Consumer Purchasing Behavior in Response to Media Coverage of Avian Influenza

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Abstract

Consumer concerns regarding food safety can have substantial impacts on their consumption patterns. Thus, understanding consumer response to food safety information is important for quantifying consumer response to food safety events, predicting market impacts, and developing appropriate risk communication strategies. Flexible demand systems have gained much popularity in analyzing effects of food safety outbreaks on consumer demand because of their ability to capture interactions between the demand for substitutable and complementary goods. Using Italian scanner data on meat sales, we show the economic importance of accounting for the impact of avian flu outbreaks on group expenditures for meats in a dynamic Almost Ideal Demand System (AIDS) specification with intertemporally optimizing consumers. Failure to account for this form of expenditure endogeneity results in a substantial understatement of the food safety effect.

Key Words: Avian influenza, food safety, Italy, meat demand, media index

JEL Classifications: Q11, Q18

INTRODUCTION

Consumer concerns regarding food safety can have substantial impacts on their consumption patterns. Understanding how consumers respond to food safety information is very important for developing appropriate risk communication strategies. In addition, this information is valuable for quantifying consumer response to food safety events and predicting potential market impacts.

The majority of studies in the meat demand literature rely on national data at a quarterly or annual frequency, but the use of higher-frequency scanner data is becoming more common as these data have become more readily available. The use of these data has implications for meat demand parameter estimates (Capps and Love, 2002; Lensing and Purcell, 2006). Among other effects, there is some evidence that using data collected more frequently and/or for more disaggregated regions is more likely to reveal effects of food safety information on demand because of the often transitory nature of these effects as well as regionalized responses to certain information, such as recalls in a particular area (e.g., Kuchler and Tegene, 2006; Piggott and Marsh, 2004). In this study, we present a methodology for analysis of consumer response using weekly Nielsen meat sales data for Italy combined with data on media coverage of AI and estimate a meat demand system to provide empirical evidence on consumer response.

MEDIA INDICES OF AVIAN INFLUENZA

In this section, we briefly review the literature on food safety and describe the construction of media indices for avian influenza news. Because the vast majority of food safety studies in the economics literature are concerned with the demand side as opposed to the supply side and because of the stated objective of this project, we focus our attention on the effects of food safety on consumer demand.

Effects of Food Safety Information on Consumer Demand

Food safety is an important issue that can potentially affect consumer demand. The demand literature has had a long tradition of constructing indices as demand shifters to approximate consumers' perceptions of product quality. For instance, Carfton, Hoffer, and Reilly (1981) argue that product recalls lower consumers' perception of the quality of a recalled automobile. The underlying assumption, either implicit or explicitly stated, of empirical studies of the economics of food safety has been that food safety information signals product quality.

A number of studies have used conditional demand systems to study effects of food safety on demand. For instance, using a conditional myopic dynamic Almost Ideal Demand System (AIDS), Burton and Young (1996) studied the impact of BSE on the demand for beef and other meats in Great Britain. They used the number of news articles on BSE as demand shifters in an Almost Ideal Demand System (AIDS). They found that negative publicity about British beef had reduced beef market share by 4.5% by the end of 1993.

Piggott and Marsh (2004) provided a formal theoretical model that explores the link between food safety information and demand for foods within a meat demand system framework. They constructed quarterly media indices for beef, pork, and poultry safety using the Lexis-Nexis search tool to find news articles on meat safety from up to 50 English-language newspapers worldwide. The number of news articles in each quarter for each meat species was then used as a demand shifter in a conditional Generalized Almost Ideal Demand System (GAIDS). They found that heightened public alert over food safety reduced per capita beef, pork, and poultry consumption by 2.21%, 0.99%, and 6.88%, respectively. In addition, Mazzocchi (2006) estimated a conditional AIDS model with time-varying parameters for the intercept terms to detect impacts of food safety news on U.S. meat demand.

Previous studies of the response of Italian meat demand to food safety information include Mazzocchi, Monache and Lobb (2006), which estimated a conditional AIDS model within the vector error correction framework to evaluate the impact of BSE on Italian meat demand, and Beach et al. (2008), which examined the impacts of HPAI outbreaks on Italian meat consumption using a log-log specification.

The study by Marsh, Schroeder, and Mintert (2004) is an exception. They estimated a complete Rotterdam demand system for U.S. meat, where they used the quarterly number of beef, pork, and poultry recalls initiated by the Food Safety and Inspection Service (FSIS) as demand shifters. They found statistically significant but economically small effects of meat recalls on U.S. meat demand. The estimated own-effect elasticities of demand are –0.00052, –0.0010, and –0.0014 for beef, pork, and poultry recalls, respectively.

Although many authors estimated regular demand equations with food safety media indices, some have used inverse demand to study the impact of food safety information on prices. Dahlgran and Fairchild (2002) estimated an inverse demand model for chicken using the U.S. weekly wholesale disappearance data during the period 1982 to 1991. They found evidence that negative publicity about *Salmonella* contamination of chicken depressed chicken demand. However, the economic effect was estimated to be relatively small, with less than a 1% reduction in chicken price at the peak of the exposure. The media index used in Dahlgran and Fairchild's study was based on weekly television and print news stories about chicken contamination and food safety weighted by circulation and viewership data.

Transforming the Media Index

An empirical issue for demand studies of food safety is determining the appropriate length and shape of the distributed lag structure for the variable measuring food safety. If advertising is expected to have protracted effects on consumer demand, it is not unreasonable to expect food safety information to have lasting effects on demand as well. Previous authors have followed several alternative strategies. In their AIDS model, Burton and Young (1996) used contemporary and cumulative numbers of BSE articles as the demand shifters for transitory and permanent quality shocks, respectively. This practice appears to be appropriate for their case, because their sample ends in the third quarter of 1993 when BSE in Great Britain showed no sign of relenting. But for food safety incidences that are more or less transitory, it seems to be more appropriate to allow the effect of media on consumption to depreciate over time.

Smith, van Ravenswaay, and Thompson (1988) constrained their milk media index to follow a second-order Almon polynomial. Dahlgran and Fairchild (2002) specified a geometric decay for their media index. The advantage of this approach is that it reduces the multicollinearity among lagged indices. A potential drawback is that it imposes a specific structure on the distributed lag, which may lead to inconsistent parameter estimates if the imposed structure is incorrect (Judge et al., 1988).

Alternatively, Marsh, Schroeder, and Mintert (2004) and Piggott and Marsh (2004) did not impose any functional structure on the distributed lags of media indices. Instead, these authors started with a relatively large number of lags and sequentially reduced the number of lags, selecting the preferred model as the one with the best statistical fit. Although this approach is free from the danger of imposing incorrect functional structure, it may be plagued by multicollinearity of the lagged media indices.

In this analysis, we use an alternative approach to investigate the lag structure of media indices. This lag structure, which was originally proposed by Mitchell and Speaker (1986), is known as the polynomial inverse lag (PIL). The PIL has several advantages over other commonly used lag structures such as the Almon (1965) lag. First, the researcher does not need to specify *a priori* the lag length or impose an endpoint restriction, because the PIL has an infinite distributed lag structure. Second, the PIL is linear in the transformed exogenous variables (i.e., the index of media information on avian influenza). As we explain below, this latter property makes it convenient to test for the best specification for the lag structure.

Avian Flu Media Indices

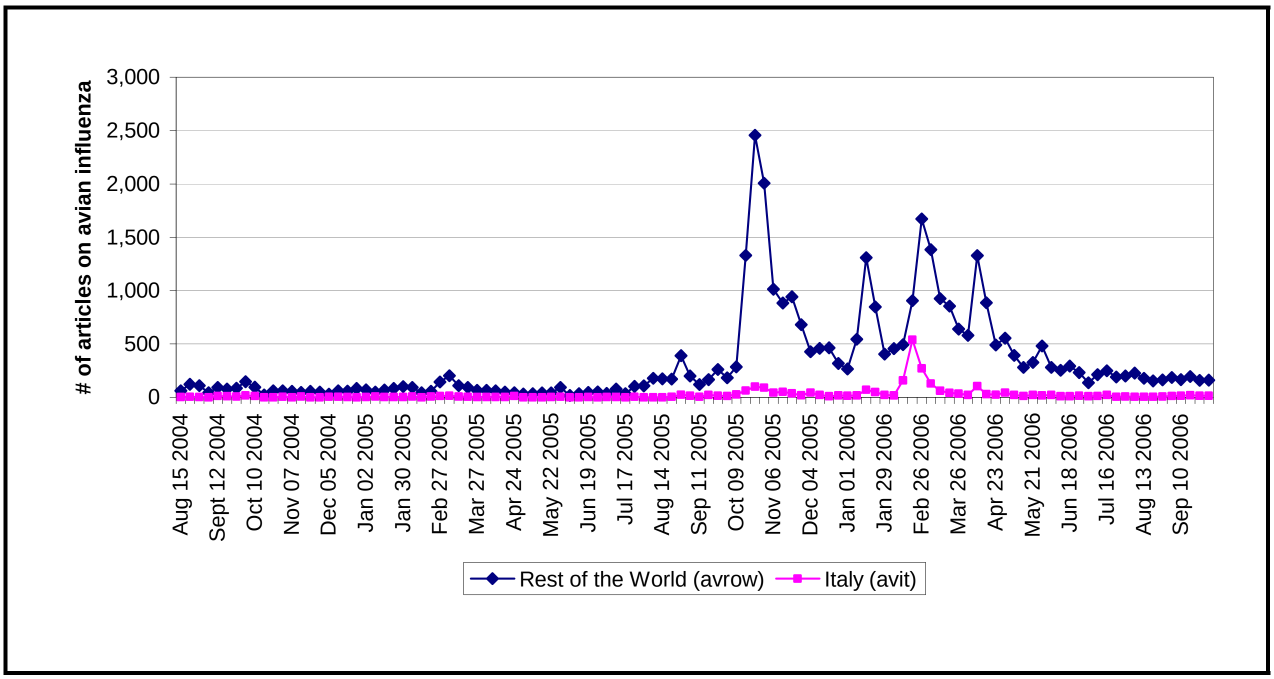
Highly pathogenic avian influenza (HPAI) has emerged as a significant threat to the poultry sector in recent years as outbreaks in Asia, Africa, and Europe have led to the culling of tens of millions of poultry and anxiety regarding the safety of poultry consumption in affected regions. However, publicly available data for quantitative evaluation of the effects of HPAI concerns on meat sales are limited. In this study, we present a methodology for analysis of consumer response using Nielsen meat sales data combined with data on media coverage of avian influenza (AI). These data on media coverage are used to construct indices representing the amount of information on avian influenza being presented to consumers over time.

We used the LexisNexis Academic search engine to search news stories related to avian influenza. Because the focus is on the Italian case, we limited the scope of the search to European news sources. As described earlier, we constructed two media series, an Italy-specific index (*avit*) and an index pertinent to the rest of the world (*avrow*). While *avit* is intended to capture information on avian flu that is related to Italy, *avrow* is designed to reflect Italian consumers' exposure to information about the situation in the rest of the world reported by European news sources.

The keywords searched were *avian flu* or *avian influenza* or *bird flu* and not *Italy* for *avrow*, and *avian flu* or *avian influenza* or *bird flu* and *Italy* for *avit*. The sample period for the media indices is from the week ending on August 15, 2004, to the week ending on October 1, 2006. Because the PIL requires the first eight observations be dropped from the analysis, the media index sample starts 8 weeks earlier than the Nielsen data to maximize the number of usable observations in the demand model.

Both *avrow* and *avit* are presented in Figure 1. Not surprisingly, the number of European news articles about avian influenza that do not specifically mention Italy is far greater than those that do refer to Italy. The average index values over the sample period are 324.4 for *avrow* and 24.7 for *avit*. Figure 1 indicates that the first wave of concern in the European media started in late July 2005 when the virus apparently moved northwesterly from its origins in Southeast Asia to the Russian Federation and adjacent parts of Kazakhstan to affect domestic and wild birds. European media attention to the disease skyrocketed in October 2005 as a result of reports that the virus had been found in Turkey, Romania, and Croatia, resulting in a high of 2,455 articles in the week ending October 23, 2005.

Figure 1. Media Indices of Avian Influenza Coverage



After that, there were additional spikes in media attention in January through April 2006 as HPAI was identified in additional countries in Europe (e.g., Austria, France, Germany, Italy, Sweden, Switzerland) and elsewhere. Since then, the media has continued to be interested in following and reporting the disease situation in Europe and other parts of the world, but the number of articles has trended strongly downward from early April 2006 through the end of our sample period. Across the entire sample, *avit* was generally relatively flat with several articles per week. The exception was a spike of 539 articles in the week ending February 19, 2006, corresponding to the discovery of the H5N1 strain of HPAI in dead wild swans in southern Italy.

Qualitative assessment of these two media indices indicates that they correspond well to the HPAI outbreak situation and appear to reasonably reflect European consumers' exposure to information about outbreaks and health risks. An advantage of media indices over variables based on the number of outbreaks or 0/1 indicator variables for whether an outbreak took place in a period or not is that they provide a continuous measure of consumer exposure to information regarding HPAI. Even if a country has not yet experienced an outbreak, consumers may respond to information on HPAI. For instance, additional media attention to outbreaks in nearby countries (or anywhere in the world, for that matter) may alter the perceived risk of poultry consumption. More generally, consumers are likely to respond not only to domestic outbreaks, but to any information that affects their perceived risk of poultry consumption. In addition, media attention may differ substantially between initial outbreaks in a region and subsequent outbreaks. To the extent that consumers are responding to new information received regarding food safety, a media index may better capture the extent of information provided to consumers in a given period than an indicator variable for outbreaks or a count of outbreaks within that period.

MODEL

We cast consumer choice of meat products in a time nonseparable preferences framework with forward-looking behavior. The conventional demand system approach has used time separable preferences in which current decisions hinge on only contemporaneous prices and expenditures (Christensen, Jorgenson and Lau [1975]; Deaton and Muellbauer [1980]). However, a number of studies have recognized that consumer preferences may not be separable over time (Boyer [1983]; Becker and Murphy [1988]; Constantinides [1990]). Intertemporally correlated preferences may take the form of habit persistence or inventory holding. Empirical studies of time nonseparable consumer demand have estimated both direct and indirect utility functions. The majority of papers in this literature use direct representation of utility and most have found that time nonseparability is an important feature of consumer preferences (Ferson and Constantinides [1991]; Becker, Grossman and Murphy [1994]; Fuhrer [2000]).

Indirect representation of preferences has proven to be very fruitful in empirical studies that assume intertemporal separability. In contrast to direct representation of utility, indirect utility functions have the advantage that integrability conditions can be imposed by setting data-independent restrictions on the parameter space (Attanasio and Weber [1995], p 1143). However, to our knowledge, there are only two published studies that estimated flexible indirect utility functions allowing for intertemporal nonseparability.[1] The reason is that these flexible indirect preferences do not have closed-form direct utility functions (Browning [1991]), which are usually used to derive the Euler equations for intertemporal optimization. Using British annual observations from 1947 to 1980 on nine commodities, Pashardes (1986) estimated a dynamic Almost Ideal Demand System (AIDS) under static price expectations. He found both forward-looking behavior and time nonseparability for the representative British consumer. Browning (1991) developed a simple nonadditive preferences (SNAP) structure and integrated it with a modified AIDS without assuming static price expectations. Using annual U.K. time-series data on 7 goods over the 1954 to 1985 period, Browning found that U.K. consumers are forward-looking and preferences are time nonseparable.

Equation (1) is an AIDS model modified to represent SNAP (Browning [1991]).

$$w_{it} = \alpha_i + \sum_s \alpha_{is} z_s + \sum_j \gamma_{ij} \ln p_j^t + \beta_i \ln\left[\frac{x_t}{a(\mathbf{p}^t)}\right] + \beta_i \sum_j \theta_j \ln p_j^{t-1} - \delta_i \left[\frac{b(\mathbf{p}^t)}{b(\mathbf{p}^{t+1})}\right]. \tag{1}$$

where $\ln a(\mathbf{p}) = \sum_j \alpha_j \ln p_j + 0.5 \sum_i \sum_j \gamma_{ij} \ln p_i \ln p_j$ and $\ln b(\mathbf{p}) = \sum_j \beta_j \ln p_j$ .Adding-up, intratemporal homogeneity and symmetry collectively require $\sum_j \alpha_j = 1$, $\sum_j \beta_j = 0$, $\sum_j \gamma_{ij} = 0$, and $\gamma_{ij} = \gamma_{ji}$. Parametric restrictions related to the intertemporal aspects of the demand are:

lagged homogeneity: $\sum_j \theta_j = 0$,

intertemporal symmetry: $\theta_i = -\delta_i$ for all *i*.

[1] A number of demand system studies have explored consumption dynamics under myopia (Heien and Durham [1991]; Holt and Goodwin [1997]; Arnade, Gopinath and Pick [2008]). That is, past demand affects current decisions but consumers do not recognize the effect of current decisions on future utility.

Presence of demand dynamics can be tested by: no SNAP: $\theta_i = \delta_i = 0$ for all *i*. Absence of forward-looking behavior is implied by: myopic behavior $\delta_i = 0$ for all *i*. The price elasticities of demand in t-1, t and t+1 with respect to an expected transitory change in price in t are:

$$\frac{\Delta \ln q_i^{t-1}}{\Delta \ln p_i^t} = \frac{\beta_j \theta_i b(\mathbf{p}^{t-1})}{w_{it-1} b(\mathbf{p}^t)},$$

$$\frac{\Delta \ln q_i^t}{\Delta \ln p_i^t} = \frac{\gamma_{ij} - \beta_i\left(\alpha_j + \sum_k \gamma_{jk} \ln p_k\right) - \beta_j \theta_i}{w_{it}} + \left(1 + \frac{\beta_i}{w_{it}}\right)\left(\frac{\Delta \ln x_t}{\Delta \ln p_j^t}\right) - 1_{ij}, \text{ and}$$

$$\frac{\Delta \ln q_i^{t+1}}{\Delta \ln p_i^t} = \frac{\beta_i \theta_j}{w_{it+1}}$$

respectively, where 1_{ij} is the Kronecker delta, which equals 1 if $i = j$, and 0 otherwise. The term $\frac{\Delta \ln x_t}{\Delta \ln p_j^t}$ is not estimated. Browning (1991, p 623) notes that the normalization used to derive the SNAP AIDS imply an intertemporal substitution elasticity of -1. Coherence suggests $\frac{\Delta \ln x_t}{\Delta \ln p_j^t}$ should be set to β_j, which then gives the Frisch demand elasticity. Alternatively, one may set $\frac{\Delta \ln x_t}{\Delta \ln p_j^t}$ to zero, which yields the conventional elasticity of conditional (on group expenditure) demand system. The conventional expenditure elasticity is given by

$$\frac{\Delta \ln q_i^t}{\Delta \ln x_t} = 1 + \frac{\beta_i}{w}$$

The above elasticities for transitory price changes can be used to calculate the intertemporal response of demand to an expected permanent price change. The period t-1, t, and t+1 demand responses of good i to an expected permanent change in price of the jth good at t are $\frac{\Delta q_i^{t-1}}{\Delta p_j^t}$, $\left[\frac{\Delta q_i^t}{\Delta p_j^t} + \frac{\Delta q_i^t}{\Delta p_j^{t+1}}\right]$, and $\left[\frac{\Delta q_i^{t+1}}{\Delta p_j^t} + \frac{\Delta q_i^{t+1}}{\Delta p_j^{t+1}} + \frac{\Delta q_i^{t+1}}{\Delta p_j^{t+2}}\right]$, respectively.

To incorporate food safety information into the preferences structure, we augment the intercept α_i as follows:

$$\alpha_i = \alpha_{i0} + \tau_i trend_t + \omega_{i1} summer_t + \omega_{i2} NewYear_t + \sum_{k=2}^{m} \eta_{ik} zavrow_{kt} + \sum_{k=2}^{n} \phi_{ik} zavit_{kt}$$

where $zavrow_k$ and $zavit_k$ are the *k*th-degree PIL transformation of the avian flu news index excluding Italy and Italy-specific avian flu news index (Mitchell and Speaker [1986]); *m* and *n* are the maximum degree of polynomials; *trend* is a linear time trend included to capture deterministic trends in sales; *summer* is a dummy variable equal to 1 if the week falls between June and August, 0 otherwise; *NewYear* is a dummy variable equal to 1 if t is a December week, 0 otherwise; α, τ, ω, ϖ, η and ϕ are parameters. Details of the PIL transformation and determination of m and n are described in the Appendix.

To account for the effect of food safety on group expenditure, we exploit the relation between group expenditure, current prices and the marginal utility of income:

$$x_t = \frac{\lambda_t}{b(\mathbf{p}^t)}. \tag{2}$$

We have to deal with the fact that marginal utility of income is unobservable. If consumers have rational expectations, the following relation holds

$$E_t[\lambda_t] = E_t[\lambda_{t+1}]. \tag{3}$$

Combining (2) and (3), using actual expenditures and prices to replace expected values and adding our PIL transformation of food safety information results in the following equation that can be estimated along with the budget share equations in (1)

$$\begin{aligned} \ln x_{t+1} - \ln x_t + \ln b(\mathbf{p}^{t+1}) - \ln b(\mathbf{p}^t) &= \varpi_1 (summer_{t+1} - summer_t) \\ &+ \varpi_2 (NewYear_{t+1} - NewYear_t) + \sum_{k=2}^{m_0} \pi_k (zavrow_{kt+1} - zavrow_{kt}) \\ &+ \sum_{k=2}^{n_0} \psi_k (zavit_{kt+1} - zavit_{kt}) + \varepsilon_t \end{aligned} \tag{4}$$

where π and ψ are parameters to be estimated; m_0 and n_0 are the highest degrees of PIL polynomials; and ε_t is the expectational residual. Assuming rational expectations, ε_t is orthogonal to variables in the information set at t and earlier.

DATA

Following assessment of available Nielsen meat sales data for countries that had experienced animal outbreaks of HPAI, we chose to use Italian data in our empirical application because those data were the most complete and consistent available from Nielsen. These sales value and volume data for poultry, beef, and pork products were available from the week ending October 10, 2004 through the week ending October 1, 2006, giving us a total of 104 weekly observations. These data were combined with the weekly media series described above. Table 1 provides descriptive statistics.

Table 1. Descriptive Statistics

Variable	Description	Average	Std. Dev.	Minimum	Maximum
avrow	Media index ROW	342.3	440.2	17.0	2455.0
avit	Media index Italy	26.1	62.7	0.0	539.0
pfrhp	Price of fresh poultry	\$7.92	\$0.26	\$7.23	\$8.49
pfrzp	Price of frozen poultry	\$7.24	\$0.27	\$6.70	\$7.92
pbf	Price of beef	\$8.33	\$0.16	\$7.99	\$8.76
ppk	Price of pork	\$5.94	\$0.10	\$5.70	\$6.27
sfrhp	Budget share of fresh poultry	0.14	0.02	0.11	0.18
sfrzp	Budget share of frozen poultry	0.22	0.04	0.15	0.28
sbf	Budget share of beef	0.37	0.06	0.29	0.48
spk	Budget share of pork	0.26	0.02	0.23	0.31

Because consumer response is expected to differ between fresh and frozen/processed poultry, we estimated separate demand equations characterizing sales of these products as a function of the media indices, prices, and indicator variables capturing seasonality. Food safety information is expected to have lasting effects on demand. Thus, we investigate the lag structure of media indices using the PIL structure. The choice of appropriate degree of polynomial is determined based on the ability of the model to fit the data.

RESULTS

We estimated the budget share equations (1) for fresh poultry, frozen poultry and beef jointly with the evolution equation (2) using generalized method of moment (GMM) (Hansen [1982]). Instruments include the log of current and one-period lagged prices, a time trend, and

PIL specifications for *avrow* and *avit* up to fifth-degree polynomials. The Wald test is used to select the optimal degrees of polynomials by starting from the fifth degree and sequentially reducing the degrees until the coefficients on the highest degree coefficients estimated are statistically significant. The procedure worked well and pointed to a fifth-degree representation for *avrow* and *avit* in the budget share equations, and third-degree polynomials for both indices in the marginal utility of income equation. Newey and West's (1994) nonparametric procedure is used to select the optimal bandwidth for the variance-covariance matrix of the moment conditions in the GMM estimation.

Table 2 reports the parameter estimates along with their standard errors. The model generally fits well, with the majority of parameters estimated statistically significant at the 1% level. Our findings are supportive of consumers displaying forward-looking behavior, consistent with the SNAP specification. In addition, our results indicate that media information regarding avian influenza had a statistically significant effect on sales of meats in Italy. Both Italy-specific and non-Italy specific news regarding AI was found to impact Italian poultry demand, which suggests that consumers are responding to changes in the perceived risk of poultry consumption prior to outbreaks in their own country.

Tables 3 and 4 present the Frisch own-price and Marshallian price and expenditure elasticities, respectively. As expected, all own-price elasticities are negative. They are also all elastic except for frozen poultry, which is likely due to the high frequency data used. Consumers are more price responsive in the short run than in the long run because of inventory behavior (e.g., Wohlgenant and Hahn [1982]; Hendel and Nevo [2006]). In our study, the Marshallian price elasticity of demand for fresh poultry was estimated to be –1.950, whereas in a study of Italian meat demand using monthly data, Fanelli and Mazzocchi (2002) found the own-price demand elasticity for poultry to be between –1.481 and –1.250, depending on model specification. The other own-price elasticities that we estimated were -0.900 for frozen poultry, -2.493 for beef, and -1.267 for pork.

Consistent with expectations, all expenditure elasticities are positive. Expenditure elasticities of less than one indicate that fresh poultry, frozen poultry, and pork are normal goods, while beef has an expenditure elasticity above one indicating it is a luxury good. The expenditure elasticity for fresh poultry is higher than that for frozen poultry, as expected.

Table 2. GMM Estimates

Coefficients	Budget Share Equations		
	Fresh poultry	Frozen poultry	Beef
α_i	0.4042*** (0.1118)	2.3339*** (0.1402)	-3.0549*** (0.2170)
τ_i	0.0003*** (<0.0001)	-0.0003*** (<0.0001)	-0.0002*** (0.0001)
ω_{i1}	-0.0250*** (0.0020)	-0.0116*** (0.0014)	0.0237*** (0.0035)
ω_{i2}	-0.0043*** (0.0015)	-0.0124*** (0.0014)	0.0110*** (0.0033)
γ_{1i}	-0.1347*** (0.0134)	0.0228 (0.0176)	0.2133*** (0.0389)
γ_{2i}	—	-0.3263*** (0.0347)	0.5880*** (0.0456)
γ_{3i}	—	—	-1.3688*** (0.0884)
β_i	-0.0035 (0.0046)	-0.1205*** (0.0054)	0.2190*** (0.0080)
θ_i	0.2519** (0.1061)	0.4101*** (0.1297)	-0.4115** (0.1716)
η_{i2}	0.0140** (0.0061)	-0.0208*** (0.0037)	-0.0145* (0.0084)
η_{i3}	-0.1127** (0.0442)	0.1361*** (0.0241)	0.0904 (0.0582)
η_{i4}	0.2185** (0.0954)	-0.2894*** (0.0487)	-0.1410 (0.1225)
η_{i5}	-0.1198** (0.0574)	0.1738*** (0.0283)	0.0646 (0.0728)
ϕ_{i2}	-0.2112*** (0.0390)	-0.3218*** (0.0226)	0.9323*** (0.0660)
ϕ_{i3}	1.6116*** (0.2680)	2.1556*** (0.1546)	-6.1900*** (0.4515)
ϕ_{i4}	-3.4422*** (0.5494)	-4.2623*** (0.3150)	12.2966*** (0.9236)
ϕ_{i5}	2.0401*** (0.3208)	2.4244*** (0.1832)	-7.0374*** (0.5389)

Expenditure equation

ϖ_1	ϖ_2	π_2	π_3
0.0054 (0.0135)	-0.0688*** (0.0219)	-0.0210*** (0.0030)	0.0234*** (0.0035)
ψ_2	ψ_3	ψ_4	ψ_5
-1.4775*** (0.4452)	8.2927*** (2.3702)	-15.3385*** (4.1132)	8.4950*** (2.1833)

Hansen's J over-identification test
9.7438

Note: All theoretical contemporaneous and intertemporal homogeneity and symmetry restrictions are imposed. ***, **, and * indicate statistical significance at 1%, 5% and 10% level, respectively. The J test is chi-square distributed with 24 degrees of freedom. Therefore, the model is not rejected by the overidentification test.

Table 3. Frisch own-price elasticities at t-1, t and t+1 with respect to a permanent own-price change at t

	Period		
	t-1	t	t+1
Fresh poultry	-0.006	-1.953	-1.959
Frozen poultry	-0.231	-1.079	-1.310
Beef	-0.246	-3.089	-3.335
Pork	0.091	-1.116	-1.025

Note: Reported elasticities are equal to the mean of elasticities calculated at every data point.

Table 4. Marshallian Price and Expenditure Elasticities

	Price			
Quantity	Fresh poultry	Frozen poultry	Beef	Pork
Fresh poultry	-1.950	0.443	1.052	-0.521
Frozen poultry	0.363	-0.900	0.448	-0.346
Beef	0.314	-0.009	-2.493	0.591
Pork	-0.230	-0.303	1.163	-1.267

Expenditure elasticities

	Fresh poultry	Frozen poultry	Beef	Pork
	0.975	0.436	1.598	0.638

Note: These elasticities measure demand responses at t to a transitory price change at t setting $\Delta \ln x / \Delta \ln p = 0$. Reported elasticities are equal to the mean of elasticities calculated at every data point.

Based on the avian flu media index elasticities in Tables 5 and 6, an increase in either avrow or avit media indices has net negative effects for fresh and frozen poultry and net positive effects on beef and pork in all cases except for the case accounting for the group expenditure effect for Italy-specific articles. In that case, all meats are negatively affected by media coverage of avian influenza. Although not necessarily the case at time t, fresh poultry sales are more responsive to media coverage than frozen at time t +1 in all cases examined. This is consistent with our expectations that consumers may have greater concerns regarding fresh poultry.

For non-Italy specific news, there is relatively little difference in the net effects with and without accounting for the group expenditures on meats. However, in the case of Italy-specific news, the reduction in group expenditures on meats substantially increases the net effects of avian influenza coverage. In addition to more negative effects on poultry, we find that the net effects on beef and pork are negative despite the substitution effect towards those meats. Our estimates of lag weights indicate that the effects of media information dissipate over time, but that substantial negative consumption impacts may continue for a period of months after the news is provided.

Table 5. Food Safety Elasticities, Media Indices Excluding News Related to Italy (avrow)

	Without group expenditure effect		With group expenditure effect	
Quantity	t	t+1	t	t+1
Fresh poultry	-0.0008	-0.0169	0.0076	-0.0249
Frozen poultry	-0.0052	-0.0143	-0.0015	-0.0177
Beef	-0.0050	0.0085	0.0089	-0.0045
Pork	0.0108	0.0082	0.0165	0.0028

Note: These food safety elasticities measure demand responses at t and t+1 with respect to a change in newspaper article count at time t.

Table 6. Food Safety Elasticities, Media Indices of Articles Related to Italy (avit)

	Without group expenditure effect		With group expenditure effect	
Quantity	t	t+1	t	t+1
Fresh poultry	-0.0030	-0.0051	-0.0105	-0.0118
Frozen poultry	-0.0053	-0.0021	-0.0085	-0.0050
Beef	0.0011	0.0059	-0.0111	-0.0053
Pork	0.0040	-0.0034	-0.0011	-0.0080

Note: These food safety elasticities measure demand responses at t and t+1 with respect to a change in newspaper article count at time t.

CONCLUSIONS

The unique data used in this study provide an excellent opportunity to examine how consumers' perceptions of the likelihood of contracting the disease and health risk evolve due to changes in information. The data cover the period when cases of a highly pathogenic strain of H5N1 were found in wild birds in Italy for the first time. The timeframe covered by these data enables us to investigate how consumers behave when presented with information suggesting increased probabilities of future outbreaks in Europe and in Italy, as well as how consumers react in the short run and intermediate run when such predictions materialize. In addition, we demonstrate the importance of accounting for both dynamic effects and changes in group expenditures when estimating net effects of food safety issues.

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Appendix: The polynomial inverse lag structure

Consider the following regression equation:

(A.1) $$Y_t = b + \sum_{i=0}^{\infty} w_i X_{t-i} + e_t ,$$

where Y_t is poultry sales in period t, X_τ is the media index in period τ with $\tau \le t$, b is a collection of other explanatory variables (e.g., meat prices, seasonal dummy variables) and their associated coefficients, and e_t is the regression residual. Although the empirical demand model may take a more sophisticated form, Eq. (A.1) can be used to provide a simple illustrative example of how the PIL works. This equation cannot be estimated directly as written due to the infinite lag distribution for X. To derive an estimable form of Eq. (A.1), Mitchell and Speaker (1986) propose the following transformation:

(A.2) $$Y_t = b + \sum_{j=2}^{n} a_j Z_{jt} + R_t + e_t ,$$

where $Z_{jt} = \sum_{i=0}^{t-1} \frac{X_{t-i}}{(i+1)^j}$, $j = 2,...,n,$ $R_t = \sum_{j=2}^{n}\sum_{i=t}^{\infty} \frac{a_j X_{t-i}}{(i+1)^j}$, and n is the degree of polynomial for the PIL structure, which has to be determined empirically. With the sample t=1,2,…,T, data are available to calculate Z_{jt}, but the remainder term R_t cannot be calculated from the data because it includes infinite lags. Mitchell and Speaker showed that with t greater than eight, R_t becomes negligible. Therefore, a practical solution to the unobserved R_t problem is to exclude the first eight data points and conduct econometric analysis on the remaining data without the R_t term.

After dropping the first eight data points, the Z_{jt}'s (t=9,10,11,…,T) are computed as follows:

For j = 2:

$$Z_{2t} = \sum_{i=0}^{t-1} \frac{X_{t-i}}{(i+1)^2} = \frac{X_t}{1^2} + \frac{X_{t-1}}{2^2} + \frac{X_{t-2}}{3^2} + \frac{X_{t-3}}{4^2} + ... + \frac{X_1}{t^2};$$

For j = 3:

$$Z_{3t} = \sum_{i=0}^{t-1} \frac{X_{t-i}}{(i+1)^3} = \frac{X_t}{1^3} + \frac{X_{t-1}}{2^3} + \frac{X_{t-2}}{3^3} + \frac{X_{t-3}}{4^3} + ... + \frac{X_1}{t^3};$$

For j = 4:

$$Z_{4t} = \sum_{i=0}^{t-1} \frac{X_{t-i}}{(i+1)^4} = \frac{X_t}{1^4} + \frac{X_{t-1}}{2^4} + \frac{X_{t-2}}{3^4} + \frac{X_{t-3}}{4^4} + ... + \frac{X_1}{t^4};$$

For $j = 5$:

$$Z_{5t} = \sum_{i=0}^{t-1} \frac{X_{t-i}}{(i+1)^5} = \frac{X_t}{1^5} + \frac{X_{t-1}}{2^5} + \frac{X_{t-2}}{3^5} + \frac{X_{t-3}}{4^5} + ... + \frac{X_1}{t^5};$$

and so on, until reaching the term Z_{nt}. A remaining issue is selection of the appropriate n—the degree of the polynomial. The selection process can start with a relatively high degree, e.g., $n = 5$, in which case Eq. (A.2) can be written as

(A.3) $$Y_t = b + a_2 Z_{2t} + a_3 Z_{3t} + a_4 Z_{4t} + a_5 Z_{5t} + e_t.$$

To determine the optimal n, regression Eq. (A.3) is fit a number of times, successively dropping the highest-degree term. The choice of appropriate degree is then determined by the ability of the model to fit the data. In determining the optimal degree of polynomials, we test the statistical significance of the highest-degree terms using the Wald test. The terms are then dropped if they are not statistically significant. We repeated the process until the coefficients on the highest-degree terms are statistically significant.

Finally, the weights (w_i) on X_τ in Eq. (A.1) can be recovered using estimates of a_j ($j = 2,...,n$). The formula for calculating weight w_i is

(A.4) $$w_i = \sum_{j=2}^{n} \frac{a_j}{(i+1)^j},\ i = 0,...,t-1.$$

Eq. (A.4), along with estimated values for a_j, is used to calculate the weights on current and lagged media indices in the demand equation. Among its other advantages, the PIL structure is able to approximate some general shapes of response with a small number of polynomials. For example, a hump-shaped response may be captured by as few as fourth-degree polynomials (Mitchell and Speaker [1986), p 331).