the subject of many empirical investigations. This paper aims to propose a flexible stochastic approach to measure the time pattern of multiple and resurgent food scares and their direct and cross-product impacts on consumer response. This can be accomplished by using an Almost Ideal Demand System (AIDS), with no need for additional explanatory variables such as a media index.

Previous studies have followed different approaches to measuring the effects of food safety information on demand. It is assumed that preferences for a commodity are influenced by consumer perception of its attributes such as quality and safety (Bausmann, 1956). Application of this framework has been prevalent in food advertising and health and food scare studies (Chiang and Kinnucan, 1991; Brester and Schroeder, 1995; Swartz and Strand, 1981; van Ravenswaay and Hoehn, 1991; Dahlgran and Fairchild, 1987). The standard approach to account for food scares requires the construction of a media coverage index, which is interpreted as a proxy of risk perception, as in Smith et al. (1988) and Liu et al. (2001). Recently, more emphasis has been placed on systemwise approaches, to account for cross-product effects. Burton and Young (1996), Verbeke and Ward (2001) and Piggot and Marsh (2004) extend the Almost Ideal Demand System (AIDS) (Deaton and Muellbauer, 1980) to account for the impact of news on the Bovine Spongiform Encelopathy (BSE) outbreak on consumption of different meat products. Similarly, Marsh et al. (2004) investigate the effects of meat product recalls on consumer demand in the US, using the Rotterdam model.

However, little attention has been paid to the phenomenon of food crisis resurgence or multiple scares affecting the same group of products. The marginal effects of novel or confirmatory food safety news should be accounted for in these types of studies. Sociologists recognise that in the aftermath of a specific food scare, even following the demand recovery, a chronic level of anxiety persists. Any new or corroborating information may lead to a further and immediate consumer reaction to the same, or an amplified, level of the initial scare (Beardsworth and Keil, 1996). As a result, it is inappropriate to assume that the marginal impact of a single piece of news is constant over time, which is the case when a single media index is devised. Furthermore, consumer demand for a product may indeed be affected by new information, regardless of whether this information is product specific. An obvious example is the occurrence of multiple and resurgent meat scares in Europe, such as the two waves of the BSE crisis, the dioxin crisis and several other minor outbreaks, like E-coli or Salmonella.

An alternative model which addresses this resurgence issue and overcomes the need for a media index also eliminates the time, cost and subjective assumptions (distinction between positive and negative information, discounting of information, memory effects) required to incorporate such media indices.

The application of Italian aggregate household demand data to two BSE scares (1996, 2000) and the Dioxin scare (1999) is particularly interesting as it allows an examination of both multiple food scares related to substitutable products (beef, chicken and other foods) as well as the resurgence of the BSE scare during the time frame. The approach proposed in this paper is based on the inclusion of a stochastic intervention variable within the AIDS framework. The model is expressed in the state-space form and estimated using Kalman filtering techniques, which allows for direct estimation of the time-varying pattern of consumer response based on actual data.

The model

As in Basmann (1956) and Swartz and Strand (1981), it is assumed that the consumer maximizes an utility function, dependent on consumer preferences, $U(x_1,\dots,x_g,\theta(\mathbf{r}))$, where $x_1,\dots x_g$ are the quantities of the g goods consumed in each period of time, given an income level Y and prices $p_1,\dots,p_g$. These preferences vary as a function θ of a set of characteristics of the goods (the vector **r**), including physical attributes, but also any information or psychological variables altering the perception of such attributes (Nayga et al, 1999). As a result, food safety information enters the utility function through the vector **r** and utility maximization yields a Marshallian demand function where the news coverage index appears as a demand shifter (Piggott and Marsh, 2004).

A flexible stochastic framework for modelling the time-varying impact of food scares is provided by a time-varying Almost Ideal Demand System. Some variations on this model have been recently employed to account for time-varying tastes and seasonality in food demand (Fraser and Moosa, 2002; Deschamps, 2003). The extension consists of allowing some or all of the model parameters to follow a pre-determined stochastic specification. In this paper we adopt a dynamic version of the complete linearly-approximated aggregate AIDS based on the partial-adjustment form suggested by Alessie and Kapteyn (1991):

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

where w_{it} is the expenditure share for the i-th good at time t, p_{jt} is the price of the j-th good, Y_t is the total expenditure, P_t^{*} is the Stone index, k_t is an aggregation index computed as in Deaton and Muellbauer (1980) to account for household heterogeneity and u_t is a white-noise normally distributed error.

The intercept in (1) is a function of the vector of lagged shares to account for habits, of a linear trend to account for gradually changing tastes and of (monthly) seasonal factors:

$$\alpha_{it}^{*} = \alpha_i + \sum_{j=1}^{n} \rho_{ij} w_{i,t-1} + \sum_{s=1}^{12} \phi_{is}\delta_{ts} + \lambda_i t \tag{2}$$

where δ_{ts} is a dummy variable equal to 1 when the time period t falls in month s and 0 elsewhere, and the sum of the seasonal factors over 12 consecutive months is constrained to be 0, $\sum_{s=1}^{12} \phi_{is} = 0$.

System (1) fulfils the demand theory requirements when the following conditions are satisfied:

$$\begin{aligned} &\sum_{i=1}^{n} \alpha_i = 1 \quad \sum_{i=1}^{n} \rho_{ij} = 0 \quad \sum_{i=1}^{n} \lambda_i = 0 \\ &\sum_{i=1}^{n} \gamma_{ij} = 0 \quad \sum_{i=1}^{n} \beta_i = 0 \quad \sum_{i=1}^{n} \phi_{is} = 0 \quad \forall j \end{aligned} \tag{3a}$$

$$\sum_{j=1}^{n} \gamma_{ij} = 0 \qquad \forall i \tag{3b}$$

$$\gamma_{ij} = \gamma_{ji} \qquad \forall i, j \tag{3c}$$

The above constraints ensure respectively adding-up (3a), homogeneity (3b) and symmetry (3c). An additional constraint is necessary to ensure identification of the dynamic system (Edgerton, 1996):

$$\sum_{j=1}^{n} \rho_{ij} = 0 \quad \forall i \tag{3d}$$

In order to measure the effect of one or more food scares occurring after time period t_0, we augment the intercept of (1) with a dummy shift whose coefficient is allowed to vary according to a random walk. The intercept allowing for a response to the food scare(s) is augmented as follows:

$$\alpha_{it}^{*} = \alpha_i + \sum_{j=1}^{n} \rho_{ij} w_{i,t-1} + \sum_{s=1}^{12} \phi_{is}\delta_{ts} + \lambda_i t + \psi_t h_t \tag{4}$$

where $h_t=1$ for all time periods after the occurrence of the first food scare and is 0 elsewhere and the stochastic coefficient Ψ_t is assumed to follow a random walk with a normal white-noise error to capture the evolving pattern of the food scare:

$$\psi_{it} = \psi_{i,t-1} + e_{it} \tag{5}$$

Estimation

The system of equations described by (1) , (4) and (5), subject to the constraints in (3), can be estimated by rewriting the model in the state-space form and applying a maximum-likelihood algorithm such as the expectation-maximisation (EM) algorithm by Dempster et al. (1977). The state-space form of the system is given by defining a *measurement equation* and a *transition equation* as follows:

$$w_t = Z_t a_t + e_t^M \tag{6a}$$

$$a_t = T a_{t-1} + e_t^T \tag{6b}$$

where the $n \times 1$ vector w_t contains the expenditure shares, the $m \times 1$ state vector a_t includes the m unknown parameters of system and the $n \times m$ matrix Z_t contains the exogenous variables and other fixed values, so that (1) is equivalent to (6a), apart from the stochastic specification of the time-varying shift. The stochastic transition pattern for the random-walk coefficient is defined in the transition equation (6b), which represents the relationship between the state vector a_t and its lagged values, through the $m \times m$ transition matrix T, whose values are known. The stochastic specification of the model is completed by the disturbance vectors e_{it}^M and e_{it}^T, each with mean zero and with covariance matrices equal to H and Q respectively. H and Q are assumed to be time-independent and Q has a diagonal structure, which implies that the errors of the transition equation are independent.

Once a model is expressed in the state-space form, the Kalman filter (KF) can be applied. The KF is a recursive procedure for computing the optimal estimates of the state vector at time t using all available information at time t, once some acceptable priors for the initial state vector and covariance matrix have been defined. The other procedure necessary for estimating (6) is the Kalman smoother (KS). The KS is a backward procedure, which starts from the state vectors computed through the KF and produces 'smoothed' estimates. Furthermore, the KF allows us to derive the log-likelihood function as a function of the unknown parameters in the system and the other parameters appearing in the state-space form, namely the error covariance matrices H and Q. The representations of the KF and KS, and the log-likelihood function are reported in the Appendix.

Maximum likelihood estimates can now be obtained using the EM algorithm. The application of this to the estimation of stochastic coefficient models is illustrated by Shumway and Stoffer (1982) and Watson and Engle (1983). The EM algorithm is an iterative maximisation procedure that starts with the definition of the initial values for the state vector, for its covariance matrix and for H and Q.

The following steps are then repeated iteratively: (1) get estimates of the state vector and its covariance matrix through the KF; (2) feed the filtered estimates into the KS to obtain smoothed estimates; (3) maximise the log-likelihood function conditional to the smoothed values to estimate the error covariance matrices H and Q; (4) use the smoothed estimates of H, Q and the initial state vector to restart the algorithm from step 1 and repeat steps 1-3 until convergence is achieved.

The EM algorithm has the desirable property that each step always increases the likelihood and convergence is guaranteed (Wu, 1983). On the other hand, the limitation of the EM algorithm is that it may stop at some local maximum, so that the appropriate starting values are provided by the SUR estimates of the constant coefficient AIDS.

Application

An ideal setting for testing the performance of the AIDS model allowing for a time-varying shock is given by aggregate Italian meat demand. Over the last decade, the Italian meat market has been subject to several food scares where consumer response has been quite strong, with a sharp and sudden fall in consumption and a slow recovery pattern. It is still debated whether these shocks have resulted in any permanent impacts. The first informational shock to Italian household was the news about a potential link between BSE and CJD in March 1996. Despite the insignificant number of BSE cases in Italy, all linked to imported cattle, the change in consumer perception of beef safety was made evident by the drop in both the quantity consumed and prices, while substitute meats showed a rather stable consumption despite a noticeable rise in prices. In April 1996, household real expenditure in beef fell by 18.0%, with respect to April 1995, and real beef prices went down by 2.8%, while real expenditure in chicken raised by 1.7% despite a 7.2% price increase. By the end of 1998, and accounting for the structural decline that characterised the market well before the BSE crisis, beef consumption had returned to the pre-BSE level, while prices were still clearly below their expected level.

At the end of May 1999 the very short, but European-wide Dioxin crisis, also affected the meat sector, specificallly chicken. In June, Italian households' real expenditure in chicken decreased by 13.9% with respect to the same month in 1998 and real chicken prices fell by 1.8%. After the summer, consumption returned to previous levels and this crisis was not comparable to BSE in terms of economic impact, however it contributed to consumer anxiety and affected the slow process of trust restoration. In November 2000, a significant increase in the number of BSE cases was registered in France, after the adoption of sample tests on cattle. Several countries including Italy suspended French beef imports. This led to a sudden and huge shock on Italian household beef consumption (-32.2% in terms of beef real expenditure and –0.7% in terms of prices with respect to November 1999), which was exacerbated by the detection of the first BSE case in Italy in January 2001. Beef consumption was almost halved (-49.2% with respect to January 2000), while real beef price went down by 1.2%. A slow recovery began in late Spring 2000, but was still far from being completed at the end the year. Real expenditure in chicken showed a sharp growth in the first months after the crisis (up to +32.0% in January 2001) and prices again reacted significantly (still +18.0% in March 2001). It is clear that a constant-coefficient demand system would yield a poor performance due to the extent of these structural breaks in the data. Furthermore, the irregular patterns over a long period (1996-2001) would prevent a simple dummy variable specification to account for the different shocks. As suggested, constructing a media index able to account for multiple scares on different products would be problematic, expensive and involve subjective choices.

Three versions of the homogeneity and symmetry-restricted dynamic Almost Ideal Demand System were estimated: (a) with no shift accounting for the food scares; (b) with a fixed dummy shift from March 1996; and (c) with a random walk shift from March 1996. The data series were obtained from the ISTAT Household Expenditure Survey. Monthly observations from January 1986 to December 2001 were used to estimate a 4-equations system for beef, chicken, other foods and a residual equation for all remaining goods. Systems (a) and (b) were estimated through an iterated Seemingly Unrelated Regression estimator, while system (c), augmented with the stochastic shift defined in (4) and (5), was estimated through the EM algorithm as discussed in previous section. The residual equation was dropped from estimation in order to avoid singularity of the covariance matrix (see Barten, 1969 or Bewley, 1986).

Stability tests on system (a) show the relevance of the multiple structural breaks implied by the food scares, while tests on system (b) are aimed to assess whether a simple dummy shift from the initial outbreak period might be able to accommodate subsequent shocks. For both models, Table 1 reports the Chow test (Fisher, 1970) and the Nyblom test of the null of constant coefficients against the alternative of at least one coefficient following a random walk (Nyblom, 1989; Leybourne, 1993). This latter test does not require any assumption on the break date.

Table 1. Stability tests on the dynamic AIDS model without intervention (a) and with dummy intervention (b)

	March 1996 (bse)	May 1999 (dioxin)	October 2000 (bse2)	
	Model (a) - No shift			
	Chow Breakpoint test		Chow Forecast test(a)	Nyblom test(b)
Beef	1.72 *	1.73 *	5.95 **	5.30 **
Chicken	2.42 **	3.07 **	3.20 **	4.05
Other foods	2.43 **	1.15	0.53	5.83 **
	Model (b) - Dummy shift on March 1996			
Beef		1.76 *	6.66 **	4.72 *
Chicken		3.40 **	4.00 **	3.96
Other foods		1.10	0.51	5.55 **

Notes:

(a) Chow Breakpoint test not applicable due to the lack of degrees of freedom

(b) Critical values at 95% (99%) confidence level are 4.43 (4.88) for the model without shift and 4.62 (5.09) for the model with a dummy shift

The stability tests show the inadequacy of model (a) which does not account for the structural breaks. Diagnostics worsen as the Dioxin crisis and the latest BSE crisis are included in the estimation sample. If no break date is assumed (as in the Nyblom test), evidence for at least one random walk coefficient emerges for beef and other foods, while there is no clear sign of structural shock for chicken. If a single and constant shift on the intercept accounting for the first BSE scare is included, as in model (b), there is no sign of improvement in the Chow test and the Nyblom test still captures the instability of at least one parameter.

Focusing on model (c), a latent random walk intervention is considered after March 1996. Estimates from the dynamic AIDS with a constant shift variable were used as starting values for the EM algorithm. Parameters estimates and some model diagnostics are reported in Table 2, while short-run and long-run Marshallian own-price elasticities and total expenditure elasticities at the sample mean are shown in Table 3.

The beef and chicken equations show high $\overline{R}^2$ statistics. However, the $\overline{R}^2$ statistic is not suitable for time-series models, as any model able to pick up a time trend will return a value close to unity (Harvey, 1989). The goodness-of-fit can be assessed with respect to the performance of a simple random-walk-plus-drift model (R_D^2) statistic or against first differences around the seasonal mean (R_S^2) (Harvey, 1989: 268-269). Positive values for these indicators suggest a better fit than the simpler models. While the stochastic shift in model (c) seems to improve the specification of the beef and chicken equations, diagnostics for the other food equations are quite poor. Finally, the Ljung-Box statistics Q, computed with five lags[1]. Only in the beef equation is the specification able to eliminate all serial correlation.

[1] We adopted the conventional approach of setting the number of lags equal to ln T. The statistic is distributed as a $\chi^2(5)$.

A significant negative trend is observed for beef and chicken indicating a sign of changing preferences over the sample period, independent from the food scares. The own-lagged shares are significant for all equations suggesting that habit persistence is a major factor in explaining consumer choice.

Table 2. Estimates from the dynamic AIDS model with a random walk shift from March 1996

	Beef	Chicken	Other foods
α	-0.0525	0.0671 **	-0.0823
λ	-0.0001 **	-0.0001 **	-0.0001 *
ρ_1	0.5170 **	-0.0872 **	-0.3671 *
ρ_2	-0.6544 **	0.2143 **	-0.3877
ρ_3	0.0526	-0.0709 **	0.5296 **
ρ_4	0.0847	-0.0560	0.2241
γ_1	0.0097	0.0002	-0.0168
γ_2	0.0002	0.0070 **	-0.0076 *
γ_3	-0.0168 *	-0.0076 *	-0.0004
β	-0.0107 **	-0.0002 **	-0.0478 **
ϕ_1	-0.0005	-0.0003	0.0036
ϕ_2	0.0001	-0.0001	-0.0005
ϕ_3	-0.0007	-0.0001 **	0.0061 **
ϕ_4	0.0004 *	0.0000	0.0002
ϕ_5	0.0001	0.0001 **	0.0028
ϕ_6	-0.0002	0.0000 **	-0.0011
ϕ_7	0.0001	0.0001	-0.0051
ϕ_8	0.0001	0.0003	-0.0014 **
ϕ_9	0.0000	0.0003	0.0005
ϕ_{10}	0.0004 *	0.0000	0.0023
ϕ_{11}	0.0001	0.0002	0.0016
ϕ_{12}	0.0002	-0.0007	0.0050 **
Min ψ_t	-0.0014 **	-0.0001	0.0006
Max ψ_t	0.0019 **	0.0001	0.0042 **
Avg ψ_t	0.0003	0.0000	0.0032
Adj. R^2	0.96	0.82	0.51
Q(5)	12.33 *	3.83	25.59 **
R^2_S	0.252	0.004	-0.391
R^2_D	0.335	0.138	-0.114

Three indicators are shown for the stochastic intervention variables: a minimum and a maximum value and the average across the shock period. On average, the meat scares have no significant influence on preferences, which implies that demand response and adjustment to the food safety information is mainly explained by the change in relative prices. However, when single time periods are considered, there is clearly a significant effect on beef demand. The peak in the BSE effect on beef consumption is observed in January 2001, i.e. with the discovery of the first BSE case in cattle bred in Italy. The maximum positive value is observed at the very end of the sample, December 2001, and is probably linked to both a real recovery in response to reassuring information (in one year only 48 cases were detected in Italy, 0.1% of tested cattle). The reprieve may also be emphasised by the Christmas effect.

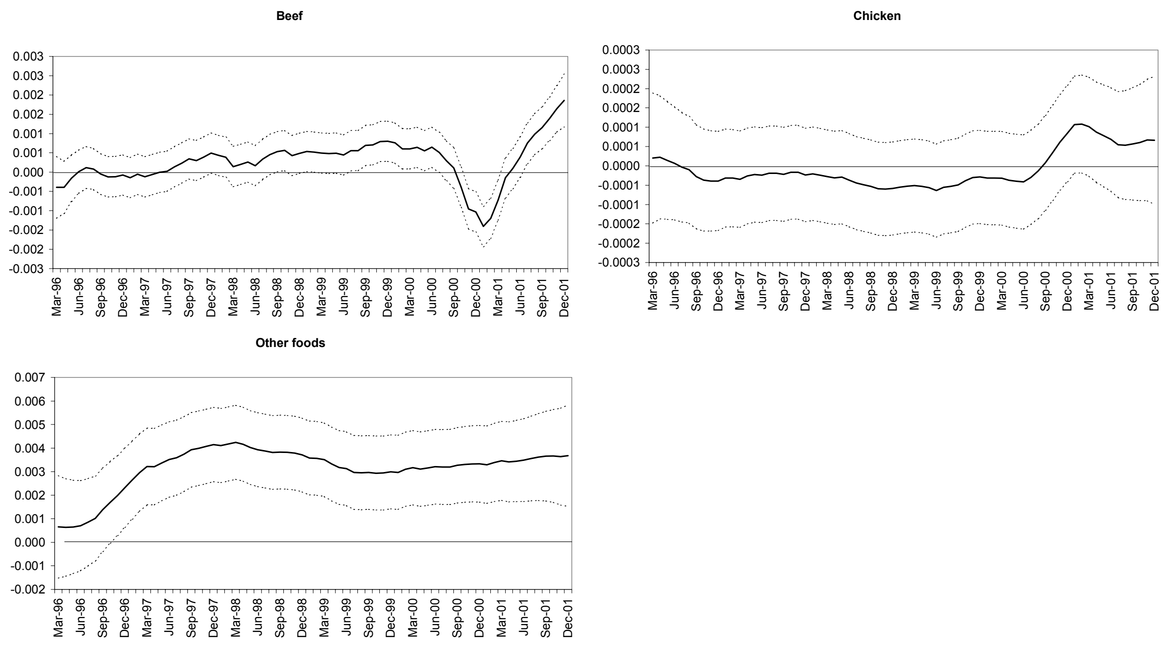
No significant impact was observed on chicken consumption, regardless of the trough corresponding to May-June 1999, i.e. an exact correspondence to the Dioxin crisis without the need of any prior information on the onset date. Again, a non-structural shift in preferences means that the market has mainly adjusted through price reaction. Finally, the aggregate group of “other foods” looks to gain the most from the meat scares, with a positive intervention value throughout the sample and a significant peak. However, due to poor diagnostics for this equation, these results should be taken with caution.

A plot of the time-varying interventions for chicken and poultry is shown in Figure 1. The first observation in the graph corresponds to the March 1996 BSE scare and highlights the expected negative effect for beef and a positive one for chicken. Such an impact is reabsorbed over the next few months and the model captures a positive trend for beef and a negative one for chicken. The Dioxin crisis itself has little relevance, even if the chicken shift registers a trough. The impact of the 2000 crisis is by far the largest. The negative shift in beef reaches its peak in January 2001, then there is a recovery pattern which is completed by mid-2001. Similarly, there is a very strong positive effect on chicken demand, which is still present by the end of 2001.

Table 3. Short and long-run elasticities

	Price				
	Beef	Poultry	Other foods	All other goods	Total expenditure
			Short-run		
Beef	-0.64	0.01	-0.60	0.25	0.62
Poultry	0.02	-0.24	-0.82	0.04	0.98
Other foods	-0.05	-0.05	-1.00	0.15	0.72
All other goods	-0.05	0.00	0.03	-1.04	1.07
			Long-run		
Beef	-0.25	0.02	-1.25	0.51	0.20
Poultry	0.03	-0.04	-1.05	0.05	0.97
Other foods	-0.11	-0.10	-1.01	0.31	0.40
All other goods	-0.04	0.00	-0.98	-1.03	1.06

Figure 1. Time-varying shifts (dotted lines plot standard errors).



The interventions plotted in Figure 1 are meant to capture the shifts in preference due to the food scares, i.e. excluding any effect due to changes in prices. For all considered crises, there is clear evidence of a social amplification process in the first month, then the negative psychological effect is recovered relatively quickly. This does not necessarily imply that beef demand has fully absorbed the effects of the scare, as consumption is increased due to lower prices and vice versa for chicken.

Conclusion

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, especially in cases where the same scare or different scares involving the same product reoccur over time. 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. A dynamic Almost Ideal Demand System with a stochastic shift on the intercept after the onset of the first scare is expected to model the evolving pattern of consumer anxiety, maintaining the capability to capture subsequent events affecting the consumption of the same foods. This model allows the isolation of the effect on consumer preferences other than the impact on demand due to the change in prices. Estimation is achieved through the Kalman-filter based EM algorithm.

The application of the dynamic AIDS model with stochastic shift is shown on Italian data, to assess the time-varying impact of two waves of the BSE crisis (1996 and 2000) and the 1999 Dioxin crisis. Empirical results show limited relevance of the Dioxin crisis in terms of preference shift, whilst not excluding the more relevant price effects. The impact of the first BSE crisis on preferences seems to be reabsorbed over the next few months, but the second wave of the scare at the end of 2000 had a much stronger effect on preferences than the first BSE scare and the positive shift in chicken demand continued to persist 14 months after the onset of the crisis.

The model could be further improved to overcome some of its limitations. Firstly, different stochastic structures such as an AR(1) shift could be tested and compared to the random walk assumption. A second issue for future reference is the stability of the price and expenditure coefficients, as consumer response to food safety information is likely to affect the behavioural response of the consumer.

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Appendix: Kalman filter, smoother and the log-likelihood function

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

$$a_{t|t-1} = Ta_{t-1} \tag{A1}$$

and its covariance matrix is

$$P_{t|t-1} = TP_{t-1}T' + Q \tag{A2}$$

where $Var(a_t) = P_t$ is the covariance matrix for the state vector. Equations (A1) and (A2) are the prediction equations of the Kalman filter. Once the actual observation w_t becomes available, the optimal estimator is updated according to the previous prediction error. This happens through the following updating equations:

$$a_t = a_{t|t-1} + P_{t|t-1}Z_t'F_t^{-1}\left(y_t - Z_t'a_{t|t-1}\right) \tag{A3}$$

$$P_t = P_{t|t-1} - P_{t|t-1}Z_t'F_t^{-1}Z_tP_{t|t-1} \quad \text{where } F_t = Z_tP_{t|t-1}Z_t' + H \tag{A4}$$

The equations described in (A1 – A4) 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, i.e. $a_{t|\tau} = E\left(\alpha_t \middle| \Im_\tau\right)$. The fixed interval smoothing algorithm (alternative algorithms are discussed in Harvey, 1989, p.150) is a backward recursive procedure, described by the following equations:

$$a_{t|\tau} = a_t + P_t^*\left(a_{t+1|\tau} - Ta_t\right) \tag{A5}$$

$$P_{t|\tau} = P_t + P_t^*\left(P_{t+1|\tau} - P_{t+1|\tau}\right)P_t^{*\prime} \tag{A6}$$

where

$$P_t^* = P_tT'P_{t+1|t}^{-1} \tag{A7}$$

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 w_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:

$$\log L(w,\Psi) = -\frac{\tau g}{2}\log 2\pi - \frac{1}{2}\sum_{t=1}^{\tau}\log\left|F_t\right| - \frac{1}{2}\sum_{t=1}^{\tau}(w_t - Z_ta_{t|t-1})'F_t^{-1}(w_t - Z_ta_{t|t-1}) \tag{A8}$$

where Ψ represents all unknown parameters of the model.