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EVIDENCE OF CONSUMERS' WILLINGNESS TO PAY FOR THE NATIONAL ANIMAL IDENTIFICATION SYSTEM OF THE UNITED STATES

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Abstract

With the United States National Animal Identification System (NAIS) in place, consumers' concerns about Bovine Spongiform Encephalopathy (BSE) are mitigated and, by inference, consumers will be willing to pay for the NAIS. We estimated twelve alternative specifications of the generalized almost ideal demand system for beef, pork, and poultry, including indexes of news coverage of BSE in the U.S. as proxies for consumers' risk perception on BSE. Using the preferred model, we constructed scenarios on the basis of hypothesized impacts of the NAIS on consumers' risk perception on BSE in meat. We found that the impact of BSE on consumer demand for meat was in itself sufficient to cover previously estimated costs of implementing the NAIS.

Keywords: animal traceability, food safety, system of demand equations, meat industry, USA

JEL classification: C22, Q11, Q13, Q18.

Abstract

Com a implantação do sistema de rastreamento animal (NAIS) dos EUA, as preocupações dos consumidores com respeito ao mal da vaca louca (BSE) serão atenuadas e, por conseguinte, os consumidores estariam dispostos a pagar pelo NAIS. Foram estimadas doze especificações alternativas do sistema de equações de demanda generalizado quase ideal para as carnes bovina, suína e de frango, incorporando índices com o número de notícias sobre BSE nos EUA como proxies da percepção de risco dos consumidores. O modelo preferido serviu para construir cenários considerando impactos hipotéticos do NAIS sobre a percepção de risco dos consumidores. Conclui-se que o impacto da BSE sobre a demanda por carnes seria suficiente para cobrir estimativas prévias dos custos com a implantação do NAIS.

Keywords: rastreabilidade animal, segurança do alimento, sistemas de equação de demanda, setor de carnes, EUA.

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1 Introduction

The United States Department of Agriculture (USDA) Animal and Plant Health Inspection Service (APHIS) had a stated goal of implementing a National Animal Identification System (NAIS) with 100% premises identification and 100% new animal identification by 2009 (USDA/APHIS 2007*a*,*b*). Under this previous Administration, USDA spent more than $120 million, but only 36 percent of producers (500,000 producers) participated (USDA/APHIS 2010).

As a result of concerns about and opposition to NAIS, USDA announced on February 5, 2010, that it will revise the prior animal identification policy and offer a new approach to achieving animal disease traceability (USDA/APHIS 2010). The new framework will only apply to animals moving interstate, but should still allow for finding animal disease, and quickly respond to it. Thus, this new framework is likely to reduce the burden on producers but will not entirely eliminate it.

Although the overall benefit of NAIS is to improve coordination and containment of any disease outbreaks in livestock, it was the discovery of the first U.S. case of Bovine Spongiform Encephalopathy (BSE) or mad-cow disease on December 30, 2003 that accelerated the process for implementation of the NAIS (GRAY, 2004). For instance, the Animal and Plant Health Inspection Service (APHIS) announced, immediately after the first BSE case, a more than tenfold increase in cattle testing relative to previous surveillance levels (Coffey et al. 2005).

Estimated costs of NAIS implementation include increased record keeping, animal tagging methods, investments in software and hardware such as scanners if technologies such as radio frequency identification are adopted, increased handling of livestock and other associated costs.

Although producers incur the immediate costs of adopting new technologies, in competitive markets the ability to pass these costs on to consumers depends on the elasticity of demand which depends also on substitution effects. Thus, the question becomes is there evidence that U.S. consumers are willing to pay for the NAIS which would help compensate producers for its implementation? This question is relevant particularly in light of the fact that as shown by Coffey et al. (2005), the primary impact on producers was generated by a loss of export markets for beef, rather than a decline in U.S. consumption. For instance, within days of the discovery of the first case of BSE in a cow in Washington state in 2003, 53 countries, including major markets such as Japan, Mexico, South Korea and Canada, banned imports of U.S. cattle and beef products (Coffey et al. 2005). Meanwhile, these same authors show that 77% of consumers in a regionally targeted survey of U.S. beef consumers did not change their consumption patterns. The banned imports of U.S. cattle and beef products increased domestic supplies and reduced domestic prices, thus negatively impacting producers. However, if U.S. consumers did not reduce their consumption, was the beef price reduction a compensation for them for taking on the increased perceived risk of BSE? If so, this could indicate that NAIS represents a transfer from U.S. consumers and taxpayers to U.S. beef producers and their export market consumers. While beef producers could clearly benefit from increased exports, the focus here is on the impact on domestic consumers. As such this paper develops a methodology for assessing whether the U.S. consumer is sufficiently willing to pay for the direct benefits they receive.

There are at least two broad approaches to this question. The first is to ask consumers directly as did Hobbs (2003) and Dickinson & Bailey (2002) using market experiments to determine whether consumers were willing to pay for traceability attributes. Criticisms of experimental methods include the issue of the hypothetical nature of experiments, especially in cases where the choice is not imminent (e.g., traceability protecting against a hypothetical contamination event). Targeted consumer survey as implemented by Coffey et al. (2005) is other manner to ask consumers directly. However, while considering the consumption effect, a consumer survey does not address consumers' willingness to pay.

A second broad approach to analyze consumer willingness to pay is to use an event study that relies on systems of demand equations to assess the impact of specific one time and multi-period events on the demand for products. Several studies including Mazzocchi et al. (2004), Burton et al. (1999) and Verbeke & Ward (2001) have employed variations of Almost Ideal Demand Systems (AIDS) for estimating the consumer welfare impacts of issues such as BSE in the U.K. or negative advertising by media regarding meat products. Problems with this approach include: data behavior is often used as a guide to defining the time of impacts which creates endogeneity in the data set; the method can be used to study only a limited number of events over time (limited by identification issues); and this type of modeling does not take into account that modifying the intercept of the AIDS model makes estimates sensitive to the units by which quantities and prices are measured.

Recognizing these shortcomings, Alston et al. (2001) show that the use of a Generalized Almost Ideal (GAI) model allows flexible and parsimonious incorporation of demand shifters in the AIDS model, while obtaining estimates invariant to changes in the units of measurement of quantities and prices. Subsequently, Piggott & Marsh (2004) used the GAI model that incorporates pre-committed quantities and varying intercepts for the expenditure share equations accounting for food safety events' impact on demand for each meat commodity over time.

Based on the relative merits of those approaches, this paper uses the modeling approach firstly taken by Piggott & Marsh (2004) and, subsequently, used by Filho (2008). We expand these previous studies to include BSE as a key food safety issue which has led to the development of NAIS. Although we use the same approach as proposed by Filho (2008) to calculate the consumers' willingness to pay for a risk mitigation strategy such as the NAIS, here we focus only on BSE. Thus, as compared to Filho (2008) this paper adopts a new specification of the news indexes only for BSE, extends the data period through 2006, thereby including actual historical response to the first case of BSE in the U.S. in December 2003, conduct a scenario analysis so to estimate the average value of the NAIS for consumers before and after the first case of BSE in the U.S., and investigate the value of the NAIS under alternative degrees of consumer's confidence on the effectiveness of the NAIS. Finally, we recognize that other animal diseases might add to the merit of NAIS but our approach relies on historical data and BSE provides an existing case demonstrating a framework to assess willingness to pay for NAIS or other mitigation strategies.

2 Conceptual demand framework

The Generalized Almost Ideal (GAI) model recommended by Alston et al. (2001) is a flexible and parsimonious method of incorporating demand shifters in the Almost Ideal Demand System (AIDS) model and is adapted here for the estimation of willingness to pay for NAIS.

The GAI model originates from a generalized expenditure function given as:

$$E(\mathbf{p}, u) = \sum_{i=1}^{N} p_i c_i + E^*(\mathbf{p}, u) \tag{1}$$

where, p_i is the price of good i, c_i is the pre-committed quantity of good i, $\mathbf{p} \in \mathbb{R}^N_{++}$ is the vector of prices for a group of N commodities, $\sum_{i=1}^{N} p_i c_i$ stands for the pre-committed expenditure on the N goods, and $E^*(\mathbf{p}, u)$ denotes the supernumerary (beyond pre-committed) expenditure. Applying Shephard's lemma to (1) and using duality identities yields the generalized Marshallian demand function, which when pre-multiplied by p_i/x yields the generalized Marshallian budget share equations as:

$$w_i = p_i c_i/x + x^* w_i^*(\mathbf{p}, x^*)/x \quad \forall i \tag{2}$$

where, $x^* = x - \sum_{i=1}^{N} p_i c_i$ is the supernumerary expenditure, and x is the total expenditure on the N goods.

The GAI model is obtained by assigning the supernumerary expenditure share $w_i^*(\mathbf{p}, x^*)$ to be the AIDS budget share equation given as:

$$w_i^*(\mathbf{p}, x^*) = \alpha_i + \sum_{j=1}^{N} \gamma_{i,j} \ln p_j + \beta_i(\ln x^* - \ln a(\mathbf{p})) \quad \forall i \tag{3}$$

where $\ln a(\mathbf{p})$ is the Translog price index given as:

$$\ln a(\mathbf{p}) = a_0 + \sum_{i=1}^{N} \alpha_i \ln p_i + \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} \gamma_{i,j} \ln p_i \ln p_j \tag{4}$$

Demand shifters are incorporated in the GAI model to account for time trend, seasonal patterns and food safety indexes for meat (Piggott & Marsh 2004). These demand shifters are introduced in the system of equations by modifying pre-committed quantities, redefining c_i's as:

$$c_i = c_{i,0} + \tau_i t + \sum_{k=1}^{s-1} \theta_{i,k} D_k + \sum_{m=0}^{L} \phi_{i,m} bf_{t-m} + \pi_{i,m} pk_{t-m} + \kappa_{i,m} py_{t-m} \quad \forall i \tag{5}$$

where t is a linear time trend, s denotes the seasonality, $D_k$are dummy variables accounting for seasonal patterns in quarterly meat demand, bf_{t-m} are news events indexes accounting for beef safety issues lagged for m quarters, pk_{t-m} are news events indexes accounting for pork safety issues lagged for m quarters, and py_{t-m} are news events indexes accounting for poultry safety issues lagged for m quarters. As compared to event study methodologies, in addition to the initial impact of the event occurring, the duration of time that the event remains (length of event L) also affects demand and is tested within the model.

Homogeneity of degree zero in prices and expenditure, and symmetry of the Slutsky substitution matrix are imposed on the system's parameters as maintained hypotheses, as for instance Fisher et al. (2001) and Piggott & Marsh (2004). As the budget shares sum to unity, the error covariance matrix is singular if the system is estimated with all equations included. The equation for poultry is deleted from the system to solve the problem of singularity so that estimates for the parameters of the poultry equation are obtained after system estimation by imposing adding-up constraints.

2.1 Autocorrelation corrections

Under autocorrelation, least square parameter estimates are unbiased and consistent but are not efficient. Moreover, the estimates of the variances of the estimated parameters are biased and inconsistent (Berndt 1996, p. 477). We use two types of autocorrelation corrections to account for autocorrelation as follows.

Berndt & Savin (1975) showed that maximum likelihood estimation of a system of $N-1$ equations satisfies invariance, and respects the adding-up constraint if it is imposed that $\mathbf{1}'\bar{R}=0$, where $\mathbf{1}$ stands for a $1\times N$ vector of ones, and$\bar{R}$is an $N\times(N-1)$ matrix with elements $R_{i,j}-R_{i,n}$ where $i=1,\ldots,N$, $j=1,\ldots,n-1$, n indexes the good whose share equation is deleted from the system of equations, and $R_{i,j}$ denotes the elements of an $N\times N$ autocorrelation matrix R. Since in practice only $N-1$ equations are estimated, $\bar{R}^*$ is a matrix formed by the first $N-1$ rows of $\bar{R}$ such that it is be the first $N-1$ elements of $\bar{R}^*$ not $\bar{R}$ or R that are estimated. This way, the constraint $\mathbf{1}'\bar{R}=0$ can be easily imposed after estimating the system of equations (Piggott et al. 1996), even though solving for individual $R_{i,j}$ is not important (Fisher et al. 2001). Thus, autocorrelation corrections are incorporated by modifying the original GAI model to:

$$W_t = \bar{R}^* W_{t-1} + \Upsilon_t C_t - \bar{R}^* \Upsilon_{t-1} C_{t-1} + \frac{x_t^*}{x_t} W_t^*(\mathbf{p}_t, x_t^*) - \bar{R}^* \frac{x_{t-1}^*}{x_{t-1}} W_{t-1}^*(\mathbf{p}_{t-1}, x_{t-1}^*) \quad (6)$$

where

$$W_t = \begin{pmatrix} w_{b,t} \\ w_{p,t} \end{pmatrix},\ \bar{R}^* = \begin{pmatrix} \rho_{b,b} & \rho_{b,p} \\ \rho_{p,b} & \rho_{p,p} \end{pmatrix},\ \Upsilon_t = \begin{pmatrix} \frac{p_{b,t}}{x_t} & 0 \\ 0 & \frac{p_{p,t}}{x_t} \end{pmatrix},\ C_t = \begin{pmatrix} c_{b,t} \\ c_{p,t} \end{pmatrix}$$

with subscripts b and p denoting beef and pork;

$$W_t^*(\mathbf{p}_t, x_t^*) = \begin{pmatrix} w_{b,t}^*(\mathbf{p}_t, x_t^*) \\ w_{p,t}^*(\mathbf{p}_t, x_t^*) \end{pmatrix};$$

$w_{i,t}$ are observed shares, $p_{i,t}$ are observed prices at time t; $c_{i,t}$ are pre-committed quantities as given by (5); and the supernumerary expenditure shares $w_{i,t}^*(\mathbf{p}_t, x_t^*)$ are AIDS budget equations as given by (3) with x_t^*replacing x_t.

Models were estimated employing a Null $\bar{R}^*$ matrix (NRM) in which all elements are zeros, a Diagonal $\bar{R}^*$ matrix (DRM) in which the main diagonal elements are equal and all off main diagonal elements are zeros, and a Full $\bar{R}^*$matrix (FRM) wherein its elements are allowed to take in any real value.

3 Data

We use quarterly data from 1982(4) to 2006(4), providing a total of 97 observations, to estimate the system of demand equations. The length of the time series corresponds to Piggott & Marsh (2004) and Filho (2008), but includes updating to 2006 to incorporate post December 2003 when the first BSE case was found in the U.S.

The data series for per capita meat quantities and retail prices are from the US Department of Agriculture, Economic Research Service (USDA/ERS 2006*b*). USDA calculates quarterly per capita disappearance for meats on a retail weight basis by conversion of the carcass equivalent identity:

$$\text{per capita disappearance of meat type } i = \text{production}_i + \text{beginning stocks}_i + \text{imports}_i - \text{ending stocks}_i - \text{exports}_i.$$

Therefore, should an export ban occur (e.g., due to a BSE event) the domestic disappearance will increase one for one by this identity and retail prices will drop to clear the market.

Prices are in dollars per pound for choice retail beef value, pork retail value, chicken as whole fryers retail price and turkey as average U.S. retail prices for whole frozen birds. Following Piggott & Marsh (2004), the time series for poultry quantity is constructed by summing quarterly chicken and turkey quantities in pounds, and poultry prices are quantity weighted sums of chicken and turkey prices.

3.1 BSE news event indexes

According to equation (5), news indexes are incorporated in the system of demand by modifying pre-committed quantities. For purposes of the NAIS we would like to include all animal disease issues, but based on preliminary searches, references to issues such as foot and mouth disease or even avian influenza in the context of poultry were so limited as to be negligible in estimation of impacts. Therefore, we focused on BSE as a case to calculate the potential value of NAIS related to animal disease outbreaks[1].

We used the academic version of Lexis-Nexis news database to compute the number of references to BSE issues found in the top fifty English newspapers in circulation in the US over the entire sample period. A search for BSE news (BSE indexes), which is assumed the reason for putting the NAIS in place, was conducted for the keywords: *BSE* or *Bovine Spongiform Encephalopathy* or *Mad Cow*. This search was narrowed to separately collect beef, pork and poultry information by conducting a search within the previously obtained results with these additional keywords: (a) and *beef* or *hamburger*, (b) and *pork* or *ham*, and (c) and *chicken* or *turkey* or *poultry*. Figure 1

[1] In earlier estimations, we included the complete set of food safety indexes used by Piggott & Marsh (2004) as a calibration of the present model and found results consistent with Piggott & Marsh (2004). These results are available from the authors upon request. For brevity only the results of the BSE index model are provided here. Furthermore, it is recognized by the literature that NAIS has impact only on the control of zoonoses which BSE is an important example.

shows a plot of the three series of indexes for the period 1982:1 to 2006:4. The large spike in 2003 represents findings of BSE in the U.S. and Canada. Other smaller spikes have occurred on news from placeEurope as well. Ultimately, we obtained series of BSE indexes for beef, pork and poultry as the sum of the number of articles referencing BSE for each quarter.

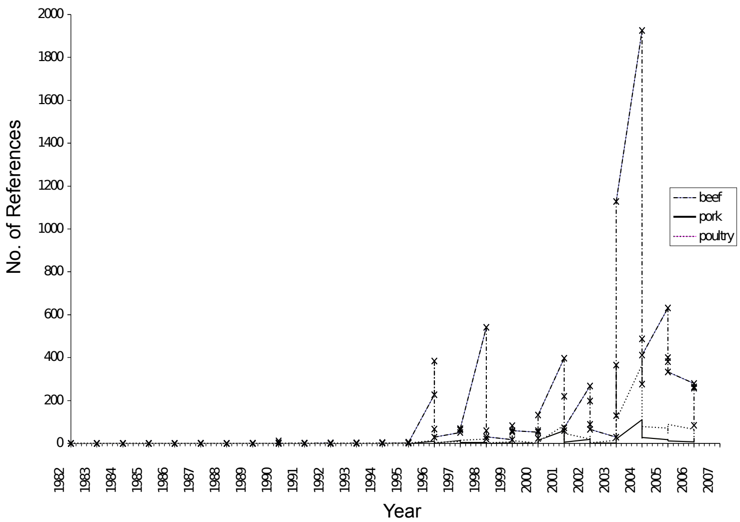

Figure 1: Beef, pork, and poultry newspaper articles mentioning BSE 1982:1 – 2006:4

One concern of simply using the number of articles to create indexes with no weighting given to content is that any reference is assumed to be interpreted in the same way by consumers. Clearly, there could be circumstances when beef is portrayed very negatively in the context of a newly found cow with BSE. In another circumstance, an article may describe how the U.S. surveillance system is being used to make sure affected cattle will not enter the human food chain. One would expect this to positively influence consumer preferences for beef. Similarly, U.S. news media could provide stories of BSE found in Japanese cattle which has occurred in recent years. However, categorizing articles over a time series would be highly time intensive and highly subjective to interpretation. Our assumption is that any news of BSE, even good news, raises the prominence of the issue of BSE in the consumer's mind and is inherently negative.

4 Estimation

The two Full Information Maximum Likelihood (FIML) algorithms to estimate the models are the Berndt, Hall, Hall, and Hausman (BHHH) algorithm for maximum likelihood problems and the Marquardt algorithm. These algorithms were combined with different starting values for the systems' parameters so that the chance of obtaining a global maximum for the multivariate likelihood function was improved. FIML's estimators are asymptotically efficient for linear and nonlinear simultaneous models under the assumption that contemporaneous errors are jointly normally distributed (Quantitative Micro Software 2000).

Table 1: Tests for the significance of the 'BSE indexes' and autocorrelation corrections

	Autocorrelation corrections				Lag lengths for BSE indexes		
Model	H_0:NRM H_a:DRM	H_0:DRM H_a:FRM	H_0:NRM H_a:FRM	Model	H_0:No-BSE H_a:$L=0$	H_0:$L=0$ H_a:$L=1$	H_0:$L=1$ H_a:$L=2$
No-BSE	20.308 **	5.062	27.540 **	NRM	18.373 **	15.330	19.241 **
$L=0$	20.812 **	3.239	23.871 **	DRM	17.576 **	21.246 **	10.509
$L=1$	25.534 **	6.501	31.810 **	FRM	15.677	24.355 **	6.499
$L=2$	15.690 **	2.597	18.125 **				
Df	1	3	4		9	9	9
$\chi^2_{0.05,df}$	3.841	7.815	9.488		16.919	16.919	16.919

Notes: An ** denotes the rejection of H_0 at the 5% level, L stands for the lag length of BSE indexes included in models, No-BSE indicates a model estimated with no BSE indexes included, *df* denotes degrees of freedom. Reported test statistics are adjusted *LR* tests calculated by adjusting the usual *LR* test statistic according to equation (7) in the text. Source: Research results.

5 Hypothesis testing and model selection

The adjusted Likelihood Ratio (*LR*) test was used to test for the most suitable demand model specification. The reason for this choice is that the usual Likelihood Ratio (LR) is biased toward rejection of restrictions imposed on demand systems in finite samples (Moschini et al. 1994). The adjusted LR test statistic is given by the following formula:

$$LRs = \{(M \times T - 0.5 \times [(ku + kr) - M \times (M+1)]M \times T\}LR \tag{7}$$

where $LR = 2(LL^U - LL^R)$ is the usual likelihood ratio, LL^U and LL^R are the maximized log-likelihood value in the unrestricted and restricted models; M is the number of estimated equations; T is the sample size, k^u is the number of parameters in the unrestricted model and k^r is the number of parameters in the restricted model. The adjusted *LR* statistic follows an asymptotic Chi-squared distribution with the number of added variables as degrees of freedom, under the hypothesis that the additional set of regressors is not jointly significant.

First, we conducted tests for detecting first order autocorrelation in the models estimated with 'BSE indexes' as presented in Table 1. For the two classes of models grouped according to the inclusion or not of the BSE indexes and to the lag length for indexes (Table 1 from column 2 to column 4), we found that[2] NRM ≻ DRM, DRM ≻ FRM, and FRM ≻ NRM. These results imply that the final order of preferences for the autocorrelation corrections is DRM ≻ FRM ≻ NRM. Therefore, first order autocorrelation in the residuals is detected in both models, but a $\bar{R}^*$ matrix with identical elements in its diagonal is adequate to correct for it.

Second, we investigated the appropriate lag length for BSE indexes within the class of models estimated with a DRM, examining their results reported in the three last columns in Table 1. We observe that H_0: No-BSE is rejected against H_a: $L = 0$, $H_0 : L = 0$ is rejected against Ha: $L = 1$ and $H_0 : L = 1$ is not rejected against $H_a : L = 2$. Hence, the order of preferences for models

[2]The symbol ≻ means "is preferred to".

estimated with a DRMis $L = 1 > L = 0 >$ No-BSE and $L = 1 > L = 2$. Summing up, for the models estimated with BSE indexes we prefer the one estimated with a DRMand with $L = 1$ that means consumers have a one quarter memory of BSE news. Filho (2008) found the preferred model did not include any lag length, but he used overall animal diseases news as the basis to construct his indexes, and the period length is also different from the one used here.

Table 2 presents the estimates for the preferred model. Other complete results are available on request. As shown in Table 2 all intercept estimates of modified pre-committed quantities respectively for beef, pork and poultry ($c_{b,0}$, $c_{p,0}$ and $c_{c,0}$) are nonnegative, as a priori expected. Except for $c_{c,0}$, they are also individually statistically different from zero by the z-test at 5%. Time trend coefficients ($\tau_i, \forall i$) are all statistically significantly different from zero, confirming the need for including the time trend variables in the models. With the exception of the coefficient for the first quarter dummy for beef$\theta_{b,1}$, all remaining seasonal coefficients ($\theta_{i,1}, \theta_{i,2}, \theta_{i,3}, \forall i$) are statistically different from zero by the z-test at 5% of significance across models.

Current own BSE index estimated coefficients for beef ($\phi_{b,0}$) and for poultry ($\kappa_{c,0}$) are both negative indicating that BSE references in the news under the context of beef and poultry respectively depress the pre-committed quantities for these two meats. The only own BSE coefficient individually statistically significant is $\kappa_{c,0}$.

The only two cross-commodity BSE index coefficients individually statistically different from zero are $\phi_{p,1}$ and $\phi_{c,1}$. Since both are positive we can conclude that BSE news in the beef context increases pre-committed quantities for pork and poultry in the quarter following the news report (spillover effect). Except for $\phi_{p,1}$ and $\phi_{c,1}$, all the other food safety coefficients do not individually statistically differ from zero by the z-test at 10%. Despite this, BSE indexes are kept in the model because they are jointly statistically different from zero as found with a series of specification tests used to detect the appropriate lag length for BSE indexes.

6 Expenditure, price and food safety index elasticities

Specific equations and derivations for elasticities in all model forms are available from the authors, but are not provided here because they follow closely the calculations shown in Piggott & Marsh (2004).

Marshallian demand' elasticities are provided for the direct (on pre-committed quantities demanded) and total (on the total quantities demanded) effects on consumption. Direct elasticities measure the percentage change in pre-committed quantity of the good i in response to a 1% increase in the BSE indexes (Piggott & Marsh 2004). BSE index elasticities (Current Direct effect) are given as (8). We do not present the formulas for their lagged version because it is straightforward to obtain those from the formulas presented in (8).

Table 2: Estimates for the model with a diagonal $\bar{R}^*$ matrix and with current and one period lagged BSE indexes

Parameter		Parameter		Parameter	
r	0.5613^{**} (0.1149)	$\theta_{c,2}$	-1.5780^{**} (0.3678)	$\kappa_{b,0}$	-0.0079 (0.0124)
$c_{b,0}$	13.0351^{**} (2.9350)	$\theta_{c,3}$	-1.2451^{**} (0.2465)	$\kappa_{b,1}$	-0.0252 (0.0167)
$c_{p,0}$	9.4978^{**} (1.9277)	$\phi_{b,0}$	-3.14×10^{5} (0.0015)	$\kappa_{p,0}$	-0.0136 (0.0098)
$c_{c,0}$	3.4819 (12.3098)	$\phi_{b,1}$	0.0017 (0.0023)	$\kappa_{p,1}$	-0.0265^{**} (0.0129)
τ_b	0.0485^{*} (0.0276)	$\phi_{p,0}$	0.0007 (0.0015)	$\kappa_{c,0}$	-0.0548^{*} (0.0304)
τ_p	0.0395^{**} (0.0137)	$\phi_{p,1}$	0.0027^{**} (0.0012)	$\kappa_{c,1}$	-0.0876 (0.0538)
τ_c	0.1891^{**} (0.0487)	$\phi_{c,0}$	3.71×10^{-5} (0.0044)	α_0	10.6067 (21.0068)
$\theta_{b,1}$	-0.1177 (0.2104)	$\phi_{c,1}$	0.0146^{**} (0.0059)	α_b	3.3978 (7.1118)
$\theta_{b,2}$	0.8310^{**} (0.2331)	$\pi_{b,0}$	0.0102 (0.0290)	α_p	-0.3876 (1.1618)
$\theta_{b,3}$	0.9808^{**} (0.1998)	$\pi_{b,1}$	-0.0048 (0.0327)	γ_{bb}	1.5990 (3.6041)
$\theta_{p,1}$	-1.0873^{**} (0.1070)	$\pi_{p,0}$	0.0070 (0.0192)	γ_{bp}	0.0435 (0.6347)
$\theta_{p,2}$	-1.3280^{**} (0.1214)	$\pi_{p,1}$	-0.0035 (0.0249)	γ_{pp}	-0.1752 (0.2304)
$\theta_{p,3}$	-1.0866^{**} (0.0930)	$\pi_{c,0}$	0.0544 (0.0666)	β_b	0.4179 (0.2854)
$\theta_{c,1}$	-2.3600^{**} (0.2706)	$\pi_{c,1}$	-0.0050 (0.0722)	β_p	-0.0639 (0.0619)
Log Likelihood	787.7828	R^2 beef	0.9777	R^2 pork	0.9060

Notes : numbers in parentheses are the estimated standard errors. An ** denotes a coefficient statistically significantly different from zero at the 5% level by the z-test. An * denotes a coefficient statistically significantly different from zero at the 10% level by the z-test. $c_{b,0}$, $c_{p,0}$ and $c_{c,0}$ are intercepts and τ_b, τ_p, and τ_c, are time trend coefficients in the modified pre-committed quantities respectively for beef, pork and poultry. $\theta_{b,1}$, $\theta_b, 2$, and $\theta_b, 3$ are coefficients of the first, second and third seasonal dummies in the modified pre-committed quantity of beef. $\theta_{p,1}$, $\theta_{p,2}$, and $\theta_{p,3}$ are coefficients of the first, second and third seasonal dummies in the modified pre-committed quantity of pork. $\theta_{c,1}$, $\theta_{c,2}$, and $\theta_c, 3$ are coefficients of the first, second and third seasonal dummies in the modified pre-committed quantity of poultry. $\phi_{b,0}$, $\pi_{b,0}$, and $\kappa_{b,0}$ are the coefficients of beef, pork and poultry BSE indexes with zero lag in the modified pre-committed quantities of beef. $\phi_{b,1}$, $\pi_{b,1}$, and $\kappa_{b,1}$ are the coefficients of beef, pork and poultry BSE indexes with one lag in the modified pre-committed quantities of beef. $\phi_{p,0}$, $\pi_{p,0}$, and $\kappa_{p,0}$ are the coefficients of beef, pork and poultry BSE indexes with zero lag in the modified pre-committed quantities of pork.$\phi_{p,1}$, $\pi_{p,1}$, and $\kappa_{p,1}$ are the coefficients of beef, pork and poultry BSE indexes with one lag in the modified pre-committed quantities of pork. $\phi_{c,0}$, $\pi_{c,0}$, and $\kappa_{c,0}$ are the coefficients of beef, pork and poultry BSE indexes with zero lag in the modified pre-committed quantities of poultry. $\phi_{c,1}$, $\pi_{c,1}$, and $\kappa_{c,1}$ are the coefficients of beef, pork and poultry BSE indexes with one lag in the modified pre-committed quantities of poultry. α_0 is the intercept of the Translog price index. ab and ap are the intercepts respectively of the beef and pork share equations. γ_{bb}, γ_{bp}, and γ_{pp} are coefficients of the AIDS budget share equations. bb and bp are coefficients of the natural log of the real expenditure with meat, respectively in beef and pork AIDS budget share equations.
Source: Research results.

$$\begin{aligned}
\omega_{i,bf_t} &= \frac{\phi_{i,0}\, bf_t}{c_{i,t}} \quad \forall i \\
\omega_{i,pk_t} &= \frac{\pi_{i,0}\, pk_t}{c_{i,t}} \quad \forall i \\
\omega_{i,py_t} &= \frac{\kappa_{i,0}\, py_t}{c_{i,t}} \quad \forall i
\end{aligned} \tag{8}$$

The a priori expectation is that the own direct demand response to BSE news should be negative for beef. In other words, BSE news related to beef is expected to reduce the pre-committed quantity for this good. It is also expected that the cross effect of BSE news in the beef context will increase the pre-committed quantities for poultry and pork since substitution is expected to occur in this case. But it is not clear how consumers will react regarding BSE news in the context of poultry and pork (but not with beef mentioned per the search conditions). It may be that news of BSE, even though only affecting beef will cause consumer concern regarding the safety of all meats if it's not clear in the article that it only affects beef. On the other hand it may be expected to increase consumption of pork and poultry as with the cross effect of BSE news in beef.

Total BSE index elasticities (current total effect) include the sum of the direct and indirect elasticity given by (9). We do not present the formulas for the lagged BSE index elasticities because it is straightforward to obtain those from the formulas presented in (9).

$$\begin{aligned}
\Psi_{i,bf_t} &= \omega_{i,bf_t}\frac{p_{i,t}c_{i,t}}{w_{i,t}x_t} \\
&\quad + \left(1+\frac{\beta_i}{w^*_{i,t}}\right)\frac{bf_t(-p_{b,t}\phi_{b,0}-p_{p,t}\phi_{p,0}-p_{c,t}\phi_{b,0})}{x^*_t}\frac{w^*_{i,t}}{w_{i,t}x_t} \quad \forall i \\
\Psi_{i,pk_t} &= \omega_{i,pk_t}\frac{p_{i,t}c_{i,t}}{w_{i,t}x_t} \\
&\quad + \left(1+\frac{\beta_i}{w^*_{i,t}}\right)\frac{pk_t(-p_{b,t}\pi_{b,0}-p_{p,t}\pi_{p,0}-p_{c,t}\pi_{c,0})}{x^*_t}\frac{w^*_{i,t}}{w_{i,t}x_t} \quad \forall i \\
\Psi_{i,py_t} &= \omega_{i,py_t}\frac{p_{i,t}c_{i,t}}{w_{i,t}x_t} \\
&\quad + \left(1+\frac{\beta_i}{w^*_{i,t}}\right)\frac{py_t(-p_{b,t}\kappa_{b,0}-p_{p,t}\kappa_{p,0}-p_{c,t}\kappa_{c,0})}{x^*_t}\frac{w^*_{i,t}}{w_{i,t}x_t} \quad \forall i
\end{aligned} \tag{9}$$

Our a priori expectation regarding the signals of the total BSE index elasticities is that, the final demanded quantities for beef should decrease with more BSE news in the context of beef whereas the demand for pork and poultry should increase with more BSE news in the context of beef.

The elasticities for the preferred Generalized AIDS model estimated with autocorrelation correction (DRM) and BSE indexes are presented in Table 3.The final elasticities are the sample means of the elasticities computed at every time observation using predicted expenditure shares.

The cross-price Marshallian elasticities show that beef, pork and poultry are gross-complements one to each other. Despite of being counter-intuitive, these results are in line with those obtained by Piggott & Marsh (2004).

Table 3: Price, expenditure, and food safety elasticities for the generalized AIDS model Estimated with a diagonal $\bar{R}^{*}$matrix and with current and one period lagged BSE indexes

Marshallian price elasticities		Expenditure elasticities		Hicksian price elasticities	
$\eta_{b,b}$	−0.502	$\eta_{b,x}$	1.077	$\epsilon_{b,b}$	−0.148
$\eta_{b,p}$	0.167	$\eta_{p,x}$	0.772	$\epsilon_{b,p}$	0.144
$\eta_{b,c}$	0.408	$\eta_{c,x}$	1.018	$\epsilon_{b,c}$	0.004
$\eta_{p,b}$	0.179			$\epsilon_{p,b}$	0.211
$\eta_{p,p}$	−0.507			$\epsilon_{p,p}$	−0.285
$\eta_{p,c}$	0.086			$\epsilon_{p,c}$	0.074
$\eta_{c,b}$	0.563			$\epsilon_{c,b}$	0.037
$\eta_{c,p}$	0.265			$\epsilon_{c,p}$	0.129
$\eta_{c,c}$	−0.190			$\epsilon_{c,c}$	−0.166
BSE index elasticities					
Current direct effect				Lagged direct effect	
$\omega_{b,bf(t)}$	−0.0002			$\omega_{b,bf(t-1)}$	0.0120
$\omega_{b,pk(t)}$	0.0038			$\omega_{b,pk(t-1)}$	−0.0019
$\omega_{b,py(t)}$	−0.0090			$\omega_{b,py(t-1)}$	−0.0299
$\omega_{p,bf(t)}$	−0.0074			$\omega_{p,bf(t-1)}$	0.0314
$\omega_{p,pk(t)}$	0.0040			$\omega_{p,pk(t-1)}$	−0.0021
$\omega_{p,py(t)}$	−0.0237			$\omega_{p,py(t-1)}$	−0.0497
$\omega_{c,bf(t)}$	0.0003			$\omega_{c,bf(t-1)}$	0.1098
$\omega_{c,pk(t)}$	0.0228			$\omega_{c,pk(t-1)}$	−0.0020
$\omega_{c,py(t)}$	−0.0699			$\omega_{c,py(t-1)}$	−0.1087
Total current effect				Total lagged effect	
$\Psi_{b,bf(t)}$	−0.0016			$\Psi_{b,bf(t-1)}$	−0.0099
$\Psi_{b,pk(t)}$	0.0023			$\Psi_{b,pk(t-1)}$	−0.0228
$\Psi_{b,py(t)}$	−0.0101			$\Psi_{b,py(t-1)}$	−0.0483
$\Psi_{p,bf(t)}$	0.0009			$\Psi_{p,bf(t-1)}$	0.0260
$\Psi_{p,pk(t)}$	−0.0019			$\Psi_{p,pk(t-1)}$	−0.0002
$\Psi_{p,py(t)}$	−0.0247			$\Psi_{p,py(t-1)}$	−0.0365
$\Psi_{c,bf(t)}$	−0.0281			$\Psi_{c,bf(t-1)}$	0.1138
$\Psi_{c,pk(t)}$	0.0413			$\Psi_{c,pk(t-1)}$	0.0471
$\Psi_{c,py(t)}$	−0.0123			$\Psi_{c,py(t-1)}$	−0.0146

Notes: $\eta_{i,j}$ and $\epsilon_{I,j}$ represent the Marshallian and Hicksian price elasticities of demand for the *i*th good with respect to the *j*th price, and $\eta_{i,x}$ is expenditure elasticities for the *i*th good, where $i, j = b$ for beef, p for pork, and c for poultry. $\omega_{i,k}$ measures the percentage change in the pre-committed quantity of the i th good in response to a 1% increase in the kth BSE index variable, where $k = bf$ for beef, pk for pork, and py for poultry food safety index, respectively. $\Psi_{i,k}$ measures the percentage change in the total quantity demanded of the i th good in response to a 1% increase in the k th food safety index variable. Estimates shown are the sample means of the elasticities computed at every data point using predicted expenditure shares.
Source: Research results.

As expected, the own price Hicksian elasticities are all negative. Especially in the case of compensated beef own-price elasticity (−0.148), it indicates that per capita compensated beef consumption changes less, proportionally, than retail price (i.e., beef demand is inelastic) as price changes. The cross-price Hicksian elasticities show that pork, beef and poultry are compensated substitutes one to each other.

The expenditure elasticities indicates that beef and poultry are luxury goods ($\eta_{i,x} > 1$ with $i = b, c$) whereas pork is a necessity ($\eta_{p,x} < 1$). Notice that these elasticities measure how a given meat's demand changes in response to a change in meat expenditure. Schroeder et al. (2004, p. 11) argues that beef demand expenditure elasticities are generally larger than income elasticities because beef demand is more responsive to changes in meat expenditure than it is to changes in consumer disposable income.

As expected, we observe that for beef the current own BSE index direct elasticity is negative; indicating that BSE news about beef contemporaneously negatively affects its own pre-committed quantities. This is not the case when we look at the lagged BSE index direct elasticities for beef. It seems that the initial reduction in the pre-committed quantities for beef recovers in the quarter after a news reference to BSE and beef has occurred.

BSE news under the context of beef will depress as expected the total demand for beef in the current and subsequent period ($\Psi_{b,bf(t)} = -0.0016$, $\Psi_{b,bf(t-1)} = -0.0099$). In addition, BSE news under the context of beef will increase, in the current and in the next period after their publication, the final demand for pork ($\Psi_{p,bf(t)} = 0.009$, $\Psi_{p,bf(t-1)} = 0.0260$) and for poultry ($\Psi_{p,bf(t)} = 0.0281$, $\Psi_{c,bf(t-1)} = 0.1138$). Therefore, if the NAIS for beef lower consumers' concerns about BSE in beef, this will cause a decrease in pork and poultry demand in current and lagged time.

7 Estimates of the economic value of the NAIS

The simulation of the consumer derived economic value of NAIS is based on the estimates for the preferred model considering a baseline and two scenarios of NAIS as follows.

No NAIS Implementation: The baseline scenario assumes that the NAIS was not implemented in the sample period that makes consumers to change their consumption by the full extent of any media reporting of BSE identified in the search of news articles. This scenario results are obtained by plugging the time series for all exogenous variables into the preferred model to obtain the predicted budget share series for beef, pork and poultry. These series are then multiplied by the total population in the US and the per capita expenditure allocated with meat consumption so to obtain the predicted revenue series that are ultimately converted into real dollar values as of September 2005 using the CPI for all goods.

NAIS Beef: The first scenario assumes that the NAIS was implemented only for beef and dairy cattle through the entire sample period. The only difference from the 'No NAIS' baseline scenario, is that the values of the beef related news indexes are set to zero. This implies we assume that consumers have complete confidence that the NAIS will work properly

Table 4: Predicted changes in the total revenue for beef, pork and poultry sectors under three alternative scenarios for period 1982:4 - 2006:4 with preferred model of BSE indexes

	Total revenue difference in U$ millions as of September 2005					
	NAIS beef – no NAIS			NAIS beef & pork – no NAIS		
	Beef	Pork	Poultry	Beef	Pork	Poultry
Minimum	−7243.83	−898.77	−9890.95	−7009.02	−774.17	−8991.73
Maximum	10 428.93	652.15	6591.69	9765.90	666.78	6342.24
Std. Dev.	1505.21	144.95	1386.26	1547.40	135.31	1430.81
Average for the period 1982:1 - 2006:4	174.43	−22.66	−151.76	201.16	−16.37	−184.80
Average for the period 2003:4 - 2006:4	1234.71	−130.73	−1103.97	1395.19	−92.65	−1302.54

Source: Research results

for identification of animals and elimination of any affected products in the food chain.

NAIS Beef & Pork: The second scenario assumes that the NAIS was implemented for both beef and pork. The only change from the NAIS Beef scenario is that the values of the pork related news indexes are also set to zero.

The average change in quarterly revenue for each meat obtained by comparing the two scenarios to the baseline are presented in Table 4.

As suggested by the elasticities values, the implementation of the NAIS increases the revenue for beef while reducing the revenues of pork and poultry. Over the entire sample period, the implementation of NAIS for beef and pork results in a quarterly gain of $174.43[3] million for the beef industry, but both pork and poultry loss because of the substitution effect with beef so it benefits the sector with NAIS and the disease concern while taking consumption away from the other. Two factors affect this relationship: (1) the model includes only meat products and (2) the model has constant expenditures so that gains to one sector must come at the expense of other sectors. As a comparison, preliminary estimates for the costs of the NAIS in the US are $550 million for a five year period (Gray 2004) or an additional cost of $27.5 million per quarter for the beef and pork sectors. Another relative benchmark is to consider the total revenue of the beef industry. The total farm value of beef cattle in the U.S. for 2000-2005 averaged approximately $30.2 billion and the average retail value of beef was about $88.8 billion[4].

The impact of NAIS is also calculated using the period 2002:4 - 2006:4 only. Clearly, with the U.S. event of BSE, the value of NAIS based on consumer

[3]Filho (2008) estimated a quarterly gain of $18.34 million for the beef industry which is much lower than $174.43 as we estimated. The main reason for this huge difference is that Resende Filho (2008) did not consider the period 2003:4 to 2006:4 which is immediately after the discovery of the first case of BSE in the U.S..

[4]Figures calculated using retail prices/farm prices and quantities available in (USDA/ERS 2006*a*).

Table 5: Predicted changes in the revenue for beef, pork and poultry sectors under three alternative scenarios considering potential reductions in the consumer risk perception about BSE (1982:4 – 2006:4)

Total revenue difference in million of dollars as of September 2005						
Consumers' confidence in the NAIS	NAIS beef – no NAIS			NAIS beef & pork – no NAIS		
	Beef	Pork	Poultry	Beef	Pork	Poultry
100%	174.425	−22.663	−151.763	201.161	−16.366	−184.795
90%	151.353	−19.553	−131.800	174.324	−13.774	−160.549
80%	129.289	−16.593	−112.696	148.684	−11.352	−137.332
70%	108.299	−13.795	−94.505	124.321	−9.111	−115.211
60%	88.456	−11.168	−77.288	101.324	−7.063	−94.261
50%	69.845	−8.725	−61.120	79.798	−5.224	−74.574
40%	52.569	−6.483	−46.086	59.869	−3.612	−56.257
30%	36.753	−4.460	−32.293	41.690	−2.250	−39.440
22%	25.566	−3.062	−22.504	28.911	−1.411	−27.499
20%	22.557	−2.680	−19.877	25.456	−1.164	−24.291
10%	10.196	−1.177	−9.019	11.428	−0.395	−11.033
0%	0.000	0.000	0.000	0.000	0.000	0.000

willingness to pay increased dramatically compared to the full sample to a level for beef of $1.234 billion per quarter. Therefore, it is likely that as events such as avian influenza reach the U.S. it will be much more likely to warrant investment in surveillance and recovery systems engendered in systems such as NAIS for poultry as well.

An additional issue is that it is unlikely that NAIS will be 100% effective or have 100% confidence of consumers – further if there are events which occur that show its ineffectiveness, its credibility will be harmed and subsequent willingness to pay may be eroded. Therefore, in evaluating NAIS investment it is also important to consider its potential reliability which may be affected by participation rates as well as information accuracy. To account for this, Table 5 provides a schedule of results pro-rated by the confidence consumers have in the NAIS or in other words, its probability of working. The top row (100%) results are identical to those in Table 4. The results are also interpreted to show that for the scenario NAIS Beef & Pork, if the NAIS is capable of sustaining the consumers' confidence at 22% of its level before a BSE news report, the beef sector would afford the additional burden of the NAIS and consumers would be willing to pay for it. However, the pork sector would never want to see the NAIS implemented because they are harmed with BSE as the primary concern. Similar inferences can be made for other scenarios of implementation, but interesting, fairly low levels would warrant implementation of NAIS.

8 Conclusion

USDA announced on February 5, 2010, that it will revise the prior animal identification policy and offer a new approach to achieving animal disease traceability (USDA/APHIS 2010). Despite this, the new NAIS will still imply a burden on producers, and relatively little information exists on its prospective benefits. This paper used a model originally developed by Piggott & Marsh

(2004) to analyze expected benefits to the meat animal sector from improved confidence consumers may have in the meat supply with an animal identification system in place. The recent detection of BSE in the U.S. provided the historical news to estimate the impact an event that the NAIS is proposed to help respond. Clearly, there are other potential disease concerns such as foot and mouth disease (FMD) or avian influenza that might also contribute but these are both hypothetical events in the U.S..

A generalized AIDS model was estimated, producing reasonable price elasticities for evaluation. However, after correcting for autocorrelation and testing for the appropriate lags of the BSE news indexes, only two coefficients were significantly different from zero, suggesting that it is not clear that the event of BSE in the U.S. has had a significant impact on consumer demand. This may be due to its relatively recent occurrence as well as its limited scope. This alone suggests that NAIS may be unwarranted, at least in the case of BSE which has been repeatedly described as a remote possibility in U.S. herds.

Never-the-less calculations were completed to estimate the value of the NAIS on meat and poultry markets, and showed that at even relatively low levels estimated in the model, the magnitude can easily exceed cost levels for the implementation of NAIS derived from other sources. Results further showed that for the estimated coefficients even relatively low adoption of NAIS or equivalently relatively low reliability (22%) may be enough to warrant its development.

We recognize shortcomings that deserve further research. First, the model only included meats which preclude the possibility that when an animal disease outbreak occurs consumers would switch to other food products (vegetables, fruits, etc.). Therefore, our estimates likely under-estimate the value of NAIS in the context of BSE and would surely be greater in the case of a multi-species disease such as foot and mouth disease or avian influenza. Second, there is significant work that can be done related to parsing out news information and assigning weightings to the content of the information, going beyond simply key-word observations. Despite this, we propose that the methodology used is useful for gaining insight into the prospective benefits, particularly, into how they are distributed among food consumers and producers.

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