Impacts of BSE and Avian Influenza on U.S. Meat Demand

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Introduction

Since the end of 2003, a highly pathogenic strain of Avian Influenza (HPAI)-H5N1 virus has spread widely reaching almost 60 countries in Asia, Europe and Africa (Sims and Narrod 2008). To date, there are 601 confirmed H5N1 human cases, resulting in 354 human deaths[1]. This expanding global outbreak and associated deaths has negatively affected demand in some regions (Alexander 2007; Jin and Mu 2012). The AI outbreak has not been very extensive in the U.S. with several cases of low pathogenic AI and one HPAI (H5N2) outbreak occurring all in poultry. Nevertheless, there may have been negative consequences for U.S. meat demand as media coverage of disease outbreaks and spread may have affected consumers' confidence in meat safety and in turn consumption. During the same period, the U.S. had three BSE cases and this may also have altered meat consumption basket. This paper reports on an examination of whether and how much AI and BSE outbreaks and associated media coverage have altered U.S. meat demand.

Background on Meat Safety and Demand Estimation

Demand models are useful tools for examining consumer behavior when the consumption goods in question are highly perishable or when they have a reasonably short shelf life, such as meat (Holt and Balagtas 2009; Eales and Unnevehr 1994; Holt and Goodwin 1997; Holt 2002; Holt and Balagtas 2009).

Several studies have examined the effects of food safety and product recall news using such demand models (Verbeke and Ward 2001; Piggott and Marsh 2004; Beach

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[1] More information is available at http://www.who.int/influenza/human_animal_interface/EN_GIP_20120405NCumulativeNumberH5N1cases.pdf. Cited 10 April, 2012.

and Zhen 2008). These studies generally employ the almost ideal demand system (AIDS) model (Deaton and Muelbauer 1980) that relates demand prices to quantity demanded , is expanded to incorporate disease related variables that enter the framework as demand shifters (Verbeke and Ward 2001; Piggott and Marsh 2004; Beach and Zhen 2008). The demand shifting variables used have involved the volume of relevant news, and timing of the event. One can also use the inverse almost ideal demand system (IAIDS) model (Eales and Unnevehr ,1994), which assumes expresses quantity as a function of prices and other factors, and also can be estimated incorporating demand shifters (Dahlgran and Fairchild 2002)

However, for estimation with aggregate data, the presumption of taking price or quantity as given is not appropriate because the choice between price-dependent and quantity-dependent functions remains arbitrary and is not trivial, with endogeneity being a problem (Wang and Bessler 2006).

Generally, these demand studies have neglected the time series effects of news coverage (Mazzocchi et al. 2006). Mazzocchi (2003; 2006) and Mazzocchi et al. (2006) examined such issues developing a time series approach and apply it to assess the impact of food scare events, as an alternative to the inclusion of news coverage. Fanelli and Mazzocchi (2002), Eakins et al. (2003) and Duffy (2003; 2006) derived two-step dynamic AIDS models including an error correction term to take care of the time series properties of demand data. However, the dynamic demand AIDS model assumes that the cointegration rank of the system equals the number of modeled equations, and prices and expenditure are still assumed weekly exogenous (Fanelli and Mazzocchi 2002).

To release this assumption, Fanelli and Mazzocchi (2002) applied a cointegrated vector error correction model (VECM) where prices and expenditures enter the system endogenously and the cointegration rank subjects to inference. In addition, Wang and Bessler (2006) also use an error correction model based on time series properties of data and allow prices and expenditures to be endogenous.

In this paper, we use a cointegrated VECM-inverse AIDS model as in Fanelli and Mazzocchi (2002) to examine the economic impacts of animal disease incidences and news coverage on U.S. meat demand. Economics implications related to welfare redistributions are also discussed based on model estimation results.

The paper is organized as follows. Section 2 introduces model specifications; Section 3 provides data, their statistical descriptions and tests of time series properties; Section 4 presents estimation results; Section 5 tests theoretical restrictions and evaluates forecasting power; Section 6 discuss policy implications and section 7 is the concluding remarks.

Model Specifications

For this study, we will use the Eales and Unnevehr (1994), generalized IAIDS demand model with the addition of animal disease information indices as the shock on the intercept (Duffy 2003). The static IADIS model is given as,

$$w_i = \alpha_i + \sum_{j=1}^{4} \gamma_{ij} \ln q_j + \beta_i \ln(Q) + u_i \text{...(1)}$$

with

$$\ln Q = \alpha_0 + \sum_{j=1}^{4} \alpha_j \ln q_j + 1/2 \sum_{i=1}^{4} \sum_{j=1}^{4} \gamma_{ij} \ln q_i \ln q_j \text{...(2)}$$

$$\alpha_i = \alpha_{i0} + \sum_{k=1}^{3} \lambda_{ik} AI_k + \theta_i BSE + \sum_{s=1}^{11} \rho_{is} D_s \text{...(3)}$$

where w_i is the budget share of the i^{th} good, AI_k is the AI information index with $k = 1$ indicating *AI-US*, $k = 2$ giving *AI-media coverage* and $k = 3$ giving *AI-human deaths*, BSE is a dummy variable telling when a BSE case occurs in the U.S. in a month, and D_s is monthly dummies; q_j is the quantity of good j. In equation (1), (2) and (3), α, β, γ, ρ, λ, and θ are parameters to be estimated. Restrictions of homogeneity and symmetry are needed but involve only the fixed, unknown coefficients and so may be easily tested or imposed (Eales and Unnevehr 1994). These restrictions are:

- $\sum_i \alpha_{i0} = 1$, $\sum_i \beta_i = 0$, $\sum_i \lambda_{ik} = 0$, $\sum_i \theta_i = 0$, $\sum_i \rho_{is} = 0$, adding-up restrictions
- $\sum_j \gamma_{ij} = 0$, homogeneity restrictions
- $\gamma_{ji} = \gamma_{ij}$, symmetry restrictions

Specifying the exact form of the demand function involves choice between a nonlinear or linear form. Hahn (1994) suggests estimating AIDS using its nonlinear form because the linear form is an approximate of the nonlinear one. Although estimation results from Eales and Unnevehr (1994) did not reject the linear IAIDS form, they indicate a nonlinear form is preferred. Most importantly, elasticities of IAIDS demand function can be calculated directly from its nonlinear form (Green and Alston 1990; 1991). Thus, this paper uses the nonlinear IAIDS (NL/IAIDS)[2].

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[2] Set $\alpha_0 = 5$ in the NLSUR algorithm according to Deaton and Muellbauer (1980).

Elasticities from the NL/IAIDS demand model are calculated following the same procedure in deriving the elasticities from the NL/AIDS by Green and Alston (1990; 1991). For NL/IAIDS, Eales and Unnevehr (1994) define the term of flexibilities as the inverse term of elasticities in AIDS, so the interpretation of flexibilities can be made in a manner similar to elasticities. For example, a demand for a commodity is said to be inflexible if a 1% increase in consumption of that commodity leads to a less than 1% decrease in the marginal value of that commodity in consumption (in absolute value). Commodities are termed as gross quantity-substitutes if their cross price flexibility is negative and as gross quantity-complements if it is positive (Eales and Unnevehr 1994).

The interpretation of scale flexibilities can be considered as the case of homothetic preferences. If the scale flexibility of one commodity is less than -1, it means this commodity is a necessity. In other words, the commodity is a luxury good if the scale flexibility is greater than -1.

An Error Corrected IAIDS model

The EC-IAIDS model is based on the static IAIDS demand function identified above (Duffy 2003; 2006). If we assume quantities and expenditure are weakly exogenous, the EC-IADIS model is written as below,

$$\Delta w_t = \alpha_i + \sum_{j=1}^{4} \gamma_j \Delta \ln q_{jt} + \beta(\Delta \ln Q_t) + \Gamma \Delta w_{t-1} + \Pi u_{t-1} + \eta_t ...(4)$$

with

$$\Delta \ln Q_t = \sum_{k=1}^{4} \alpha_k \Delta \ln q_{kt} + 1/2 \sum_{k=1}^{4} \sum_{j=1}^{4} \gamma_{kj} \Delta(\ln q_k \ln q_j)_t ...(4)$$

$$\alpha_i = \sum_{k=1}^{3} \lambda_k \Delta AI_{kt} + \theta \Delta BSE_t + \sum_{s=1}^{11} \rho_s \Delta D_{st}$$

where Δ represents the first difference operator; Δw_{it-1} captures consumers' habits and $u_{t-m1} = w_{t-m1} - [\alpha + \sum_{k=1}^{3} \lambda_k AI_k + \theta BSE + \sum_{s=1}^{3} \rho_s D_s + \sum_{j=1}^{4} \gamma_j \ln q_j + \beta \ln(Q)]_{t-m1}$ is the estimated residual lag from the static IAIDS model and u_t is assumed to be a white noise stationary series process. Γ_1 is the 3×1 vector and Π_1 is the 3×3 matrix and η_t is a vector of innovations that may be contemporaneously correlated with each other but are uncorrelated with their own lagged values and uncorrelated with all of the right-hand side variables If Π_1 has ranks r_1 with $r_1 < 3$, then w_t is cointegrated with r_1 cointegrating vectors, reflecting long-run relationship among variables in the system (Wang and Bessler 2003).

From equations (3) and (4), the EC-IAIDS model that incorporates short-run estimates is an error correction representation of the generalized static IAIDS model. This dynamic form allows for disequilibrium in the short-run by treating the error term u_i in equation (1) as the equilibrium errors and these errors tie the short-run behavior of the dependent variable to its long-run value (Eakins et al. 2003).

The first-differenced terms on the right hand side capture the short-term disturbances. The error correction term u_{t-m1} captures long-term equilibrium relationship given by the static IAIDS model and Π_1 measures the speed of adjustment to the long-run equilibrium with $\Pi_1 = 1$ indicates instantaneous adjustment. If Π_1 is large or closer to one in absolute value then there is a rapid adjustment and a smaller Π_1 indicates a slower speed to go back to the long-term equilibrium.

Flexibilities from the static IAIDS demand function are treated as the long-run equilibrium. The EC-IAIDS model gives the short-run flexibilities. The difference between the long-run and short-run equilibrium is adjusted by Π_1, the coefficient of the error correction term.

A General Error Corrected Model[3]

Since one purpose of this study is to examine the performance of the EC-IADIS in a forecasting point of view, it is useful to have a relatively simple base or reference model (Klaiber and Holt 2010). One such possibility is to assume all prices, quantities and expenditures are endogenous, so the general error correction model is chosen, which is presented as below with $m_2 - lag$,

$$\Delta y_t = \sum_{m_2=1}^{T} \Gamma_{2m_2} \Delta y_{t-m_2+1} + \Pi_2 y_{t-m_2} + \Phi D_t + \varepsilon_t$$

where Γ_2 is the 9×1 scalar, Π_2 is the 9×9 matrix, Φ is 9×3 matrix, D is the 3×1 vector of seasonal dummies and y_t is 9×1 vector of endogenous variables, including price and quantity of beef, pork, chicken and turkey as well as the total expenditure. Π_2, Γ_2 and Φ are coefficients to be estimated and ε_t is a vector of innovations that may be contemporaneously correlated with each other but are uncorrelated with their own lagged values and uncorrelated with all of the right-hand side variables (Engle and Granger 1987). If Π_2 has a rank r_2 with $r_2 < 9$, then y_t is cointegrated with r_2 cointegrating

[3] Due to the assumption of weakly exogenous in the demand model, the purpose of using the general error correction model (ECM) is to test the robustness of the two-step demand estimation. Initially, the ECM model has no economic meaning for estimated parameters, but it could be helpful to release the exogenous assumption and determine the forecasting ability when doing the evaluation of the two-step demand model.

vectors, reflecting long-run relationship among variables in the system(Wang and Bessler 2003; 2006).

There are two popular ways to determine the rank and lag in the EC-IAIDS and the ECM model. The conventional approach is a two-step procedure involving system-based likelihood ratio (LR) tests to determine r and k sequentially (Park et al. 2008). This procedure is first to determine the lag length using information matrices; and then to determine the rank of cointergration vectors based on a trace test (Johansen1988). The second approach is the model selection method based on information criteria (Aznar and Salvador 2002; Baltagi and Wang 2007; Phillips and McFarland 1997; Park et al. 2008).

Table 2 reports selection-order criteria for lag m_1 and Johansen tests for cointegration r_1. We could see that different information criteria give different length of lags, which could affect rank for cointegration. If we choose $m_1 = 2$ or $m_1 = 3$ based on information criteria, we have $r_1 = 2$ for sample before disease outbreak in United States and $r_1 = 0$ for the whole sample.

However, it is difficult to determine the rank for the sample after disease outbreaks in the United States since there is zero rank if $m_1 = 2$, and two ranks if $m_1 = 3$. Therefore, we need the more advanced morel selection procedure to determine the lag and rank simultaneously. Table 3 provides information criteria from model selection approach and indicates that $m_1 = 2$ and $r_1 = 2$ has the minimum Hannan and Quinn (HQIC) loss as well as the Schwarz-loss criterion (BIC) loss for both subsamples for the EC-IAIDS model.

Based on the rank and lag selection results, we estimated the EC-IAIDS model with $r_1 = 2$ and $m_1 = 2$ using a one-step, simultaneous, non-linear seemingly unrelated regression (NLSUR) approach (McElroy et al. 1995). This method also allows for correlations in the residual variance-covariance matrix which will lead to more efficient estimates both asymptotically and in most small samples (Shaken and Zhou 2000) and Elder (1997) also find that this NLSUR algorithm is more stable and robust with respect to poor initial values.

For the general ECM model, we use the model selection approach to determine m_2 and r_2. Figure 3 shows the minimum point for BIC is at $r_2 = 4$ and $m_2 = 1$.Therefore, we estimate the general ECM model with $r_2 = 4$ and $m_2 = 1$.

Data

Demand estimation will be done for beef, pork, chicken and turkey. We drew monthly data on retail price and per capita consumption from USDA and Census Bureau sources from January 1989 to December 2010. The beef and pork price data are the average retail value, and turkey prices are measured by the retail value per pound of whole frozen birds. The chicken price is a composite price averaged across whole bird, chicken breast, and chicken legs weighted by quantity demanded.

The per capita consumption data for chicken and turkey are from the USDA Poultry Yearbook. Since the per capita consumption of beef and pork is not available in the USDA Red Meat Yearbook, we divide the total consumption of beef or pork, which is measured by the retail disappearance and population that is collected from the Population Division of the U.S. Census Bureau, to calculate the per capita consumption of beef or pork.

Four animal disease indices are constructed,

- A count variable of the number of articles covering AI outbreaks and spread information (*AI-media coverage*).We searched for news articles related to AI from up to 50 English-language newspapers worldwide using the LexisNexis Academic search engine[4]. The number of news articles in each month is as AI index in month
- A variable identifying the cumulative number of confirmed AI human deaths reported by the World Health Organization (WHO) from January 2003[5] to December 2010 (*AI-human deaths*)
- An AI dummy variable indicating whether an AI poultry case occurred in the U.S. with ones for November 2003, February 2004 and March 2004 (*AI-US*)
- A BSE dummy variable (*BSE-US*) of whether a BSE event occurred in the United States with ones for December 2003, June 2005 and March 2006

Figure 1 shows the total expenditure and budget share of beef, pork and chicken from January 1989 to December 2010 in the level and in the first difference. Vertical dash lines indicate the BSE cases in beef budget share and the AI cases in chicken budget share. With the AI cases, chicken expenditure dropped significantly. However, with the BSE announcements, there was no significant change of beef expenditure. Because BSE cases were announced during the same process with AI outbreaks both in the U.S. and in

[4] The keywords searched were “avian influenza” or “bird flu” over the period January 1989 to December 2010

[5] The World Health Organization (WHO) only provides confirmed AI human cases since January 2003, so we assume that there was no confirmed AI human case before that. We also checked webpage information, and it seems that no confirmed AI human case was reported before 2003.

other countries, it is possible that effects of AI outbreaks dominate the impacts of BSE and offset its negative effects.

Numbers of AI articles were shown in Figure 2. Since 1997[6], there has been increasing numbers of newspaper articles reporting AI outbreaks, spread and human deaths. Since 2003, AI outbreaks have occurred at unprecedented levels in terms of scale and geographic distribution, initially through East and Southeast Asia in 2003–2004 and then into Mongolia, southern Russia, the Middle East and to Europe, Africa and South Asia in 2005–2006, with outbreaks recurring in various countries in 2007 (Sims and Brown 2008; Jin and Mu 2012).

Hypotheses Test and Empirical Results

Due to the time trend appeared in Figure 1, we use the Augmented Dickey-Fuller (ADF) test to test whether prices, expenditure and budget shares have unit root in the level and in their first difference. Table 1 presents ADF test results showing that turkey budget share, price of beef, pork and chicken are non-stationary in the levels, while all variables in their first differences are stationary.

We need to notice that one weakness of the ADF test is its potential confusion of structural breaks in the series as evidence of non-stationary. Therefore, we use the test proposed by Clemente, Montanes and Reyes (1998) to allow for structure breaks. Table 1 also reports results of unit root test with one structure break. Consistently, most variables in the level cannot reject the null hypothesis of unit root with one structure break, and all variables in first differences are stationary if we allow for a gradual shift in the mean of the series (IO model), which means that variables in the level have unit roots and thus in

[6] The first known human cases were reported in Hong Kong in 1997 and involved deaths of six out of 18 infected persons (Chan 2002; Peiris et al. 2004).

the absence of cointegration. Therefore, parameters and elasticities estimates from demand models in the level are spurious (Eakins et al. 2003; Mazzocchi et al. 2006), suggesting a dynamic demand model would be appropriate considering time series properties of demand data.

For the static IAIDS model, estimated parameters for the budget share equations are presented in table 4 with model diagnostics. The results presented here are from a regression over three samples from January 1989 to October 2003, January 1989 to July 2006 and the whole sample[7]. Since all variables entering the static regression are stationary at first difference, interpreting the results from this regression relies on the stationary of residuals. We use the Augmented Dickey-Fuller t test to test whether residuals from the static IAIDS equations are stationary and results in Table 4 reject the null hypothesis of unit root at the 1% confidence level. Thus, the following results can be stated.

If we only consider impacts of AI media coverage, results from sample January 1989 to October 2003 show that it only increases pork budget share and has insignificant impacts on other meat. Under a static situation, the confirmed AI human deaths in other countries affect beef expenditure positively and chicken expenditure negatively over two samples. In particular, impacts of overseas AI human deaths on U.S. meat demand are statistically significant while much small, equaling 0.02% for beef, -0.005% for pork, and -0.01% for chicken for sample from January 1989 to July 2006. Moreover, it has smaller impacts on meat expenditure when we use the whole sample.

[7] Sample of January 1989 to October 2003 is the sample without animal disease incidence occurred in the U.S., January 1989 to July 2006 is the sample with animal disease incidence occurred in the U.S.

Since AI human cases have not occurred in the U.S. and there were only several poultry cases in history, it seems that nearby outbreaks and deaths would have larger effects than overseas information. This is also proved by results from the general AI media coverage all over the world because it has positive and significant impact on chicken expenditure for the sample from January 1989 to July 2006 and increases beef expenditure and reduce pork expenditure in the whole sample. Distinguishing where the information comes from is necessary when defining situations like animal disease.

For BSE impacts, it increases pork expenditure and decrease chicken expenditure in the whole sample and has insignificant effects on beef. We suspect that AI effects, which comes from strong and intensity media reports of AI disease spread and human deaths, offset BSE effects. Nevertheless, results show that adverse information from the nearby disease outbreaks have negative impacts on meat demand and these are consistent to previous study in Italy by Piggott and Marsh (2004) and Beach and Zhen (2008). The later also argue that similar but smaller impacts on chicken consumption in the United States would be expected.

Table 5 reports the uncompensated own and cross flexibilities as well as the scale (expenditure) flexibilities along with the appropriate standard errors from the static IAIDS model. All the flexibilities were calculated at the sample means. Note that all own-quantity flexibilities are negative as theoretically expected and all own-quantity flexibilities estimates were less than one in absolute value, indicating beef, pork and chicken demands in the United States are quantity inflexible. In addition, we find beef, pork and chicken are substitutes with all signs negative, which is consistent with results in Eales and Unnevehr (1994).

When look at the AI media coverage flexibility, it is interesting to see that in a long run, pork consumption is increased if we just consider overseas disease outbreaks. However, it increases chicken consumption and reduce pork consumption when we taking account of domestic animal disease outbreaks. It is possible because the shock on international market, so consumers benefit from a lower price of chicken. Alternative reason is people switch to chicken when BSE disease announced. Since AI and BSE disease occurred across each other, we think both possibilities exist in a long-run equilibrium. We suspect a short-run analysis could tell us which reason is more important, so we could target disease prevention and control plans.

As we expected, information related to human deaths causes more attention from people and they become more cautious when purchasing meat. In the long term, beef consumption increases as the number of confirmed AI human deaths increases, while pork and chicken consumption decreases.

There are three criteria to determine a preferred long-run equilibrium model (Eakins et al. 2003), which could be used for estimating the dynamic one. First, whether the estimated elasticities/flexibilities imply a downward sloping demand curve; second, whether the regression model passes various diagnostic tests, such as goodness-of-fit and serial correlation, etc.; third, whether the model indicates a stationary pattern of residuals. As we could see in Table 4, model diagnostics suggest that the static IAIDS model meets all three criteria. Table 6 reports regression results for the EC-IAIDS model based on equation (3) and (4).

The error correction term Π_1 for beef is -12% when there was no AI and BSE outbreak in the United States, which implies that 12% of the disturbance to the long-run equilibrium in the previous period is corrected or adjusted back to long-run equilibrium in this period. However, with the animal disease outbreaks, the adjustment rate is 30%, indicating there is quick adjustment after disease outbreaks. For chicken expenditure, 11% of the disturbance to the long-run equilibrium is adjusted when there were AI outbreaks overseas, and with AI and BSE outbreaks within the United States, the adjustment rate decreases to 0.3% and 4%, suggesting there is a slower adjustment speed for chicken demand.

In the short term, information of disease outbreaks overseas is insignificant on meat expenditure. However, information of domestic disease outbreaks has statistically significant impacts. Beef expenditure increases as AI outbreaks and decrease as BSE outbreaks. Moreover, pork expenditure goes up as BSE outbreaks. Results also show shifts in consumers' meat demand habits are strong and significant at the 1% confidence level for all three samples, which indicates consumers are persistent to their consumption behaviors over time.

Table 7 gives estimates of short-run own- and cross-price and expenditure flexibilities. The short-run own-price flexibilities of beef, pork and chicken are close to their long-run flexibilities. Combined with the error correction coefficients in table 6, the quantity frequencies of demand for beef, pork and chicken do not move far from its long-run flexibilities.

Following Deaton and Muellbauer (1980), we also test for symmetry and homogeneity constraints using the likelihood-ratio (LR) test, which is written as

$$T_1 = -2(\log L^R - \log L^*)$$

where L^R is the likelihood from the restricted estimation and L^* is from the unrestricted estimation. Since the standard LR test approach provides biased results towards rejection of the null hypothesis (Meisner 1979), we use three alternative test statistics as proposed in Deaton(1972;1974) and Baldwin et al. (1983), which are presented below,

$$T_2 = T \times tr[(\tilde{\Omega}^R)^{-1}(\tilde{\Omega}^R - \tilde{\Omega}^*)]$$

$$T_3 = \frac{tr[(\tilde{\Omega}^R)^{-1}(\tilde{\Omega}^R - \tilde{\Omega}^*)]/[(n/2)(n-1)]}{tr[(\tilde{\Omega}^R)^{-1} \times \tilde{\Omega}^*]/(n-1)[T-k]}$$

$$T_4 = \frac{tr[(\tilde{\Omega}^R)^{-1}(\tilde{\Omega}^R - \tilde{\Omega}^*)]}{tr[(\tilde{\Omega}^R)^{-1} \times \tilde{\Omega}^*]/(n-1)[T-k]}$$

In all three equations, $\tilde{\Omega}^R$ is the estimated variance-covariance matrix of the error terms from the restricted model and $\tilde{\Omega}^*$ is from the unrestricted model; n is the number of equations, k is the number of explanatory variables and T is the total observations for estimation. T_1, T_2 and T_4 are all asymptotically distributed as $\lambda^2[n(n-1)/2]$ under the null hypothesis and T_3 is asymptotically distributed as $F(n(n-2)/2, (n-1)[T-(n+2)])$ under the null hypothesis.

Table 8 reports tests results from T_1 to T_4 with significant level. We could see that the null hypothesis of homogeneity or symmetry or both restrictions hold is rejected at the 1% confidence level in the static IAIDS model. However, for all test statistics, we cannot reject the null hypotheses of economic restriction holds at the 1% confidence level in the EC-IAIDS model for two subsamples, which suggest that imposing the dynamic term of consumption habits and the adjustments of short-run disturbance from the long-run equilibrium is helpful to explain U.S. meat demand patterns following the economic theory.

For the whole sample, T_1 and T_2 reject the null hypothesis if homogeneity or both homogeneity and symmetry restrictions are imposed, while T_3 and T_4 cannot reject these two restrictions at the 1% confidence level. Our results are consistent with previous studies using the same statistics (Deaton 1972; 1974).

Table 8 also shows that the EC-IAIDS model performs better than the IAIDS model. However, we need to check the robustness of the EC-IAIDS model by testing its forecasting ability. To do this, we use the general ECM model by treating all prices, quantities and expenditures endogenous. Since both homogeneity and symmetry, restrictions cannot be rejected in the EC-IAIDS model based on test statistics T_3 and T_4, we compare forecasting results of the EC-IAIDS model with both homogeneity and symmetry imposed and the general ECM model without any restrictions.

Forecasting Evaluation

As indicated above, we need to check the robustness of the EC-IAIDS model because of the weakly exogenous assumption of quantities and expenditure. Using two subsamples estimated above, we predict one-step ahead forecast for the rest of the data, i.e. from November 2003 to December 2010 and August 2006 to December 2010, respectively. We repeat the same procedure for the general ECM model. According to previous studies (Kastens and Brester 1996; Klaiber and Holt 2010; Bessler and Wang 2011), we evaluate models by two approaches, the root mean squared forecast errors (RMSFE) and the encompassing tests following Chong and Hendry (1986) and Wang and Bessler (2003). The compassing tests require that we estimate the following,

$$e_{it} = \Gamma(e_{it} - e_{jt}) + \varepsilon_{it}$$

where e_{it} and e_{jt} represents forecast errors from model i and j, respectively. We test the null hypothesis of model i encompasses model j by testing $\Gamma = 0$. A t test or a likelihood ratio test statistics could be used to perform the test. A significant p-value indicates that the forecasts generated from model i and model j are different and do not encompass each other (Klaiber and Holt 2010).

Table 9 reports the root mean squared forecast error (RMSFE) and statistics on the encompassing tests. In both subsamples, ECM performs better for the beef and chicken forecasting, while the EC-IAIDS model fits the data better for the pork equation. Our encompassing tests results also show that the ECM and the EC-IAIDS models are different and cannot encompass each other. In other words, the EC-IAIDS model proposed in this study is also important to capture the meat consumption pattern in the U.S. Figure 4 and Figure 5 shows predicted and observed values.

Conclusion

In this paper, we analyzed the economic impacts of animal disease on US meat consumption using the error corrected inverse almost ideal demand model (EC-IAIDS) which is based on the data generating process.

By testing the time series properties of the data, we find that employing a dynamic demand model is appropriate. Examining the EC-IAIDS model, we find that in short term, people are more cautious to nearby disease outbreaks than that occurred overseas, while in long-run, all information related to animal disease outbreaks will hurt consumers’ consumption patterns. Although the economic impacts of animal disease on meat consumption are statistically significant but they are economically small.

Based on restriction tests and forecast evaluation, this paper also shows that the EC-IAIDS model performs better to fit the data. In particular, both homogeneity and symmetry restriction hold for subsamples based on alternative test statistics proposed by Deaton (1972; 1974). From a comparison with the benchmark ECM model which is usually considered as the superior model in forecasting (Wang and Bessler 2003), however, results of RMSFE and the encompassing tests present that the ECM model cannot encompass the EC-IAIDS model. In other words, both models are important in forecasting.

References

Aznar, A., M.,Salvador, Selecting the rank of cointegration space and the form of the intercept using an information criterion. *Econometric Theory* 18(2002): 926–947.

Baldwin, M.A., M. Hadid, and G.D.A. Phillips, "The Estimation and Testing of a System of Demand Equations for the U.K., *Avelied Economics* 15(1983):81-90.

Baltagi, B. H., Z., Wang, Testing for cointegrating rank via model selection: Evidence from 165 data sets. *Empirical Econ.* 33(2007) 41–49.

Baum, Christopher F. Stata: The language of choice for time series analysis? *Stata Journal*, Vol. 1 (1) (2001): 1-16.

Beach R. H. and Zhen C., "Consumer Purchasing Behavior in Response to Media Coverage of Avian Influenza", Selected Paper prepared for presentation at the Southern Agricultural Economics Association Annual Meeting, Dallas, Texas, February 2-5, 2008.

Burton, M.P. and T. Young, "The impact of BSE on the demand for beef and other meats in Great Britain." *Applied Economics*. 28(1996):687-93.

Chambers, M.J. Forecasting with demand systems, *Journal of Econometrics*, 44(1990):363–376.

Chong, Y.Y., and D. F. Ilendry, Econometric Evaluation of Linear Macro-Econometric Models, *Review of Economic Studied*, 53(1986):671-90

Clemente, J., A. Monta˜n´es, and M. Reyes. Testing for a unit root in variables with a double change in the mean. *Economics Letters* 59(1998): 175–182.

Deaton, A. and J. Muellbauer, An Almost Ideal Demand System, *The American Economic Review* 70(1980): 312-326.

Deaton, A. S., The Analysis of Consumer Demand in the United Kingdom, 1900-1970, *Econometrica*, 42(1974): 341-367

Deaton, A. S., The Estimation and Testing of Demand Equations: A Note, *European Economic Review*, 3 (1972): 399-411.

Duffy, M. Advertising and food, drink and tobacco consumption in the United Kingdom: a dynamic demand system, Agricultural Economics, 28(2003): 51–70.

Duffy, M. Tobacco consumption and policy in the United Kingdom, *Applied Economics*, 38(2006): 1235–57.

Eakins, John M and Liam A Gallagher Dynamic Almost Ideal Demand Systems: An Empirical Analysis of Alcohol Expenditure in Ireland, *Applied Economics*, 35(9) (2003):1025-36.

Eales, J.S., and L.J. Unnevehr. "The Inverse Al-most Ideal Demand System." *Eur. Econ. Rev.* 38(1994):101-15.

Engle, Robert F. and C.W.J. Granger, Co-integration and error correction: Representation, estimation and testing, Econometrica 55(1987): 251–276.

Green, R. D. and J. M. Alston, "Elasticities in AIDS Models." *American Journal of Agricultural Economics*. 72(1990):442-45.

Green, R. D. and J. M. Alston, "Elasticities in AIDS Models: A Clarification and Extension." *American Journal of Agricultural Economics.* 73(1991):874-75.

Hahn, W., "Elasticities in AIDS Models: Comment", *American Journal of Agricultural Economics*. 76(1994):972-77.

Ishida, T., Ishikawa, N., and Fukushige, M., "Impact of BSE and bird flu on consumers' meat demand in Japan", *Applied Economics*, 42(1) (2008):49-56

Johansen, S., Statistical analysis of cointegration vectors*. J. Econ. Dyn. Control* 12(1988), 231–254.

Karagiannis, G., Katranidis, S., Velentzas, K., An error correction almost ideal demand system for meat in Greece, *Agricultural Economics*, 22 (2000):29–35

Klaiber, H. A., and M. T. Holt. The Role of Theoretical Restrictions in Forecasting with Inverse Demand Models. *American Journal of Agricultural Economics* 92(1) (2010):70–85.

Marsh, T. L., T. C. Schroeder, and J. Mintert. "Impacts of meat product recalls on consumer demand in the USA." *Applied Economics.* 36 (2004): 897-909.

Mazzocchi, M., D. Delle Monache, and A. E. Lobb, A structural time series approach to modeling recurrent meat scares in Italy, *Applied Economics*, 38 (2006): 1677-1688

Mazzocchi, Mario, "No News is Good News: Stochastic Parameters versus Media Coverage Indices in Demand Models after Food Scares." *American Journal of Agricultural Economics.* 88 (2006):727-741.

Mazzocchi, Mario, “Time-varying coefficients in the Almost Ideal Demand System: an empirical appraisal.” *European Review of Agricultural Economics.* 30 (2) (2003):241-270.

Morana, C. Modelling evolving long-run relationships: an application to the Italian energy market*, Scottish Journal of Political Economy*, 47(2000), 72–93.

Pelzel A. M., B. J. McCluskey, and A. E. Scott. “Review of the highly pathogenic avian influenza outbreak in Texas, 2004.” Journal *of American Veterinary Medecine Association.* (2006) 228(12).

Phillips, P., McFarland, J., Forward exchange market unbiasedness: The case of the Australian dollar since 1984. *J. Int. Money Fin.* 16(1997.): 885–907.

Piggot, N. E. and T. L. Marsh, “Does food safety information impact U.S. meat demand?” *American Journal of Agricultural Economics.* 86 (2004):154-74.

Senne, D., A., “Avian Influenza in North and South America, 2002–2005”, *Avian Diseases*: 51(2007):167–173.

Sims, L.D., “Lessons learned from Asian H5N1 outbreak control”. *Avian Dis.*51 (2007): 174-181.

Sims, L.D., and C. Narrod, Understanding avian influenza(chapter 1 to 3). 2008. Available at http://www.fao.org/avianflu/documents/key_ai/key_book_preface.htm.

Verbeke, W.R. W. Ward, “A Fresh Meat Almost Ideal Demand System Incorporating Negative TV Press and Advertising Impact.” *Agricultural Economics*. 25(2001):359-74.

Wang, Z., D.A. Bessler. Forecasting performance of multivariate time series models with full and reduced rank: An empirical examination. *International Journal of Forecasting* 20(2004):683–695.

Wang, Z., D.A. Bessler. The homogeneity restriction and forecasting performance of VAR-type demand systems: An empirical examination of U.S. meat consumption. *Journal of Forecasting* 21(2002):193–206.

Wang, Z., D. A., Bessler.,Forecast evaluations in meat demand analysis. *Agribusiness.* 19 (2003): 505–524.

Wang, Z., D. A., Bessler, Price and quantity endogeneity in demand analysis: evidence from directed acyclic graphs. *Agricultural Economics. 34 (2006): 87–95.*

Table 1 Unit Root Tests with and without Structural Change

Variables	Descriptions	Augmented Dickey-Fuller tests for zero structure break		Clemente, Montanes and Reyes (1998) test for one structure break (IO model)		for one structure break (AO model)	
		Level	difference	level	difference	level	difference
w1	Budget share of beef	-4.250**	-14.965**	-3.947	-5.456**	-2.811	-4.421**
w2	Budget share of pork	-5.730**	-13.221**	-2.918	-5.401**	-2.362	-4.764**
w3	Budget share of chicken	-3.386**	-21.855**	-3.573	-5.232**	-2.928	-5.489**
w4	Budget share of turkey	-2.568	-13.764**	-4.372**	-4.4**	-0.945	-5.976**
lnp1	Retail price of beef (cents/lb)	-0.358	-13.013**	-3.151	-5.761**	-2.714	-3.85**
lnp2	Retail price of pork(cents/lb)	-0.921	-12.911**	-2.93	-4.396**	-3.054	-3.295
lnp3	Retail price of chicken(cents/lb)	-2.000	-19.756**	-2.391	-9.436**	-3.664**	-9.98**
lnp4	Retail price of turkey(cents/lb)	-3.954**	-15.416**	-2.043	-5.427**	-0.649	-5.002**
lnq1	consumption of beef (lb/capita)	-10.275**	-30.243**	-3.499	-7.569**	-1.982	-7.639**
lnq2	consumption of pork(lb/capita)	-8.259**	-25.916 **	-2.082	-5.749**	-2.006	-5.629**
lnq3	consumption of chicken(lb/capita)	-4.449**	-34.857**	-2.365	-8.632**	-1.912	-12.53**
lnq4	consumption of turkey(lb/capita)	-10.461**	-25.291**	-2.371	-6.958**	-1.868	-4.744**
lnexp	Expenditure on meat (cents/capita)	-3.527**	-34.655**	-1.195	-6.891**	-1.15	-7.096**
	5% critical value	-2.879	-2.880	-4.27	-4.27	-3.56	-3.56

Note: the null hypothesis of Augmented Dickey-Fuller test is that there is a unit root at some level of confidence; ** indicates we cannot accept the null hypothesis of a unit root at the 5% critical value. The AO model captures a sudden change in a series and the IO model allows for a gradual shift in the mean of the series.

Table 2 Selection-order Criteria for Lag (m_1) and Johansen tests for Cointegration (r_1)

	Selection-order criteria for lag			Johansen tests for cointegration	
Lag	AIC	HQIC	BIC	Lag=2	Lag=3
1989m1-2003m10 (before animal disease outbreaks in U.S.)					
0	-18.1863	-18.1642	-18.1318	81.4043	77.9229
1	-22.8225	-22.7341	-22.6046	26.8317	19.1338
2	-23.0637	-22.9091*	-22.6825*	2.9682*	2.6257*
3	-23.064*	-22.8431	-22.5194		
4	-23.0581	-22.7708	-22.35		
1989m1-2006m7(after animal disease outbreaks in U.S.)					
0	-18.2971	-18.2776	-18.2488	93.0585	91.6218
1	-22.7335	-22.6554	-22.5403	34.3344	23.573
2	-22.9378	-22.801*	-22.5997*	4.0414	3.3972*
3	-22.9842*	-22.7889	-22.5012		
4	-22.9635	-22.7096	-22.3356		
1989m1-2010m12 (whole sample)					
0	-18.1603	-18.1438	-18.1192	101.2958	103.9294
1	-22.8086	-22.7426	-22.6443	33.5604	21.8731
2	-23.0387	-22.923	-22.7511*	5.2282	4.1758
3	-23.1165*	-22.9513*	-22.7056		
4	-23.1097	-22.8949	-22.5756		

Note: in this table, $AIC = 2k - 2\ln(L)$ where k is the number of parameters in the statistic model and L is the maximized value of the likelihood function for the estimated model; $BIC = n\ln(\hat{\sigma}_e^2) + k\ln(n)$, where $\hat{\sigma}_e^2$ is the error variance for the estimated model; $HQIC = n\log(\frac{RSS}{n}) + 2k\log\log(n)$, where n is the number of observation and RSS is the residual sum of squares that results from the statistical model.

Table 3 Model Selection Procedure for Rank (r_1) and Lag (m_1)

Lag	Rank	1989m1-2003m10		1989m1-2006m7	
		HQIC	BIC	HQIC	BIC
1	1	-22.706	-22.6207	-22.6124	-22.5365
1	2	-22.7689	-22.6516	-22.6808	-22.5764
2	1	-22.8627	-22.6807	-22.7269	-22.5649
2	2	**-22.9423**	**-22.7282**	**-22.8237**	**-22.6332**
3	1	-22.8249	-22.5454	-22.7532	-22.5047
3	2	-22.8629	-22.5512	-22.8019	-22.5248
4	1	-22.7551	-22.3774	-22.6804	-22.3448
4	2	-22.7761	-22.366	-22.7102	-22.3458
5	1	-22.8341	-22.3575	-22.715	-22.2917
5	2	-22.829	-22.3199	-22.7152	-22.263

Table 4 Estimation Results from the Static IAIDS and Model Diagnostics

		Model Estimation				Model Diagnostics			
		AI-US	AI-media coverage	AI-human death	BSE-US	DW test on residual	Unit Root Test on residual	RMSE	R-sq
1989m1	Beef		-0.0036			2.2164	-8.340***	0.0080	0.9997
-			(0.0023)						
2003m10	Pork		0.0032*			2.5930	-8.629***	0.0060	0.9995
			(0.0017)						
	chicken		0.0001			1.8368	-8.180***	0.0069	0.9992
			(0.0019)						
1989m1	Beef	1.0231*	-0.0006	0.0168***	-0.3473	1.9522	-5.051***	0.0092	0.9996
-		(0.5730)	(0.0004)	(0.0023)	(0.4321)				
2006m7	Pork	-0.4283	-0.0002	-0.0051***	0.9061	2.2027	-8.103***	0.0071	0.9993
		(0.4352)	(0.0003)	(0.0018)	(0.5625)				
	chicken	-0.5372	0.0007**	-0.0136***	-0.6775	1.5601	-5.292***	0.0068	0.9993
		(0.4232)	(0.0003)	(0.0017)	(0.4140)				
1989m1	Beef	0.8375	0.0005*	0.0052***	-0.3704	2.5680	-9.995***	0.0085	0.9997
-		(0.5184)	(0.0003)	(0.0005)	(0.3862)				
2010m12	Pork	-0.4167	-0.0005**	-0.0022***	1.1046**	2.4600	-10.460***	0.0064	0.9994
		(0.3916)	(0.0002)	(0.0004)	(0.5075)				
	chicken	-0.3822	-0.0001	-0.0055***	-0.6996**	2.4733	-11.409***	0.0058	0.9995
		(0.3541)	(0.0002)	(0.0003)	(0.3475)				

Note: Coefficients and standard errors are multiplied by 100;*, **, *** indicate significant at the 10%, 5% and 1% level; Standard errors are in parenthesis.

Table 5 Long-run Own- and Cross-Price and Expenditure Flexibilities

	1989m1-2003m10			1989m1-2006m7			1989m1-2010m12		
	beef	pork	chicken	beef	pork	chicken	beef	pork	chicken
beef	**-0.8713*****	-0.1457***	-0.0885***	**-0.9248*****	-0.1156***	-0.0774***	**-0.8914*****	-0.1266***	-0.0700***
	(0.0248)	(0.0093)	(0.0057)	**(0.0251)**	(0.0083)	(0.0055)	**(0.0193)**	(0.0067)	(0.0040)
pork	-0.1119***	**-0.8316*****	-0.0142***	-0.0405	**-0.8412*****	-0.0283***	-0.0677***	**-0.8347*****	-0.0251***
	(0.0254)	**(0.0112)**	(0.0037)	(0.0301)	**(0.0086)**	(0.0051)	(0.0223)	**(0.0074)**	(0.0048)
chicken	0.0036	0.0139	**-0.8590*****	0.0346	-0.0117	**-0.8600*****	-0.0103	-0.0242***	**-0.8568*****
	(0.0363)	(0.0145)	**(0.0083)**	(0.0340)	(0.0125)	**(0.0082)**	(0.0230)	(0.0079)	**(0.0030)**
expenditure	-1.0771***	-0.9773***	-0.8737***	-1.0998***	-0.9192***	-0.8573***	-1.0681***	-0.9269***	-0.9248***
	(0.0261)	(0.0343)	(0.0443)	(0.0261)	(0.0356)	(0.0386)	(0.0216)	(0.0288)	(0.0290)
AI media coverage	-0.0072	0.0112**	0.0005	-0.0012	-0.0008	0.0025**	0.0010	-0.0018**	-0.0005
	(0.0046)	(0.0060)	(0.0071)	(0.0008)	(0.0010)	(0.0010)	(0.0005)	(0.0007)	(0.0007)
AI human deaths				0.0324***	-0.0171***	-0.0482***	0.0100***	-0.0076***	-0.0196***
				(0.0044)	(0.0059)	(0.0061)	(0.0009)	(0.0013)	(0.0011)

Note: we calculated the Marshallian own- and cross price flexibilities using equation $\varepsilon_{ij} = -\delta_{ij} + \frac{\gamma_{ij} + \beta_i(\alpha_j + \sum_{i=1} \gamma_{ij} \ln q_k)}{w_i}$ and the expenditure flexibilities using equation $f_i = -1 + \frac{\beta_i}{w_i}$, where δ_{ij} is the Kronecker delta with $\delta_{ij} = 1$ if $i = j$ and $\delta_{ij} = 0$ if $i \neq j$. *, **, *** indicate significant at the 10%, 5% and 1% level; Standard errors are in parenthesis.

Table 6 Estimation Results from the EC-IAIDS Model

		AI-US	AI-media coverage	AI-human death	BSE-US	Δw_{t-1}	$u_{beef,t-2}$	$u_{pork,t-2}$	$u_{chicken,t-2}$	RMSE	R-sq
1989m1-2003m10	Beef		0.0336			-11.1821***	**-11.9550***	-12.3468	-3.5983	0.0040	0.8725
			(0.0334)			(2.5491)	**(6.5747)**	(8.2662)	(6.3261)		
	Pork		0.0179			-7.9512***	4.0262	**3.3013**	4.3918	0.0031	0.9290
			(0.0255)			(2.3362)	(5.0379)	**(6.3276)**	(4.8332)		
	chicken		-0.0261			-6.1812**	-3.7455	-6.6925	**-10.5372****	0.0034	0.7391
			(0.0283)			(3.1049)	(5.5451)	(7.0431)	**(5.3526)**		
1989m1-2006m7	Beef	0.5226**	0.0084	0.0041	-0.3989***	-12.7952***	**-29.9868*****	-24.9069***	-19.7354**	0.0043	0.8533
		(0.2356)	(0.0339)	(0.0084)	(0.1288)	(2.3516)	**(7.6247)**	(8.7519)	(8.5523)		
	Pork	-0.2292	0.0105	0.0052	0.3710**	-9.3800***	5.6888	**0.7484**	-3.0699	0.0030	0.9323
		(0.1613)	(0.0232)	(0.0058)	(0.1873)	(2.1080)	(5.2317)	**(6.1330)**	(6.1115)		
	chicken	-0.2843	-0.0060	-0.0113	0.0025	-7.6040***	4.4136	1.5689	**-0.3776**	0.0039	0.7188
		(0.2144)	(0.0308)	(0.0076)	(0.1722)	(2.7641)	(6.9959)	(8.1480)	**(7.7560)**		
1989m1-2010m12	Beef	0.5211**	0.0124	0.0020	-0.4188***	-10.9211***	**-30.1533*****	-13.2837**	-20.8174**	0.0045	0.8413
		(0.2374)	(0.0336)	(0.0067)	(0.1346)	(2.1534)	**(8.5169)**	(6.5043)	(9.4714)		
	Pork	-0.1971	0.0015	0.0016	0.3961**	-9.2270***	1.7190	**4.4262**	0.3583	0.0032	0.9233
		(0.1673)	(0.0237)	(0.0047)	(0.1909)	(1.9230)	(5.9993)	**(4.4580)**	(6.6950)		
	chicken	-0.3040	-0.0017	-0.0058	-0.0126	-7.9034***	4.6507	-4.7119	**-4.1110**	0.0040	0.6983
		(0.2126)	(0.0300)	(0.0059)	(0.1726)	(2.4709)	(7.6468)	(5.8834)	**(8.4790)**		

Note: coefficients and standard errors in this table are all multiplied by 100 to make them more comparable;*, **, *** indicate significant at the 10%, 5% and 1% level; Standard errors are in parenthesis

Table 7 Short-run Own- and Cross-Price and Expenditure Flexibilities

	1989m1-2003m10			1989m1-2006m7			1989m1-2010m12		
	beef	pork	chicken	beef	pork	chicken	beef	pork	chicken
beef	**-0.7936*****	-0.1183***	-0.0935***	**-0.7978*****	-0.1111***	-0.0958***	**-0.7951*****	-0.1109***	-0.0969***
	(0.0092)	(0.0049)	(0.0082)	**(0.0093)**	(0.0047)	(0.0084)	**(0.0086)**	(0.0043)	(0.0076)
pork	-0.1193***	**-0.8084*****	-0.0622***	-0.1120***	**-0.8117*****	-0.0684***	-0.1115***	**-0.8100*****	-0.0692***
	(0.0052)	**(0.0049)**	(0.0052)	(0.0048)	**(0.0043)**	(0.0051)	(0.0045)	**(0.0040)**	(0.0045)
chicken	-0.0914***	-0.0635***	**-0.8412*****	-0.0939***	-0.0696***	**-0.8317*****	-0.0950***	-0.0706***	**-0.8319*****
	(0.0088)	(0.0052)	**(0.0107)**	(0.0089)	(0.0050)	**(0.0107)**	(0.0080)	(0.0045)	**(0.0094)**
expenditure	-1.0254***	-0.9967***	-0.9756***	-1.0245***	-0.9932***	-0.9819***	-1.0277***	-0.9842***	-0.9858***
	(0.0088)	(0.0118)	(0.0145)	(0.0088)	(0.0108)	(0.0153)	(0.0079)	(0.0098)	(0.0134)
AI media coverage	0.0676	0.0633	-0.0969	0.0170	0.0372	-0.0224	0.0250	0.0052	-0.0064
	(0.0673)	(0.0901)	(0.1050)	(0.0682)	(0.0820)	(0.1143)	(0.0677)	(0.0837)	(0.1115)
AI human deaths				0.0079	0.0177	-0.0401	0.0038	0.0055	-0.0205
				(0.0162)	(0.0195)	(0.0270)	(0.0128)	(0.0159)	(0.0211)

Note: *, **, *** indicate significant at the 10%, 5% and 1% level; Standard errors are in parenthesis.

Table 8 Tests of Homogeneity and Symmetry Restrictions in the Demand Model

Mode l		Unrestricted V.S. Homogeneity (3)	Unrestricted V.S. Symmetry (3)	Homogeneity V.S. Restricted (3)	Symmetry V.S. Restricted (3)	Unrestricted V.S. Restricted (6)
			1989m1-2003m10			
IAIDS	T1	26.26 ***	34.74 ***	27.77***	19.29***	54.03***
	T2	21.93***	31.61***	26.61***	18.24***	47.80***
	T3	4.12***	6.06***	5.05***	3.40**	9.48***
	T4	12.37***	18.17***	15.15***	10.21**	28.43***
ECM-IAIDS	T1	9.64**	0.68	0.9	9.86**	10.54
	T2	9.34**	0.68	0.90	9.56**	10.22
	T3	1.47	0.11	0.14	1.51	1.61
	T4	4.41	0.32	0.42	4.52	4.84
			1989m1-2006m7			
IAIDS	T1	28.29***	26.33***	17.14***	19.10***	45.43***
	T2	17.55***	21.17***	16.71***	17.51***	33.95***
	T3	4.99***	7.23***	4.14***	4.15***	4.26***
	T4	14.96***	21.69***	12.43***	12.44***	12.79**
ECM-IAIDS	T1	7.87**	8.40**	3.48	2.95	11.35*
	T2	7.67	8.07	3.47	2.88	11.06*
	T3	1.87	0.14	1.90	1.90	1.92*
	T4	5.60	0.41	5.70	5.69	5.77
			1989m1-2010m12			
IAIDS	T1	43.93***	22.51***	12.99***	34.41***	56.92***
	T2	38.91***	21.01***	12.74***	32.56***	50.98***
	T3	7.78***	9.50***	5.42***	5.57***	5.70***
	T4	19.80***	28.49***	16.27***	16.70***	17.11***

ECM-IAIDS	T1	16.01***	2.98	2.64	15.67***	18.65***
	T2	15.45***	2.98	2.64	15.12***	18.06***
	T3	2.78**	0.18	2.59*	2.64**	2.65**
	T4	7.67*	0.55	7.78*	7.91**	7.94
			Critical values			
	df	0.1		0.05		0.01
λ^2	3	6.2513		7.8147		11.3448
	6	10.6446		12.5915		16.8118
F	3	2.0838		2.6049		3.782
	6	1.7741		2.0986		2.802

Note: degree of freedom of each test is listed in the parentheses.

Table 9 RMSFE and Statistics on Encompassing Tests

	2003m11-2010m12			2006m8-2010m12		
	beef	pork	chicken	beef	pork	chicken
ECM	0.0037	0.0046	0.0034	0.0036	0.0040	0.0027
ECM-IAIDS	0.0056	0.0034	0.0051	0.0064	0.0037	0.0047

Tests of Two-way Encompassing

	Coefficients	Test statistics	Coefficients	Test statistics
ECM encompasses ECM-IAIDS	0.4060	F(1,256)=181.14 Prob>F=0	0.3160	F(1,157)=67.17 Prob>F=0
ECM-IAIDS encompasses ECM	0.5939	F(1,256)=387.71 Prob>F=0	0.6840	F(1,157)=314.76 Prob>F=0

Note: we did the following transformation of forecast values to get the forecast budget share of $\hat{w}_t = \exp(\ln p_t + \ln \hat{q}_t - \ln \exp_t)$, where $\ln \hat{p}$, $\ln \hat{q}$ and $\ln \hat{\exp}_t$ are one-step ahead forecast value from the ECM model.

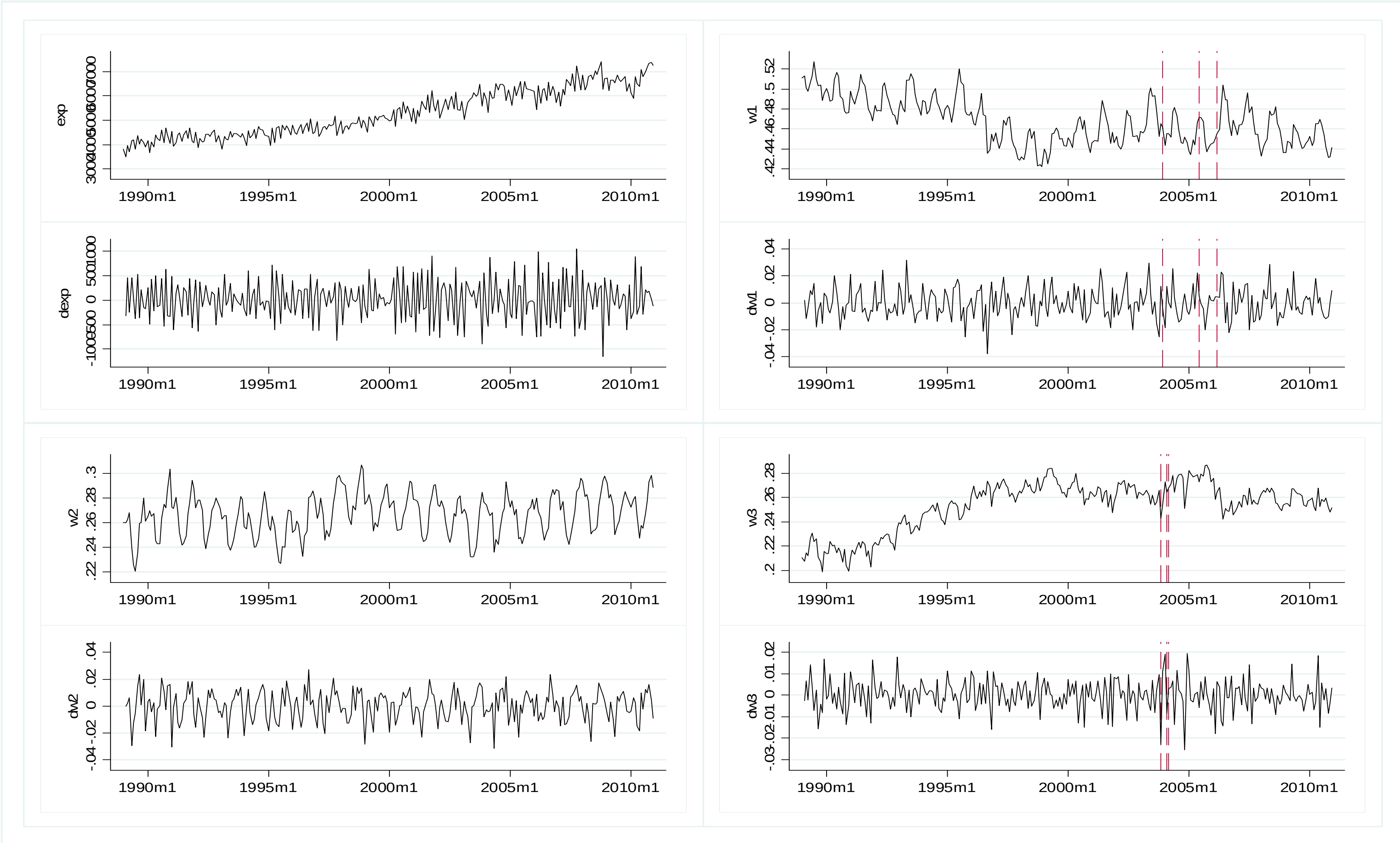

Figure 1 Meat expenditure and budget share for beef, pork and chicken in the level and in the first difference

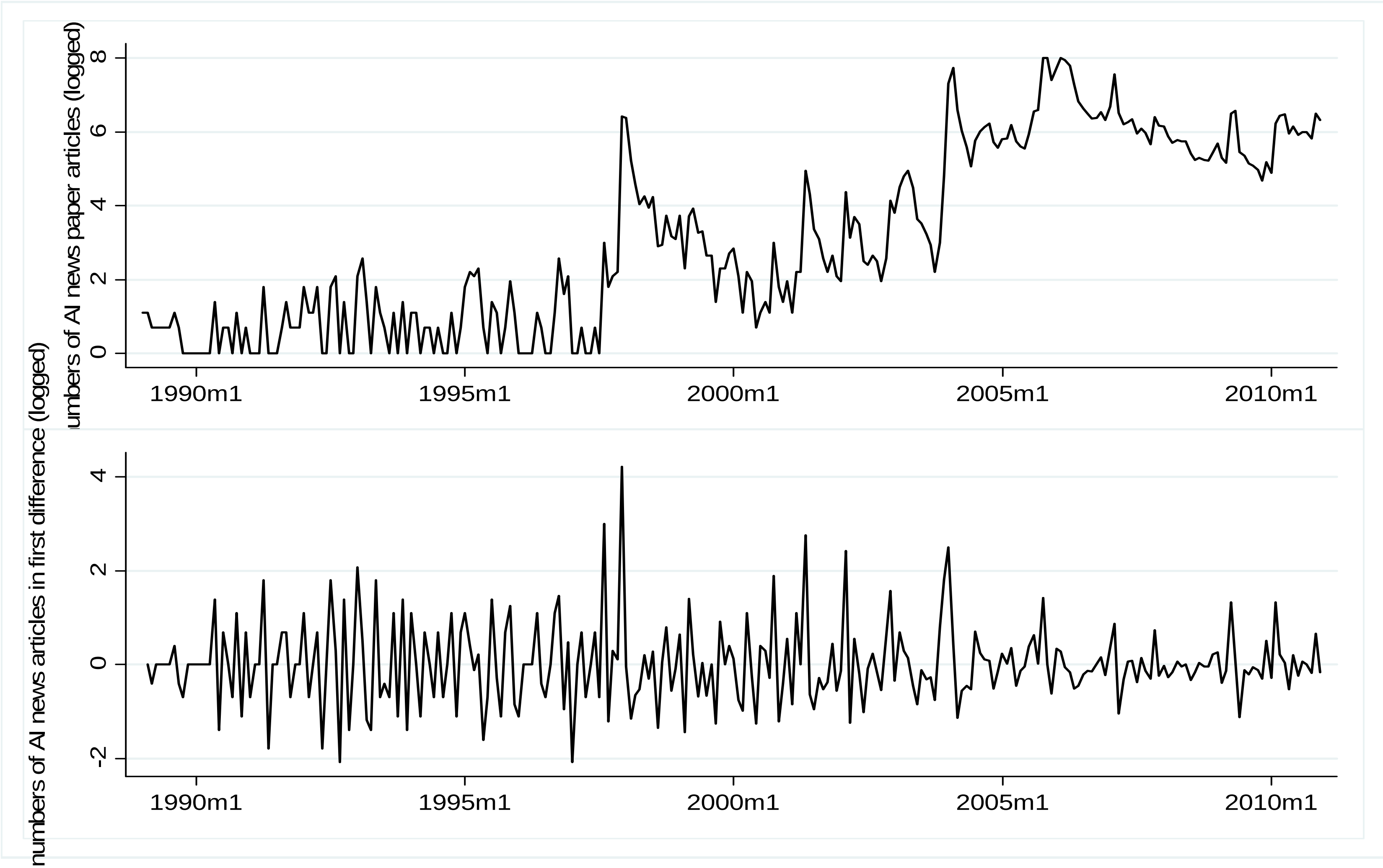

Figure 2 Numbers of AI newspaper articles in level and in first difference