An Analysis of Meat Demand in Canada

By

Jing Yan Lu

(4267643)

Major Paper presented to the

Department of Economics of the University of Ottawa

In partial fulfillment of the requirements of the M. A. Degree

Supervisor: Professor Kathleen Day

ECO 7997

Ottawa, Ontario

July 2006

CONTENTS

ACKNOWLEDGMENTS

I would like to thank my advisor, Professor Kathleen Day for her strong support, valuable advices and well-organized guidance during this study. Her encouragement and patience in helping me to improve this paper is very appreciated.

I also thank my friends Andy Baldwin, who works for Statistics Canada and Leo Curtin, who works for Agriculture Canada for helping me collecting the data and providing me valuable thoughts and suggestions.

My sincere gratitude goes to my husband and my family for their love and support.

ABSTRACT

Meat is important in the Canadian diet, but the pattern of meat consumption has changed over the last 30 years. The main objective of this study is to conduct an econometric analysis of meat demand in Canada using Canadian time series data for the period 1971-2003 to obtain updated estimates of demand elasticities and to investigate the factors that caused the pattern of meat consumption to change. Three major meats are included in the model: beef, pork and chicken. Both static and dynamic demand equations are estimated for this study, using the two-stage least square method and the ordinary least square method. The main finding is that prices and income cannot explain fully the meat consumption pattern. Changes in consumers' preferences and tastes over time due to health concerns and food scares capture part of the structural change in meat consumption patterns.

1. INTRODUCTION

In Canada, as in other countries, consumption patterns for meat products have changed considerably over the last few decades. This empirical evidence is illustrated in figures1-3, using annual per capita disappearance of beef, pork and chicken over the period 1963-2003. [1] Figure 1 shows that at the retail level, beef consumption increased from 33.8 kg per capita in 1963 to the peak level of 50.9 kg in 1976, and then fell continuously until reaching a low of 30.1 kg in 2002. It went up again after 2002. Figure 2 indicates that pork consumption has shown year-to-year variation from 1963 to 2003, reaching its lowest level of 23.5 kg per capita in 1966 and its highest level of 32.0 kg per capita in 1980. Figure 3 shows that per capita consumption of chicken has grown considerably from 1963 to 2003, rising from 8.9 kg in 1963 to 30.7 kg in 2003. Figure 4 presents the per capita consumption of fish over the period 1971-2003. It shows a continuously increasing trend, with a low of 5.5 kg in 1971 and a high of 10.0 kg in both 1999 and 2002, though there is a small amount of variability during that period. All these figures are evidence of the structural change in meat consumption.

The most striking feature is the steady increase in chicken consumption. Moreover, beef consumption has declined sharply since 1976. A significant gain in poultry productivity resulting in lower real retail prices for poultry can partly explain this phenomenon. Other experts postulate that the recent shift from beef to poultry in consumption is not entirely caused by changes in relative prices or income, but also due to other factors such as demographic change (see Pollak and Wales [1980, 1981]),

---

[1] Consumption data are not easy to collect. Disappearance data are used as a proxy for consumption in practice. Disappearance data for beef and pork are published in CANSIM II Table 003-0035, while similar data for chicken can be found in CANSIM II Table 003-0030017. It is measured using the formula

Disappearance = Consumption = Production + Change in Inventory –(Exports – Imports)

Per capita consumption = per capita disappearance = disappearance / population advertising (see Piggott et al. [1995], Brester and Schroeder [1995], Kinnucan et al. [1997], and Goddard et al. [2005]) and an evolution in consumers' preferences driven by a growing awareness of health and food quality (see Chalfant and Alston [1988], Dahlgran [1988], Robenstein and Thurman [1996], Burton and Young [1996], Gao and Shonkwiler [1993], Gao et al. [1997], Lloyd et al. [2001] and Love [2005]).

Several studies have indicated that this structural change in meat consumption is also due to meat substitutes (see Pearson [1976] and Lambert et al. [2005]). People can obtain nutrition from different food sources. For instance, the Chinese have a history of substituting soybean products for animal products; for example, they drink soya milk instead of cow's milk. There are many other examples. Fish and meats are alternative protein sources in the human diet. The increase in fish consumption likely reflects the consumers' belief that fish is a healthy food. People would like to use fish as a meat substitute. Therefore, meat demand studies that include fish can help to explain movements in meat consumption.

This study should be of interest to researchers for several reasons. First, I consider the impact of substitutes on consumer behavior. This is at least of interest to meat producers. For example, beef producers have been steadily losing share to poultry products for many years. Anderson and Shugan (1991) pointed out that shortly after World War II, beef had been holding a 3:1 market share advantage over poultry, but as beef consumption declined gradually over time, beef and poultry possess almost the same market share now. Knowing beef consumption trends can help producers to design strategies that will bring them success. Second, besides prices and income, factors such as demographic variables, health concerns and advertising play an important role in the meat industry.

The common problem arising is how to incorporate those factors into the estimating equation. There are several ways to do that. My study does so using dummy variables. This method is of interest to researchers since it is easier to implement compared to other methods especially in dealing with time series data. Third, meat consumption trends can be a good indicator for policy makers who are concerned about such issues as agricultural trade. Information about meat demand can help them to regulate the particular industries.

It is demand elasticities that usually draw researchers' attention, and there is some earlier Canadian literature on this issue. To the best of my knowledge, the most recent demand estimates for Canada were obtained using 1960-1987 annual Canadian time series data and a single-equation model (Chen [1991]). In this paper, annual Canadian time series data from 1971 to 2003, at the retail level, are used to study how prices, incomes and other factors affect consumers' consumption of meats such as beef, pork and chicken. The principle objective of the analysis is to build the correct model incorporating demand shocks, and then to use an appropriate econometric approach to estimate the model using recent Canadian data to obtain detailed and updated estimates of demand elasticities, namely price elasticities and income elasticities, which are often of interest to policy makers.

The structure of the paper is as follows: section 2 briefly reviews previous relevant studies and the theoretical framework. The data sources and data manipulation procedures are described in section 3. Section 4 presents the empirical model, the estimation technique, the results and their implications. The final section outlines the conclusions and areas for future research.

2. REVIEW OF STUDIES AND THEORETICAL FRAMEWORK

2.1 Literature review

The economic study of demand is based on neoclassical consumer theory. Consumer demand equations are derived from this theory, which states that consumers' consumption behavior is to maximize their utilities subject to their budget constraint. The single demand equation derived from the individual's utility-maximization behavior can be expressed as $Q_i = Q(P_i, P_j, Y)$, where P_i stands for the own price, P_j stands for the prices of all other goods including substitute goods and complementary goods and Y stands for income (Intriligator et al. [1996], 248-250).

Tests of demand theory are formulated by requiring that the demand equations be consistent with utility maximization. Specifically, a system of demand functions taking the quantity consumed of each commodity as a function of income and the prices of all commodities is specified. The underlying utility function that has been the most commonly used is the double logarithmic or constant elasticity form, leading to the following specification for the individual demand equation as

$$\ln Q_i = \alpha + \beta_1 \ln P_1 + \beta_2 \ln P_2 + ... + \beta_n \ln P_n + \gamma \ln Y + e_i \quad (i = 1,2,3,...,n). \quad (1)$$

Once data on consumers' per capita consumption, retail prices and per capita disposable income have been collected, econometric methods can be used to estimate the parameters of the demand equations and verify whether the empirical results are consistent with economic theory. If the results are consistent with consumer theory, the parameter estimates will satisfy the three conditions implied by consumer theory, specifically, homogeneity of degree zero in prices and income, Slutsky symmetry of the cross effects of demand functions, and the adding up condition (the estimated demand functions multiplied by their respective prices add up to total expenditure). In other words, adding up, homogeneity and symmetry conditions can be imposed on this system.

The first person to apply consumer theory to define and modify demand equations was Stone (1954), who developed the famous Linear Expenditure System, a system in which expenditures on individual commodities are expressed as linear functions of total expenditure and prices. In other words, each quantity demanded is a function of income Y and of all prices (the own price P_i and the prices of all other goods). He also estimated this system of demand equations, and analyzed the pattern of demand for consumers' goods in terms of this system using annual British data for the years 1920-1938. Ever since then, researchers have attempted to improve upon the structure of the Linear Expenditure System.

Theil (1965) approached demand analysis differently in a probabilistic way. Specifically, he developed the expenditure share (the proportion of total expenditure spent on a particular commodity) to formulate price and quantity index numbers and demand equations. His model was called the Rotterdam model. It may be written as

$$w_i d\ln(q_i) = \theta_i d\ln(Q) + \sum_{j=1}^{n} \pi_{ij} d\ln(P_j) \ , \qquad (2)$$

where $d\ln(Q) = \sum_i w_i d\ln(q_i)$ is the Divisia volume index, and θ_i, and π_{ij} are parameters to be estimated (Nayga and Capps [1994]). In this model, w_i corresponds to the expenditure share of the ith commodity in time period t; q_i denotes the quantity of the ith commodity in time period t; and P_j stands for prices in time period t. Like Stone, Theil also used this model to test consumer theory. The interpretation of the Rotterdam model is that log differentials are approximated by log differences in empirical applications. Consequently, the Rotterdam model is a flexible approximation to an unknown demand system.

In the 1970s and 1980s, more emphasis was placed on flexible functional forms (FFF) derived from utility or cost functions.[2] The traditional empirical studies rely on either quantity-dependent or price-dependent equations with the assumptions that prices are predetermined and quantities are predetermined in the demand system respectively. Basically they are derived from direct and inverse demand functions. However those assumptions are not quite appropriate. In analyzing simultaneous equations where prices and quantities interact at the same time, the flexible functional form has the advantage. It allows one to estimate both demand and supply functions in a simultaneous equations framework (Chavas [1983]). Also, the combined development of duality theory and flexible functional forms allows researchers to use a number of system approaches to model consumer behavior (Moschini and Meilke [1989]).

The basic idea is to approximate the direct utility function or indirect utility function by some specific functional form that has enough parameters to be regarded as a reasonable approximation to whatever the true unknown function may be (Deaton and Muellbauer [1980]). For example, the Linear Expenditure System and the Rotterdam model discussed above are examples of FFF. Chalfant et al. (1991) pointed out that the use of flexible functional forms gave researchers the ability to model consumer preferences with no restrictions on the nature of substitution or complementarity relationships between pairs of goods.

[2] Intriligator et al. (1996), pp. 257, defined flexible functional forms as follows: "Flexible Functional Form guarantees that it is an arbitrarily close local approximation to any general set of demand functions and which allows at least one free parameter for measurement of each effect of interest, such as the effect of total expenditure and the effects of the n prices."

The Translog model, developed by Christensen et al. (1975), is another example of a FFF. In their paper, they approximated the indirect utility function V by a function which is quadratic in the logarithm of the ratios of prices to the value of total expenditure

$$\ln V = \alpha_0 + \sum_i \alpha_i \ln \frac{p_i}{E} + \frac{1}{2} \sum \sum \beta_{ij} \ln \frac{p_i}{E} \ln \frac{p_j}{E} \quad , \qquad (3)$$

where $\sum P_i X_i = E$, and X_i is the quantity consumed of the i th commodity. Using this form for the indirect utility function and applying Roy's identity, they obtained the demand equation. They used this Translog model to test the theory of demand by estimating their demand system without imposing the assumptions of additivity and homotheticity as hypotheses. They concluded that demand theory was invalidated by the rejection of the null hypothesis that the restrictions implied by demand theory are valid for either direct or indirect utility functions.

Another popular model is the Almost Ideal Demand System (AIDS) model developed by Deaton and Muellbauer (1980). They proposed and estimated this new model, which was more general than the Rotterdam and Translog models and more desirable. The AIDS model is more general than the Rotterdam and Translog models in that it provides an arbitrary first-order approximation to any direct or indirect utility function, while the Rotterdam and Translog models are second-order approximations. Also, the AIDS model had considerable advantages over both of them, in the sense that its functional form was more consistent with known household budget data and was easier to estimate because it could be linearized using the Stone price index, largely avoiding nonlinear estimation. Also, it could be used to test the restrictions of homogeneity and symmetry through linear restrictions on fixed parameters. The static version of the AIDS model is derived from the price-independent generalized logarithmic expenditure function using Shephard's Lemma, and is expressed in budget share form as

$$w_i = \alpha_i + \sum_{j=1}^{n} \gamma_{ij} \ln P_j + \beta_i \ln(\frac{X}{P}) \ , \qquad (4)$$

where in each period w_i and p_j are the expenditure share and price of the i th good in the system, X is the total expenditure on all n goods, and P is a price index defined by

$$\ln P = \alpha_0 + \sum_{j=1}^{n} \alpha_j \ln P_j + \frac{1}{2} \sum_{i}^{n} \sum_{j}^{n} \gamma_{ij} \ln P_i \ln P_j \ . \qquad (5)$$

The demand system described by (4) and (5) is a non-linear specification since $\ln P$ is a quadratic function of $\ln P_j$. The linearized almost ideal demand system (LA/AIDS) is obtained by replacing $\ln P$ by the linear approximation of Stone's Price Index, $\ln P^*$, where:

$$\ln P^* = \sum_{k=1}^{n} w_k \ln P_k \ , \qquad (6)$$

This typically provides a good approximation to the original system and is relatively easy to estimate. Deaton and Muellbauer estimated the model using annual British data from 1954 to 1974 on food, clothing, housing services, fuel, drink and tobacco. The estimation results suggested that the AIDS model with its simple static structure static was consistent with consumer theory.

Since the introduction of the AIDS model by Deaton and Muellbauer, there have been many applications of the model to the analysis of consumer demand for meat commodities. These have included studies by Blanciforti and Green (1983), Eales and Unnevehr (1988), Moschini and Meilke (1989), and Chalfant et al. (1991). Except for Blanciforti and Green (1983), these studies have applied the linear approximation of the

AIDS model using Stone's geometric price index (known as LA/AIDS) to obtain demand elasticities.

Although the AIDS model has been widely used in meat demand analysis due to its desirable properties and its consistency with consumer theory, it has some underlying problems. For example, Buse (1994) pointed out that

$$w_{it} = \alpha_i^* + \sum_{j}^{n} \gamma_{ij} \ln P_{jt} + \beta_i \ln(\frac{X_t}{P_t^*}) + u_{it}^*, \tag{7}$$

where $u_{it}^* = u_{it} - P_{it}(\ln \xi_t - \ln \xi_0)$; $\alpha_i^* = \alpha_i - \beta_i \ln \xi_0$; u and ξ are random errors; and $w, P, X,$ and P^* are defined as in equations (4) to (6).[3] This is a classic errors-in-variables problem with explanatory variables correlated with disturbance terms. It reveals that the seemingly unrelated regression (SUR) estimator is inconsistent and furthermore, a consistent instrument variables (IV) estimator cannot be constructed.

The earliest demand studies were based on the simple demand equation (1), which emphasizes prices and income. The development of the linear expenditure system model, the Rotterdam model, the Translog model and the AIDS model made it easier to test the predictions of consumer theory in empirical work. However, it became apparent that those models did not completely explain consumption patterns. For example, the observed meat consumption pattern suggests that there may have been structural changes in meat consumption patterns. If so, the implicit assumption that consumer preferences and hence demand function parameters are stable may not be valid. Alternatively, researchers could explore extensions of the basic demand models, to estimate the meat demand equations not only with prices and income, but also the inclusion of additional

---

[3] ξ_t is a random constant of proportionality between P_t and P^*_t, with $E(\ln \xi_t) = E(\ln \xi_0)$. Note that Buse adds a subscript t for the observation.

explanatory variables such as health concerns, advertising about meat products etc.

During the 1980s and 1990s, the linear expenditure system model, Rotterdam model, Translog model and AIDS model, with their extensions, were used to estimate the demand for food products, and more complex flexible forms were also developed. During this period, there was further research on the inclusion of explanatory variables other than prices and income. In particular, that research examined how the stability of the parameters of demand equations, advertising on meat products, health and nutrition, and food scares will affect food consumptions. Moschini and Meilke (1989) presented the idea that the observed meat consumption patterns of the last two decades cannot be fully explained by the dynamics of prices and income. To support this idea, they generated two regimes of expenditure share equations based on the four-meat AIDS model. One was a standard version with the hypothesized consistency of the parameters and the other included a time-varying component similar to a dummy variable to allow for structural change in the coefficients. The estimation method was the iterative seemingly unrelated regressions procedure, applied to U.S. expenditure survey quarterly data with 252 effective observations (3 equations and 84 quarters). The hypothesis of no structural change in the full set of parameters was rejected at the 5% significance level, which suggested that there was some degree of structural change over the period 1967 to 1987. These results indicated that structural change partly explained the observed U.S. meat consumption patterns.

As noted above, variables such as advertising and information on health concerns may also enter the meat demand system. However, these kinds of explanatory variables are difficult to measure, and proxy variables are often used in these approaches. There are several ways to incorporating qualitative variables into the model to be estimated. The index approach was first used by Brown and Schrader (1990). They developed the cholesterol index, which was based on the number of articles in medical journals that link cholesterol and arterial disease. The hypothesis underlying their cholesterol index is that consumers' attitudes towards cholesterol change slowly as scientific information is accumulated. They concluded that cholesterol information had reduced shell egg consumption by 19% by the end of 1986. Consumers receive health information from different sources including newspapers, television, friends, etc., so that the number of articles in scientific journals is just a simplification of the distribution of health information.

The Brown and Schrader index has been used, modified and updated in several studies. Chern et al. (1995) estimated four demand models for fats and oil in the U.S.A. They incorporated a health-risk variable into one of their models using the cholesterol index. Annual data from 1950-1988 were used for the empirical study. The results demonstrated that the model with health beliefs included produced more reasonable predictions of consumption effects due to health risk. Kinnucan et al. (1997) included the cholesterol-information index in a demand system to study the demand for meat in the USA. They examined the steady increase in per capita poultry consumption and decrease in beef consumption in U.S. Data for the period 1976 through 1993 were used to estimate the model. The estimating equation included the health information index and its first period lag. The results suggested that changes in meat consumption patterns in the U.S.A., i.e. the decrease in beef consumption and the increase in poultry consumption, were influenced by price, expenditure, and cholesterol-information elasticities. They also found that the health information elasticities in general were larger than the price elasticities, which suggested that small percentage changes in health information had larger impacts on meat consumption than small percentage changes in relative prices. Rickertsen et al. (2003) used an extended and modified version of the index, that is two newly constructed indices to study how information about cholesterol affected the demand for meat and fish in the Nordic countries. The global index (GI) includes all English language journals, while the Nordic index (NI) includes articles in all languages mentioning at least one of the Nordic countries. Annual data for 1966-1996 was used. The results implied that health information as measured by the indices had led to health-improving changes in consumption in all countries studied except for Denmark.

Using dummy variables is another approach to incorporate qualitative variables into a demand model. Chen (1991) included a time dummy variable in the dynamic Translog model to test for structural change in meat demand in Canada during the late 1970s, using time series data from 1967-1987. He introduced an intercept dummy variable and interaction variables to allow parameters to vary in the econometric model to account for the hypothesized structural break, which was in 1976. A likelihood ratio test was employed to test the hypotheses of common intercept coefficients and slope coefficients respectively. Although the null hypothesis of no change in the slope coefficients could not be rejected, the null hypothesis of a common intercept was rejected, indicating that there was a structural shift in meat demand in Canada. This finding confirmed that observed meat consumption patterns in Canada could not be fully explained by changes in relative prices and consumer real incomes.

The dummy variable method has been used elsewhere also. Blundell et al. (1993) specified their model together with household characteristics and other conditional variables such as demographic factors and seasonal factors using dummy variables. They estimated this model using data from the British family expenditure survey for the years 1970-1984. The results implied that the variation over time in factors such as household characteristics played an important role in meat demand analysis.

2.2 Canadian studies of meat demand

There have been several analyses of Canadian meat demand over the years. Earlier studies published in the 1970s focused on prices and income as well. Kulshreshtha and Wilson (1972) estimated a demand equation for beef only, within the Canadian beef sector, using aggregate annual data for the period 1949-1969. The parameter estimates were obtained using the two-stage least squares regression procedure (2SLS). The results suggested that the demand for beef at the retail level was positively related to consumers' income and the price of pork and negatively to its own price.

Tryfos and Tryphonopoulos (1973) estimated demand functions for beef, veal, pork, and chicken meat in Canada simultaneously, based on aggregate annual data for the period 1954 to 1970. The per capita consumption of meats (defined as per capita disappearance) was the dependent variables, while deflated retail prices (using the CPI for each meat) and per capita real disposable income were independent variables. They applied Zellner's Seemingly Unrelated Regression (SUR) estimator to obtain the estimates. The results suggested that a large proportion of the variation in the demand for meat in Canada was explained by the model. The income elasticity estimates displayed a positive sign and surprisingly large magnitude for chicken and negative signs for pork and lamb. They argued that these results could be attributed to changes in consumers' tastes over time. The findings also implied that consumption of each meat was sensitive to its own price, and that substitution effects might not be symmetric.

Since the early 1980s, the causes underlying the structural changes in meat consumption have been of interest to some Canadian researchers. The observed rise in the consumption of white meats such as chicken and fish, and the decline in the consumption of red meat, can be explained by both price and income factors and shocks. Health concerns, food scares and demographic factors are some examples of those shocks. Numerous Canadian studies have contributed to the investigation of structural change using aggregate time series data. Chalfant et al. (1991) conducted a meat demand study for Canada using the AIDS model. Specifically, they relied on aggregate time series data covering the 1960 through 1988 period to analyze beef, pork, poultry and fish demand in Canada. They assumed weak separability for meat groups, to estimate the second step of a two-stage demand system. Thus, they were able to treat total meat expenditure as exogenous. A time trend was added to capture the stable preferences hypothesis that structural change happens gradually each year. Also, they introduced some dynamics into the AIDS specification in this way. The elasticity estimates implied that meats were substitutes overall. The coefficient of the time trend was significant in all meat models, while it was negative for beef and pork and positive for chicken and fish. It was consistent with the observed trends, which were the decline in red meat (beef, pork) consumption and increase in white meat (poultry and fish) consumption.

Demand for meat products over time can be related to the traditional variables of prices and income, but also many varied variables such as advertising, health concerns, food scares and demographic factors, so it is important to integrate these factors into a meat demand system. Goddard et al. (2005) estimated beef, pork, chicken and turkey demand equations incorporating demand shock variables such as a health information index; a Canada's Food Guide index; and real aggregate expenditures on generic advertising, brand advertising, and fast food advertising of all meats respectively. The meat demand system was estimated using quarterly Canadian data over the period 1979 to 2003. The findings indicated that meat consumption over the last thirty years in Canada has exhibited patterns that were very similar to those in other industrialized countries, with decreasing beef consumption and increasing consumption of poultry products, largely chicken.

Saha et al. (2006) analyzed and estimated the impacts of demand and supply shocks resulting from BSE in the beef sector and avian influenza in the poultry sector.[4] Depending on the source of shocks, they incorporated food scares relative to BSE and avian influenza into the model using a media index to represent demand shocks, and BSE and avian influenza impacts on the number of live cattle and chicken entered into the supply chain as supply shocks. The methodological approach used in this study was a vector autoregressive framework (VAR). Provincial data on retail and farm level prices from January 1992 to July 2005 were used. The results suggest that demand shocks in the form of food scares may have short-term impacts on prices, but may not influence the

[4] "Avian influenza ('bird flu') is an infectious disease of birds caused by the Type A strains of influenza virus (WHO, 2006b). Among the subtypes of the virus, H5 and H7 are more pathogenic. The first documented outbreak of human infections with H5N1 occurred in Hong Kong in 1997. The outbreak of in South-East Asia in mid-2003 triggered world attention as the H5N1 was transmitted to human beings causing deaths. World reach of H5N1 is increasing as wild migratory birds are found to spread the virus." Saha et al. (2006, 1).

market in the long-run. Supply shocks may have short-term impacts on prices, but may persist for longer periods.

As mentioned earlier, the objective of this study is to analyze meat demand in Canada. Thus, I only need to estimate the demand equations. Demand shocks will enter into the demand equations as explanatory variables, while the supply shocks will enter as instrumental variables in the demand system due to the problem of simultaneity between prices and quantities.

2.3 Dynamic demand model versus static demand model

Traditional consumer theory assumes perfect information and that tastes are unchanging. The static demand equation (1) is based on this unchanged preferences assumption. Consumers are assumed to fully and instantly adjust their optimal purchase of commodities to current changes in prices and income in the static model, which is rarely common. Pollak (1970) pointed out that past consumption patterns were an important determinant of present consumption patterns. He made the demand function dynamic by adding a lagged dependent variable, the level of consumed quantities, into the static model based on the habit formation assumption. A fundamental assumption of the habit formation model is that the individual does not consider his current purchase to be a function of his future preferences and future consumption. That is why one only includes lagged dependent variable among the explanatory variables. This structure is widely used in empirical work.

Deaton and Muellbauer (1980) applied their static AIDS model to annual British data from 1954-1974, but the rejection of homogeneity and symmetry of parameter estimates implied that their static model did not explain consumer behavior well. It could not capture consumers' habit formation behavior. Deaton and Muellbauer suggested generalizing their static model by including stock effects or errors in price perceptions etc.

Blanciforti and Green (1983) made the AIDS model dynamic by incorporating habit effects into the AIDS model. They extended the intercept term to be a linear function of previous consumption levels to reflect persistence in consumption patterns. Annual U.S. time series data for 1948-1978 were used to estimate a demand system for 11 aggregate commodities including food. The results indicated that the dynamic demand system incorporating habit formation appeared to be a more viable demand system to use in modeling consumer behavior.

In this study, both static and dynamic demand models are estimated to examine consumption patterns and investigate consumer behavior.

2.4 Macro-data versus Micro-data

Many meat demand studies have focused on aggregate consumption using time-series data, known as macro-data, to obtain estimates of demand elasticities. However, one limitation of macro-data is that it does not permit researchers to take into account the effect on meat expenditures of various demographic factors. Research using micro-data has shown that it is important to take these factors into consideration when modeling the meat demand system. Unfortunately, much information about consumer behavior is lost through aggregation. Furthermore, it is difficult to incorporate socio-demographic effects in models estimated using aggregate data. The estimation results will be misleading due to the lack of those structural change factors. Therefore, some studies focus instead on using micro-level data in the econometric analysis of consumer demand. In comparing the performance of macro-data and micro-data regarding meat demand analysis, both have some advantages and problems.

Although the aggregate model using macro-data neglects information on time-varying household characteristics and should therefore have worse forecasting performance, it has an advantage over using micro-data because it allows for the easy computation of meaningful price and income elasticities. Micro-data has become increasingly popular recently because it was realized that demographic variables affect household expenditures and therefore meat consumption; micro-data can be used to integrate such variables and household characteristics into the econometric model. Unfortunately, there are some problems with using micro-data. One problem is the presence of zero reported consumption simply due to not consuming a good. For example, meat is never purchased by vegetarian consumers. This raises econometric issues that must be addressed in analyzing such data. Also, survey data are expensive to collect. Surveys are not conducted every year, which is always a problem to the researchers if they need the most recent survey data. Also, even though the survey is conducted, it does not provide detailed information on each item. Sometimes it is not enough for researches. For example, the most recent food expenditure survey in Canada was conducted in 2001 by Statistics Canada. It contains the total expenditure on meats, but fails to provide the detailed expenditure on individual meats. Thus, I cannot analyze current meat demand using this survey data.

The micro-data and macro-data issue has drawn more and more attention from demand researchers. Blundell et al. (1993) assessed the importance of using micro-data in the econometric analysis of consumer demand. In order to do so, they used UK survey data, pooled over the 15 years, covering about 4,000 households in each of the 15 years. They employed models considering household characteristics, seasonal factors and aggregation. They used the instrumental variable (IV) estimation method to obtain estimates from different aggregation procedures. They concluded that in assessing the relationship between models of consumer demand based on individual and aggregate data, it was important to establish the presence of nonlinearity in the micro-level Engle aggregation condition and the need for interaction with household specific characteristics, since either of these would rule out simple linear aggregation across individuals. They also drew the implications of working with the aggregate data. Aggregate models ignoring the interaction of individual characteristics with consumption expenditure led to biased estimates in explaining commodity demand.

In a word, the comparison of micro-data versus macro-data in meat demand analysis suggests that individual data are able to incorporate individual characteristics such as demographic factors into demand equations to explain structural changes in meat demand over time. However, it has several disadvantages including the zero consumption phenomenon and discontinuity of survey data. Macro-data also has some disadvantages such as the difficulty of incorporating demographic factors into the estimating equation. But, macro-data is widely available from data agencies such as Statistics Canada, which allows researchers to look at longer time periods. It is easy to obtain the demand elasticities by estimating an aggregate model. It still can capture structural shifts in meat demand using time trend, (Moschini and Meilke [1989], Eales and Unnevehr [1993] and Burton and Young [1996]). Therefore, aggregate annual Canadian data for the period 1971-2003 is adopted in this study.

3. DATA

Demand system estimation requires either micro- or macro- data on per capita consumption of commodities, retail prices and per capita disposable income. For this study of meat demand, I am interested in the changing pattern of meat consumption over time in Canada. Therefore, annual macro-data are employed. Most of the data for this study were obtained from Statistics Canada. The exact sources of data are listed in Table 1. Since the time period for which each data series is available is different, in order to form a complete data set, the sample period is restricted to the thirty-three year period 1971 to 2003.

Empirically, disappearance is used by Statistics Canada to approximate the total quantity consumed, using the formula:

$$\textit{Disappearance} = \textit{Consumption} = \textit{Production} + \textit{Change of Inventory} - (\textit{Exports} - \textit{Imports}). \quad (8)$$

The per capita disappearance is obtained by dividing by population. The per capita data are obtained directly from Statistics Canada. Since beef and pork per capita disappearances are measured in pounds, I converted them into kilograms to match the units of per capita disappearance of chicken. The formula for this conversion is

$$\textit{per capita disappearance (kg)} = \textit{per capita disappearance (pounds)} * 0.454 . \quad (9)$$

The Consumer Price Index (CPI) is an indicator of the consumer prices encountered by Canadians.[5] In this study, like many studies, I use the Consumer Price Index (CPI) for meats as the retail meat price rather than the actual or average meat price. In the past, the actual or average meat prices were collected in cities across Canada, but these data have been discontinued since they are costly to collect and not of too much interest. Since the actual or average price data are not available from Statistics Canada, while current information on the CPI is readily available from Statistics Canada, most researchers use CPIs for meats instead of the actual or average meat prices. Continuous time series for the CPIs of beef and chicken for the period 1971-2003 were obtained from CANSIM II.

It is not uncommon for some observations to be missing in some data series. In order to construct a complete data set, researchers often have to find observations from different sources and do some necessary conversions. For example, the annual consumer price index for pork is available in CANSIM II, but only for the years 1978 to 2005. In order to increase the number of observations, I took data on consumer price indexes of food products from Table 31 of the *Handbook of Food, Expenditures, Prices and Consumption,* published by Agriculture Canada's Policy Branch in 1990. These data were also contained in Statistics Canada catalogue 62-010, *Prices and Price Indexes*. However, the *Handbook* does not provide the CPI for pork for the period 1971-1977 directly; instead, it includes CPIs for different cuts of pork. Therefore, I took the

[5] According to the Government of Canada's website, the CPI "is obtained by calculating, on a monthly basis, the cost of a fixed 'basket' of commodities purchased by a typical Canadian consumer during a given month. The basket contains products from various categories, including shelter, food, entertainment, fuel and transportation. Since the contents of the basket remain constant in terms of quantity and quality, the changes in the index reflect price changes. The CPI is a widely used indicator of inflation (or deflation) and indicates the changing purchasing power of money in Canada." http://canadianeconomy.gc.ca/english/economy/cpi.html.

unweighted average of the CPIs of those cuts as the proxy for the CPI of pork, since the appropriate weights were not available.

Another problem was that this series was on a base of 1986=100. In order to make it conformable to the other data, I had to rebase it from 1986 to 1992, and then 1992 to 1997 using the following formula:

$$p_{y/97} = \frac{p_{y/92}}{p_{97/92}} * 100 \quad , \tag{10}$$

where y is year, $p_{y/92}$ is the official price index (1992=100) for year y and $p_{97/92}$ is the value of $p_{y/92}$ for the year 1997. [6] The same logic applies in rebasing the data from 1986 to 1992.

I encountered similar problems in trying to construct a CPI for fish, and followed the same procedure to construct the data. For the CPI for fish, series v735334 of Table 326-0001 of CANSIM II contains the observations from 1979-2005. However, observations for the period 1971-1978 are not available in v735334. Instead, data on consumer price indexes for different types of fish products are available in Table 35 of the *Handbook of Food, Expenditures, Prices and Consumption* and in Statistics Canada catalogue 62-010, *Prices and Price Indexes*. Since an aggregate CPI for fish was not available for the period 1971-1978, I took the unweighted average of the CPIs for different fish as a proxy. The different series were then rebased to obtain a continuous time series with base year 1997.

[6] In fact, the data were rebased from 1992 = 100 to 1997 = 100 by Andy Baldwin of Statistics Canada.

Nominal per capita disposable income is also available from Statistics Canada. [7] Real per capita disposable income was constructed by me using nominal per capita disposable income divided by the CPI for all items (1997=100).

One of the applications of CPI is to be a deflator, that is to transform various macro-data expressed in nominal dollars into real dollars. In this study, I also use the all items CPI on a base of 1997=100, obtained from CANSIM II, to deflate the CPIs for beef, pork, chicken and fish to obtain the real CPIs (or relative prices) of meats. These real CPIs are used as the price variables in my estimating equations.

In the estimation of the demand model, because of the simultaneity problem between price and quantity, the instrumental variables (IV) technique is employed. In this study, two types of IVs are included, namely the exogenous or predetermined demand-side variables and the exogenous or predetermined supply-side variables. The demand – side instruments for the static model are the log values of the price of fish $(\ln Pf)$ and per capita disposable income $(\ln Y)$; the time trend (t); and a dummy variable for food scares due to BSE. BSE, defined to equal one in 1996, the year that BSE became a public concern in the U.K., and 0 otherwise. The price of fish is included as an instrument under the arbitrary assumption that it is exogenous to the meat markets. For the dynamic model, the one period lag of beef consumption $(\ln Qb(-1))$, the one period lag of pork consumption $(\ln Qp(-1))$ and the one period lag of chicken consumption $(\ln Qc(-1))$ are included in the list of instruments.

The supply-side IVs capture the effect of supply shocks on meat demand. They do not enter into the demand equations directly, but they are included in the demand

[7] Per capita disposable income can be constructed by dividing annual disposable income, series v647037 of CANSIM II Table 380-0019, by the population of Canada, series v466668 of Table 051-0001.

estimation system as IVs. Specifically they are three variables that represent the prices of farm products, namely the log of the farm product price indexes (FPPI) for cattle $(\ln FPb)$, hogs $(\ln FPp)$ and poultry $(\ln FPc)$.[8] Data on the FPPIs for the period 1971-1997 were obtained from Statistics Canada. Real FPPIs are obtained by dividing by the all items CPI (1997=100).

Besides these three supply-side IVs, dummy variables for several supply side shocks are also included: bans on beef (BANSB, a dummy variable defined as equal to one in 2003, when the U.S. closed its border to Canadian beef, and 0 otherwise); and American countervailing duties on Canadian cattle and beef (CDB, defined as one in 1998 and 0 otherwise) and pork (CDP, defined as one in 1985, 1989, 1990, 1991, and 0 otherwise). The reason I chose these variables as supply-side instrumental variables is to take supply side factors into consideration when estimating demand equations, because in meat demand analysis, the observed prices are also influenced by the supply side of the market. Also, in my simultaneous-equations model, any variables other than the six endogenous variables are all exogenous variables, which should be included among the IVs. That is why the constant term is included as well.

4. ESTIMATION AND RESULTS

4.1 Regression model and Estimation method

An important issue in the estimation of meat demand is the choice of functional form. The static version of retail demand for meat i in period t can be written as

$$Q_{it} = f(P_{it}, P_{jt}, Y_t, z_t) , \qquad (11)$$

[8] The FPPI for chicken is not available. The FPPI for poultry is used as a proxy for the FPPI for chicken, since about 80% of poultry meats consumed are chicken.

where Q_{it} is the annual Canadian per capita consumption (i = beef, pork or chicken); P_{it} is the relative price of meat i in year t; P_{jt} is a vector of relative prices of other goods in year t, for example, the substitutes and complements for meats; Y_t is real per capita disposable income; and z_t is a vector of demand shocks. Using relative prices and real income ensures that the demand equations satisfy the homogeneity condition. The dynamic version of the retail demand for meats is specified as $Q_{it} = f(Q_{it-1}, P_{it}, P_{jt}, Y_t, z_t)$, where the subscript $t-1$ represents a lag of one period. The other variables are defined as in the static model.

Specifically, the beef, pork and chicken demand equations are

$$\begin{aligned}\ln Qb_t = {} & \alpha_0 + \alpha_1 \ln Pb_t + \alpha_2 \ln Pp_t + \alpha_3 \ln Pc_t + \alpha_4 \ln Pf_t + \alpha_5 \ln Y_t \\ & + \alpha_6 t + \alpha_7 BSE_t + eb_t,\end{aligned} \tag{12}$$

$$\begin{aligned}\ln Qp_t = {} & \beta_0 + \beta_1 \ln Pb_t + \beta_2 \ln Pp_t + \beta_3 \ln Pc_t + \beta_4 \ln Pf_t + \beta_5 \ln Y_t \\ & + \beta_6 t + ep_t,\end{aligned} \tag{13}$$

$$\begin{aligned}\ln Qc_t = {} & \gamma_0 + \gamma_1 \ln Pb_t + \gamma_2 \ln Pp_t + \gamma_3 \ln Pc_t + \gamma_4 \ln Pf_t + \gamma_5 \ln Y_t \\ & + \gamma_6 t + ec_t.\end{aligned} \tag{14}$$

The dynamic versions of the meat demand equations can be written as

$$\begin{aligned}\ln Qb_t = {} & \alpha_0 + \alpha_1 \ln Pb_t + \alpha_2 \ln Pp_t + \alpha_3 \ln Pc_t + \alpha_4 \ln Pf_t + \alpha_5 \ln Y_t + \alpha_6 t \\ & + \alpha_7 BSE_t + \alpha_8 \ln Qb_{t-1} + eb_t,\end{aligned} \tag{15}$$

$$\begin{aligned}\ln Qp_t = {} & \beta_0 + \beta_1 \ln Pb_t + \beta_2 \ln Pp_t + \beta_3 \ln Pc_t + \beta_4 \ln Pf_t + \beta_5 \ln Y_t \\ & + \beta_6 t + \beta_7 \ln Qp_{t-1} + ep_t,\end{aligned} \tag{16}$$

$$\begin{aligned}\ln Qc_t = {} & \gamma_0 + \gamma_1 \ln Pb_t + \gamma_2 \ln Pp_t + \gamma_3 \ln Pc_t + \gamma_4 \ln Pf_t + \gamma_5 \ln Y_t \\ & + \gamma_6 t + \gamma_7 \ln Qc_{t-1} + ec_t,\end{aligned} \tag{17}$$

where t is a time trend variable that takes the value 1 in 1971 and increases by 1 in every subsequent period. BSE is a dummy variable representing the food scare due to BSE,[9] which takes the value 1 when the year equals 1996 and 0 otherwise, because 1996 is the year that BSE was first reported in the United Kingdom. ei $(i = b, p, c)$ is the disturbance terms, which are assumed to satisfy the following assumptions:

$$E(ei_t) = 0, \tag{18}$$

$$E((ei)_t^2) = \sigma^2, \tag{19}$$

$$E(ei_t ei_s) = 0 \text{ for } t \neq s. \tag{20}$$

The variable definitions are summarized in Table 2.

In demand analysis, the hypothesis of structural change is often framed in terms of changing tastes and preferences. Researchers sometimes add a time trend to capture the structural change in consumer preferences and tastes over time, especially when dealing with annual time series data. Chalfant et al. (1991) included a trend term that took the value 1 in 1975 and increased by 1 in every subsequent period. They chose a trend that began in the middle of their sample to test the hypothesis of structural change in meat demand in Canada. Chern et al. (1995) pointed out that a time trend variable had often been used to explain the effects of health information on consumption due to the fact that beliefs about the health risk might change over time. Moschini (1995) mentioned that a time trend or dummy variable was the simplest approach to modeling the effect of structural change over time. In this study, the demand shocks causing structural change in meat consumption, such as health concerns and advertising on meat etc. are captured by adding a time trend. The limitation of this approach is that it assumes constant change in

[9] Footnote 1 of Saha et al. (2006) states "Bovine Spongiform Encephalopathy (BSE) is a neurodegenerative brain disease of cattle transmissible to human beings (WHO, 2006a). The disease has an incubation period of four to five years, but is fatal for cattle within weeks to months of its onset. BSE first came to world attention in 1986 with the diagnosis of a new form of the disease in cattle in the UK. Since then, BSE has been found in 23 countries worldwide (CFIA, 2006)."

each year, but I am unable to obtain more direct measures of health concerns or advertising. By adding a time trend, I am also implicitly assuming that the data are trend stationary.

Researchers often wish to estimate dynamic meat demand equations because consumers' preferences and tastes do not change instantly, but rather change gradually over time. They take habit formation into consideration by constructing a dynamic model, by including the lagged dependent variable on the right-hand side of the equation as an explanatory variable. Burton and Young (1996) demonstrated that a dynamic model incorporating habit formation is more viable than the static model in modeling consumer behavior.

It is well known that "double log" demand equations of the type estimated here are inconsistent with utility theory. They do not automatically satisfy the adding-up, symmetry and homogeneity conditions. Despite these defects, many researchers use double logarithmic demand functions because of their merits such as good goodness-of-fit, easy estimation, and the ready interpretation of the estimated parameters. Also, Hassan and Johnson (1976, 22-24) note that "since demand parameters are estimated from market variables it may be argued that the log-log function in some sense approximates aggregated individual maximizing behavior. This is, however, a conjecture and contrary to the previously suggested approaches, it casts the empirical analysis in *ad hoc* framework, since the theory cannot be directly employed in setting the hypotheses to be tested."

The competitive market determines price and quantity simultaneously. Prices on the right-hand side of equations are also endogenous. Thus, simultaneous-equations estimation methods are appropriate for meat demand analysis. They allow one to obtain consistent estimates of the target meat demand equations despite the simultaneous relationships existing among demand, supply, and prices.

Like this study, some previous studies have used similar approaches in meat demand analysis. Kulshreshtha and Wilson (1972) used annual data covering 1949-1969 and employed the two-stage least squares regression procedure to obtain the estimates. Thurman (1986) tested for endogeneity in a demand and supply framework. He analyzed the U.S. demand for poultry meat in a simultaneous demand and supply system using annual data from 1955-1981. The instrumental variables estimator used in his study was the two-stage least squares (2SLS) estimator, with instrumental variables of real feed price, real labor price, real energy input price and a conversion efficiency variable. [10]

In this study, there are three structural equations, namely the beef demand equation, the pork demand equation and the chicken demand equation. As for any simultaneous model, it is important to check whether the system has an identification problem or not before estimation, since if the equations are underidentified, 2SLS estimates will not exist. Accordingly, I checked the order condition of identification for the static beef model to verify whether it was identified or not.[11] The total number of endogenous variables in the complete model, M, is equal to six in this study ($\ln Qb, \ln Qp, \ln Qc, \ln Pb, \ln Pp, \ln Pc$). There are m = 4 endogenous variables in the static

[10] Thurman (1986, 645) pointed out that "if not a priori certain as to the proper normalization of demand, run Wu-Hausman tests on both price-dependent and quantity-dependent equations. If both tests reject, then instrumental variables or a similar technique is called for. If only one test rejects, one can either normalize the demand equation to put the predetermined variable on the right-hand side or use instrumental variables. This choice should be based on the perceived relative power of the two tests."

[11] Gujarati (2003, 748) defines the order condition as follows: "In a model of M simultaneous equations, in order for an equation to be identified, the number of predetermined variables excluded from the equation must not be less than the number of endogenous variables included in the equation less 1, that is,

$$K-k \geq m-1$$

If $K-k = m-1$, the equation is just identified, but if $K-k > m-1$, it is overidentified."

beef equation ($\ln Qb, \ln Pb, \ln Pp, \ln Pc$). The number of predetermined variables in the static model (K), including the intercept, is eleven, while the number of predetermined variables in the beef equation (k), is five ($\ln Pf, \ln Y, t, BSE$ and constant). Therefore, K – k = 11-5 = 6, which is greater than m -1 = 4-1 = 3, which implies that the beef equation is overidentified. The 2SLS estimation method can thus be applied to the beef static model.

In a similar manner, I checked the identification of the other five demand equations. The results are reported in Table 3. One can see that the difference between K-k and m-1 is always positive, which indicates that all these demand equations are overidentified. Therefore, 2SLS is applied to all the demand equations.

4.2 Diagnostic Tests

Several diagnostic tests are conducted to further check the statistical validity of the estimated models. I applied the diagnostic tests to both the static and dynamic version models.[12] Unless otherwise indicated, the tests were applied to the OLS estimates of the equations.

First, I looked at the normality of error terms. The results are reported in Table 4. Normality of the error terms is necessary for valid hypothesis testing; it ensures that the t and F statistics have t and F distributions respectively in small samples. For the beef, pork and chicken dynamic demand equations, the Jarque-Bera test results in Table 4 imply that, at the 5% significance level, one cannot reject the null hypothesis of normally-distributed errors. However, the p-values for the Goodness of Fit test for normality are all greater than 0.05, which implies that one must reject the null hypothesis

[12] The tests were carried out using SHAZAM version 10.0

or in other words, that the error term is not normally distributed. The overall conclusion is that the error terms may not be normally distributed for all the meat demand equations. For the static model, the error terms appear to be non-normal too.[13]

In a model with many explanatory variables, multicollinearity is always a potential problem. The individual t-values, F-value and R^2 value for the OLS estimates displayed an obvious symptom of existence of multicollinearity: a high R^2 and a high F-value, which indicate that the model explains fit a large proportion of the variation in the dependent variable, accompanied by a number of insignificant t values, implying that the corresponding variables should not be included in the model. [14] Next I checked for multicollinearity using the auxiliary R^2 s method. The auxiliary R^2 s are presented in Table 5. The results are mixed in all three equations. Some of the auxiliary R^2 values are greater than 0.8 while some are not, which suggests that there exists a multicollinearity problem involving some explanatory variables, but not all of them. By closely examining the results, one can see that most of the variables exhibiting strong interrelationships are prices, the time trend and disposable income. This is likely because all these meat commodities are either substitutes or complements. The prices and disposable income all follow the same time trend.

In addition, I tested for heteroscedasticity using the Breusch-Pagan-Godfrey BPG test, the results of which are reported in Table 4. Since I have already found that there exists a non-normality problem, one should use Koenker's modified BPG statistic. For the beef, pork and chicken dynamic demand equations, at the 5% significance level, the p-values are all greater than 0.05, which suggests that one cannot reject the hypothesis of

---

[13] For further information on these tests, see Gujarati (2001) pp. 148-149 (Jarque-Bera test) and pp. 81-87 (Goodness of Fit test).
[14] The OLS estimates for three of the six equations are presented in table 7.

no heteroscedasticity. This result implies that hereroscedasticity does not exist which means that the error terms in all the meat estimating equations are homoscedastic. For the static version, the error terms are homoscedastic too at the 5% significance level. At $\alpha = 10\%$, one would reject H_0 for pork, which suggests that the error term may be heteroscedastic in the static and dynamic pork equations.

Finally I examined the model specification using the RESET, FRESETS, and FRESETL tests. The p-values for these statistics are reproduced in the Table 6. In the beef model, at 5% significance level, the p-values for the third version of the RESET, FRESETL and FRESETS are smaller than 0.05, which suggests that one should reject H_0. Therefore, the beef model is misspecified. For the dynamic pork model, all the p-values for the third version of the RESET, FRESETL and FRESETS tests are greater than 0.05, so one cannot reject the null hypothesis of no specification error. This implies that the pork model is correctly specified. In the dynamic chicken model, two of the p-values of the third version of RESET, FRESETL and FRESETS are smaller than 0.05 which leads to the rejection of the null hypothesis and the conclusion that the chicken model is misspecified. The conclusions are similar for the static version of each model. Actually, in the static version of the chicken model, two of the p-values of the third version of RESET, FRESETL and FRESETS are greater than 0.05. There appears to be less evidence of misspecification in this model.

As mentioned earlier, price and quantity are simultaneously determined in the system. Endogeneity is the common problem arising. Before estimation, one should perform a Wu-Hausman test to decide whether OLS estimation or 2SLS estimation is more appropriate. The instrumental variables used in carrying out the test are those listed in section 3. The test results for both versions, six equations, are reported in Table 4. For the static chicken model, for example, the Wu-Hausman test F-statistic equals 6.2780, with 3 and 23 degrees freedom and a p-value of 0.0029. For the dynamic chicken model, the Wu-Hausman test F-statistic equals 2.9516, with 3 and 21 degrees freedom and a p-value of 0.0562. Thus in both cases, they lead to the rejection of the null hypothesis that prices are predetermined at least at the 10% significance level, which implies that there exists an endogeneity problem between quantity and prices. By the same criterion, there exists an endogeneity problem between quantity and prices in beef static model. However, there does not exist an endogeneity problem between quantity and prices in the beef dynamic and pork static or dynamic models. Therefore, the 2SLS estimation method is appropriate for the beef static, the chicken static and dynamic models. The OLS estimation method is appropriate for the beef dynamic, the pork static and dynamic models.

In any study dealing with time series data, it is always possible that autocorrelation exists. To check for autocorrelation, I applied the Breusch-Godfrey Serial Correlation Lagrange Multiplier test to the 2SLS estimates of the equations.[15] The results of which are reported in Table 4. For the static model, the p-values for the beef and pork equations are smaller than 0.10, which implies that one can reject the null hypothesis of no autocorrelation the 10% significance level. This means that the static beef and pork models suffer from autocorrelation problems. But, for the static chicken model, the p-value is greater than 0.05, which suggests that one cannot reject the hypothesis of no autocorrelation. There is no autocorrelation in static chicken model. There appears to be no autocorrelation problem in the beef, pork and chicken dynamic models since the p-

[15] The test results are obtained using EVIEWS version 5.0

values for all three equations are greater than the 5% significance level, which does not lead to rejection of the null hypothesis of no autocorrelation. Therefore, the test results suggest that the dynamic models, which include the lagged dependent variables, do not have autocorrelation problems.

4.3 Results

Since the Wu-Hausman test results suggest that 2SLS is the appropriate estimation method for beef static, chicken static and dynamic models; the OLS is the appropriate estimation method for beef dynamic, pork static and dynamic models, these 2SLS and OLS estimates of the corresponding static and dynamic models are reported in Table 7. The Newey-West correction for autocorrelation is applied to the 2SLS standard errors of static model for beef and the OLS standard errors of static model for pork. For the other equations, the usual 2SLS and OLS standard errors were used.[16] In this study, the instrumental variables are listed in section 3, namely, the price of fish; per capita disposable income; the farm product prices of cattle, hogs and poultry; the time trend; a dummy variable for food scares due to BSE; bans on beef, and American countervailing duty on beef and pork; lagged consumption of beef, pork and chicken (for the dynamic model only) and the constant term.

The estimated own price elasticities of beef in both the static and dynamic models are negative and statistically significant as expected, which indicates that beef consumption will go down when its relative price goes up, holding all else constant. The magnitude is larger in the static model than it is in the dynamic model, which suggests that the own price elasticity of beef is more elastic in the static model. The cross price

[16] The uncorrected and corrected t-statistics and p-values can be found in Table 8.

elasticities are positive for pork and chicken and negative for fish in static model, while the cross price elasticities are all positive in dynamic model. They imply that pork and chicken are substitutes for beef while fish and beef are complements in the static model and pork, chicken and fish are all substitutes for beef in the dynamic model. Also, these price coefficients are all significant at the 10% level in the static model, while they are all insignificant at the 5% level in the dynamic model, which suggests that prices of pork, chicken and fish all have impacts on beef consumption if we do not consider the consumers' habit formation behaviors. However, the prices of pork, chicken and fish do not have impacts on beef consumption if we assume that there is habit formation in consumers' behavior. The income coefficients are positive in the static and dynamic models, which suggest that beef consumption will increase as people's disposable income goes up. However, both the magnitudes are statistically insignificant at $\alpha = 5\%$ level. Per capita disposable income does not appear to have much impact on beef consumption.

My findings for the static and dynamic beef models are similar to those of Kulshreshtha and Wilson (1972), who used Canadian annual data covering the period 1949-1969. They found that beef consumption at the retail level is positively related to consumer income and the price of pork and negatively related to its own price, which is consistent with my results; however, the magnitude of the income coefficients is insignificant in this study and was significant in their study. It implies that consumer income is becoming less responsive to beef consumption.

For the pork model, the estimated own price elasticities are negative in both versions of the model, which means pork consumption will decrease if its price increases. The own price elasticities are also statistically significant at the 5% level, which implies that the price of pork has an impact on pork consumption. The cross price elasticities in the dynamic model show that beef and fish are substitutes and chicken is complementary to pork, but only the coefficient of the price of beef is statistically significant at the 5% level. It seems that the price of beef most likely has an impact on pork consumption. In the static model, the signs of the coefficients suggest that beef and fish are substitutes for pork and chicken is complementary to pork as well. The magnitudes of the coefficients of the price of beef and the price of fish are statistically significant at $\alpha = 5\%$ level, which implies that the prices of beef and fish have an impact on pork consumption. Disposable income is negatively related in both the static and dynamic models. However, the magnitudes are statistically insignificant at the 5% level. This suggests that pork is an inferior good. Pork consumption will decrease as people's disposable income increases. But it also implies that the disposable income does not affect pork consumption too much.

Similarly, in the chicken model, the own price elasticities of chicken are negative in both versions, implying that the demand curve for chicken is downward-sloping. The coefficient estimates are statistically significant at the 5% level, which indicates that the price of chicken has a negative impact on consumption. The cross price elasticities in the static and dynamic models are all positive, which indicates that beef, pork and fish are all substitutes for chicken. However, the coefficient of the price of pork is statistically insignificant at the 5% level in both models, which implies that the price of pork does not have much impact on chicken consumption. Disposable income is positively related to chicken consumption in both the static and dynamic models and the coefficient estimates are statistically significant at the 5% level, which suggests that disposable income has a positive impact on chicken consumption. People consume more chicken when their disposable income increases.

From the above results, one can conclude that disposable income does not explain the consumption of meats at the retail level too much in the beef and pork models in the two versions. But disposable income does do a good job in both versions of the chicken model. Specifically, the results indicate that disposable income does not have much influence on beef consumption and pork consumption. But, as disposable income increases, chicken consumption will definitely go up.

In comparing my results with the previous Canadian studies, for example that of Tryfos and Tryphonopoulos (1973), I found that in their study, the income elasticity estimates of chicken displayed a positive sign and large magnitude, while their estimates for pork and lamb had negative signs and smaller magnitudes. My results for income elasticities in both the static and dynamic versions are consistent with their findings. These coefficients have positive signs and are statistically significant at the 5% level in two versions of the chicken model. However, they are statistically insignificant in both the beef and pork static and dynamic models, and do not even have the expected positive sign in the pork static and dynamic models.

Overall, the own price estimates and cross price estimates are good because the signs are consistent with expectations and the magnitudes are statistically significant at the 5% level, but the income coefficients are not plausible in the sense that the signs are not as expected and the magnitudes are not significant. One possible explanation for these insignificant income coefficients is that as consumers become more affluent over time, they become more likely concerned about health. It is true that as income rises, people have more time to inform themselves about health issues. Another explanation might be that as people become richer, they will pay more and more attention to education. More educated people are most likely health-oriented. Therefore, as income increases, people's meat consumption pattern will change due to a change in preferences rather than the classical income effect: they would like to switch from unhealthy red meats, beef and pork, to healthy white meats, chicken and fish. Their meat consumption decisions are not based simply on their income. Besides these possible explanations, the existing multicollinearity problem between real disposable income and the time trend may contribute to unexpected results as real disposable income increases every year following the same time trend. Some of the income effect is captured by time trend in explaining the variations in meat consumption.

The time trends also appear to contribute to the models. For beef, the estimated parameter of the time trend is negatively related to beef consumption in both the dynamic and static versions. This result is consistent with the observed decline in beef consumption since the mid-1970s. However, the coefficient estimate is statistically insignificant at the 5% level in the dynamic model, which indicates that it does not have a big impact on beef consumption. But its coefficient estimate is significant in the static model at the same significance level, which indicates that the time trend has an impact on beef consumption. The time trend coefficients in the pork models are both negative, but not significant. It seems that the time trend does not explain too much in the pork model, which is consistent with the empirical evidence of frequent fluctuations in pork consumption from year to year. As for the chicken model, the trend coefficients are positive and the magnitudes are statistically significant at the 5% level in both versions.

This finding suggests that the time trend has a big impact on chicken consumption. There has been a considerable increase in chicken consumption over time, independent of changes in prices and income. This result is consistent with the empirical chicken consumption pattern.

In the dynamic beef model, the coefficient of the one-period lag of quantity has a positive sign and is significant at the 5% level, which indicates that habit formation plays a role in beef consumption. As for the pork result, the positive sign of the lagged quantity coefficient implies that people will continue to consume pork. However, the coefficient estimate is insignificant at the 5% significance level. This coefficient does not provide too much information of habit formation. In the chicken equation, the coefficient of lagged consumption is negative, but it is not statistically significant at the 5% level, which suggests that there is no obvious habit formation in chicken consumption.

The negative coefficient for the BSE dummy variable in the beef equation suggests that as people become more aware of BSE, they become more concerned about food quality and will consume less beef. The coefficient estimate is statistically significant at 5% level for the static model, but not statistically insignificant even at the 10% level in the dynamic model. This result suggests that BSE has an impact on consumers' beef consumption due to the food scares. However, consumers' consumption habits do not change instantly; once the consumption of beef becomes a habit, the food scare due to BSE does have a negative impact on their beef consumption, but not that much.

To further analyze the results, in the beef dynamic model I decomposed the fitted value of beef consumption to examine how much of the change in consumption can be explained by price and income factors, how much has been captured by the time trend and how much has been accounted for by food scares due to BSE. The calculation is as follows.

$$\ln \hat{Q}b = 1.4190 - 0.1899 \ln Pb + 0.0483 \ln Pp + 0.1561 \ln Pc + 0.0552 \ln Pf + 0.0174 \ln Y$$
$$- 0.0052t - 0.0313 BSE + 0.5870 \ln Qb(-1).$$

I picked 2003 and 1976 (the most recent year in my sample and the year of peak beef consumption [figure 1]) to do the following calculation.

$$\Delta \ln \hat{Q}b = -0.1899(\ln Pb_{2003} - \ln Pb_{1976}) + 0.0483(\ln Pp_{2003} - \ln Pp_{1976})$$
$$+ 0.1561(\ln Pc_{2003} - \ln Pc_{1976}) + 0.0552(\ln Pf_{2003} - \ln Pf_{1976}) + 0.0174(\ln Y_{2003} - \ln Y_{1976})$$
$$- 0.0052(33 - 6) - 0.0313(1 - 0) + 0.5870(\ln Qb(-1)_{2003} - \ln Qb(-1)_{1976}).$$

Dividing through the equation by $\Delta \ln Qb$, one can obtain the proportion of the change in $\ln Qb$ that is explained by prices and income, the time trend and BSE respectively. After substituting in the numerical values of the explanatory variables, I obtained the following result (see table 9): for the beef model, the time trend explains a greater proportion of the change in consumption than prices and income in both versions. The lagged dependent variable captured more of the change in consumption in the dynamic version. The results suggest that the change in beef consumption over time is more due to the change in consumer preferences and tastes regarding health concerns and food scares. Habit formation behavior also plays a role in beef consumption. The price and income impact on pork consumption is partially offset by the time trend impact in both the static and dynamic models. This result is consistent with the empirical fluctuations in the pork consumption pattern over time. For the chicken model, the time trend explains much more of the change in consumption than prices and income do in the static version, which implies that consumers' preferences for healthy meat led to the continuous increase in chicken consumption over time. The time trend variable contributes even more to the explanation of changes in chicken consumption in the dynamic model. The price and income impact is more than offset by the habit formation variable. These results further confirm the conclusion that the considerable increase in chicken consumption over time is due to change in consumers' preferences and tastes regarding health concerns and food scares. They switched from red meat consumption to white meat consumption.

In general, the estimates of the static and dynamic models are similar. Previous research suggests that the dynamic model should perform better in terms of analyzing meat consumption patterns. The overall fits of the estimated equations are good, as can be inferred from figure 5, in which actual meat consumption is compared to two versions of fitted meat consumption. One can see that the fitted values for the chicken models fit very well with the actual value. For beef model, the two estimated equations fit pretty well with actual value until 1988. There are some discrepancies between the fitted values and actual value between 1989 and 1997, but still the static model and the dynamic model fit fairly well with each other. For the pork model, the static and the dynamic model correspond well to each other from 1971-2003, while the two versions of estimated equations fit pretty well with the actual model from 1971-1988. There are some discrepancies with actual data from 1989-2003.

Furthermore, the squared correlations between actual and fitted values (r^2) in the static and dynamic models are calculated to further examine the performance of two versions.[17] The results are reported in table 7. In the beef model, the difference between the r^2 for the dynamic model and the r^2 for the static model is about 0.0289. There is a

[17] The values are obtained using EVIEWS version 5.0

difference of 0.0126 in the pork model and 0.0003 in the chicken model. Therefore, the goodness of fit of both versions are good in general. They are both good approximations to the true model.

After comparing the performances of the static and dynamic models in this study, the overall conclusion regarding which model is the best would be that the dynamic model has the advantage over the static model since there is no autocorrelation in the beef, pork and chicken dynamic equations, while there is the autocorrelation in the static beef and pork models. The existence of autocorrelation makes hypothesis tests invalid. Also the estimates including the habit formation variable contribute more to the interpretation of the results. As previous studies have shown, the dynamic version is more appropriate model theoretically.

5. CONCLUSION

In this study, annual Canadian time series data from 1971-2003 are used in the estimation. Relative retail CPIs for beef, pork, chicken and fish, real per capita disposable income, a time trend and food scares due to BSE are included as explanatory variables in the double log functional form demand equations, with the retail weight of meat consumption as the dependent variables. The two-stage least square (2SLS) estimation method is used to obtain the demand estimates. Two versions of the demand model, the static and dynamic models, are estimated.

The empirical results can not explain completely the observed meat consumption patterns in Canada. There are several reasons why this is the case. First, the observed changes in meat consumption patterns over time is mostly due to changes in consumers' preferences and tastes. It cannot be explained only by the numerical estimates of the parameters. Second, specification error was found in the estimating equations, which leads to the biased estimation results. The specification error may due to the omission of variables or errors in the functional form. For example, because of a lack of micro-data in Canada, I am unable to incorporate demand factors such as demographic characteristics into the model, which are key factors in explaining structural change. Also, because of data limitations, I could not construct a health information index, a meat advertising information index or a food scares index to include in the model. These are variables that should be included. Third, the appropriate functional form is important in estimation to ensure the reasonable results. Again because of the inaccessibility of micro-data, I am unable to estimate the AIDS model, which has been proven to be consistent with the consumer theory. Fourth, the multicollinearity problem does not violate any assumptions, but it can lead to imprecise estimates such as the unexpected signs and statistical significance of coefficients.

There are some areas worthy of future study. First, this study provided the model goodness-of-fit and the squared correlation between actual and fitted values, but I did not carry out any formal tests to determine whether the static or the dynamic model is the best. Second, in this study, I use a time trend to capture changes in preferences and tastes over time, but if the data to construct a health index were available, it would be of interest to use this index rather than the time trend to capture the changes in preferences and tastes. Third, the dummy variable BSE denoted the food scares due to BSE is defined only to capture an event such as the BSE case exposure to public in the United Kingdom. The impact is arbitrarily assumed to disappear after that event. Fourth, the study did not test for structural change in the parameters. One could test the intercept using a dummy variable to test for a structural shift in meat consumption patterns. Finally, if micro survey data were available, it would be a good idea to estimate the AIDS model and incorporate demographic factors and other demand factors into the equations. This could lead to better empirical results.

REFERENCES

Anderson, Eugene W., and Steven M. Shugan (1991)"Repositioning for Changing Preferences: The Case of Beef versus Poultry." *The Journal of Consumer Research,* Vol. 18, No.2, 219-232

Blanciforti, Laura and Richard Green (1983) "An Almost Ideal Demand System Incorporating Habits: An Analysis of Expenditures on Food and Aggregate Commodity Groups." *The Review of Economics and Statistics*, Vol. 65, No. 3, 511-515.

Blundell, R., Panos Pashardes, and Guglielmo Weber (1993) "What Do We Learn About Consumer Demand Patterns from Micro Data?" *The American Economic Review*, Vol.83, No.3, 570-597.

Brester, Gary W., and Ted C. Schroeder (1995) "The Impacts of Brand and Generic Advertising on Meat Demand." *American Journal of Agricultural Economics*, Vol.77, No.4, 969-979.

Brown, Deborah J., and Lee F. Schrader (1990) "Cholesterol Information and Shell Egg Consumption." *American Journal of Agricultural Economics*, Vol.72, No.3, 548-555

Burton, M., and T. Young (1996) "The Impact of BSE on the Demand for Beef and other Meats in Great Britain." *Applied Economics* 28, 687-693.

Buse, Adolf (1994) "Evaluating the Linearized Almost Ideal Demand System." *American Journal of Agricultural Economics*, Vol.76, No.4, 781-793.

Canadian Food Inspection Agency (2006), Canada's Assessment of the North American BSE Cases Diagnosed from 2003 to 2005 (Part II), http://www.inspection.gc.ca/

Chalfant, James A., and Julian M. Alston (1988) "Accounting for changes in Tastes." *The Journal of Political Economy* 96, 391-410.

Chalfant, James A., Richard S. Gray, and Kenneth J. White (1991) "Evaluating Prior Beliefs in a Demand System: The Case of Meat Demand in Canada." *American Journal of Agricultural Economics*, Vol.73, No.2, 476-490.

Chavas, Jean-Paul (1983) "Structural Change in the Demand for Meat." *American Journal of Agricultural Economics*, Vol.65, No.1, 148-153.

Chen, P. Yanping (1991) "An Analysis of Market Demand for Meats in Canada." Unpublished Ph.D. thesis, Department of Rural Economy, University of Alberta, Alberta, Canada.

Chern, Wen S., Edna T. Lochman, and Steven T. Yen (1995) "Information, Health Risk Beliefs, and the Demand for Fats and Oils." *The Review of Economic Studies*, Vol.77, No.3, 555-564.

Christensen, Laurits R., Dale W. Jorgenson, and Lawrence J. Lau (1975) "Transcendental Logarithmic Utility Functions." *The American Economic Review*, Vol.65, No.3, 367-383.

Dahlgran, Roger A. (1988) "Changing Meat Demand Structure in the United States: Evidence from a Price Flexibility Analysis." *North Central Journal of Agricultural Economics*, Vol. 10, No.2, 165-176.

Deaton, A., and J. Muellbauer (1980) "An Almost Ideal Demand System." *The American Economic Review*, Vol. 70, No. 3, 312-326.

DeBenedictis, L. F., and D. E. A. Giles (1998) "Diagnostic Testing in Econometrics: Variable Addition, FRESET, and Fourier Approximations." In A. Ullah and D. E. A. Giles, *Handbook of Applied Economic Statistics*. New York: Marcel Dekker, 383-417.

Eales, James S., and Laurian J. Unnevehr (1988) "Demand for Beef and Chicken Products: Separability and Structural Change." *American Journal of Agricultural Economics*, Vol.70, No.3, 521-532.

Eales, James S., and Laurian J. Unnevehr (1993) "Simultaneity and Structural Change in U.S. Meat Demand." *American Journal of Agricultural Economics*, Vol.75, No.2, 259-268.

Gao, X. M., and J. S. Shonkwiler (1993) "Characterizing Taste Change in a Model of U.S. Meat Demand: Correcting for Spurious Regression and Measurement Errors." *Review of Agricultural Economics*, Vol. 15, No. 2, 313-324.

Gao, X. M., Eric J. Wailes, and Gail L. Cramer (1997) "A Microeconometric Analysis of Consumer Taste Determination and Taste Change for Beef." *American Journal of Agricultural Economics*, Vol. 79, No. 2, 573-582.

Goddard, E., M. Lerohl, Sean B. Cash, and J. Lomeli (2005) "Canadian Agricultural Polices and Health: An Example from the Meat Sector." Contributed Paper Department of Rural Economy, University of Alberta.

Gujarati, Damodar N. (2001) *Basic Econometrics,* 4th edition. Boston, MA: McGraw Hill

Hassan, Zuhair A. and S. R. Johnson (1976) "Consumer Demand for Major Foods in Canada." *Agriculture Canada, Economics Branch*

Intriligator, Michael D., Ronald G. Bodkin, and Cheng Hsiao (1996) *Econometric Models, Techniques, and Application,* 2nd edition. Place of publication: Prentice Hall, Upper Saddle River, NJ 07458

Kinnucan, Henry W., Hui Xiao, Chung-Jen Hsia, and John D. Jackson (1997) "Effects of Health Information and Generic Advertising on U.S. Meat Demand." *American Journal of Agricultural Economics*, Vol.79, No.1, 13-23.

Kulshreshtha, S. N., and A. G. Wilson (1972) "An Open Econometric Model of the Canadian Beef Cattle Sector." *American Journal of Agricultural Economics*, Vol.54, No.1, 84-91.

Lambert, R., B. Larue, C. Yélou, and G. Criner (2005) "Fish and Meat Demand in Canada: Regional Differences and Weak Separability." Centre for Research in the Economics of Agrifood, Laval University, Quebec.

Lloyd, T., S. McCorriston, C.W. Morgan, and A. J. Rayner (2001) "The Impact of Food Scares on Beef and Inter-Related Meat Markets." Selected Paper, American Agricultural Economics Association Annual Meeting, Chicago, IL.

Love, H. A. (2005) "An Investigation of the Effects of BSE on the Canadian Cattle and Beef Markets." Department of Agricultural Economics and Department of Information and Operations Management, Texas A & M University.

Moschini, Giancarlo (1995) "Units of Measurement and the Stone Index in Demand System Estimation." *American Journal of Agricultural Economics*, Vol.77, No.1, 63-68.

Moschini, G., and Karl D. Meilke (1989) "Modeling the Pattern of Structural Change in U.S. Meat Demand." *American Journal of Agricultural Economics*, Vol.71, No.2, 253-261.

Nayga, Rodolfo M., Jr., and Oral Capps, Jr.(1994) "Tests of Weak Separability in Disaggregated Meat Products." *American Journal of Agricultural Economics*, Vol.76, No.4, 800-808.

Pearson, A. M. (1976) "Meat Extenders and Substitutes." *Bioscience,* Vol. 26, No. 4, 249-256.

Piggott, Roley R., Nicholas E. Piggott, and Vic E. Wright (1995) "Approximating Farm-Level Returns to Incremental Advertising Expenditure: Methods and an Application to the Australian Meat Industry." *American Journal of Agricultural Economics*, Vol.77, No.3, 497-511.

Pollak, Robert A. (1970) "Habit Formation and Dynamic Demand Functions." *The Journal of Political Economy*, Vol.78, No.4, 745-763.

Pollak, Robert A., and Terence J. Wales (1980) "Comparison of the Quadratic Expenditure System and Translog Demand System with Alternative Specifications of Demographic Effects." *Econometrica*, Vol.48, No.3, 595-612.

Pollak, Robert A., and Terence J. Wales (1981) "Demographic Variables in Demand Analysis." *Econometrica*, Vol. 49, No.6, 1533-1551.

Ramsey, J. B. (1969) "Tests for Specification Error in Classical Least Squares Regression Analysis." *Journal of the Royal Statistical Society* B31, 250-271.

Rickertsen, K., D. Kristofersson, and S. Lothe (2003) "Effects of Health Information on Nordic Meat and Fish Demand." *Empirical Economics* 28, 249-273.

Robbins, Linda G. (1990) *Handbook of Food Expenditures, Prices and Consumption.* Agriculture Canada Publication, Policy Branch.

Robenstein, Rodney G., and Walter N. Thurman (1996) "Health Risk and Demand for Red Meat: Evidence from Futures Markets." *Review of Agricultural Economics*, Vol. 18, No. 4, 629-641.

Saha, Bishnu, Verna Mitura, and Andy Baldwin (2006) "Price Transmission in Canadian Beef and Poultry Sectors: The Role of Market Power and the Impact of Food Scares." Unpublished paper, presented at conference in Montreal.

Stone, Richard (1954) "Linear Expenditure Systems and Demand Analysis: An Application to the Pattern of British Demand." *The Economic Journal*, Vol. 64, No. 255, 511-527.

Theil, H. (1965) "The Information Approach to Demand Analysis." *Econometrica*, Vol. 33, No.1, 67-87.

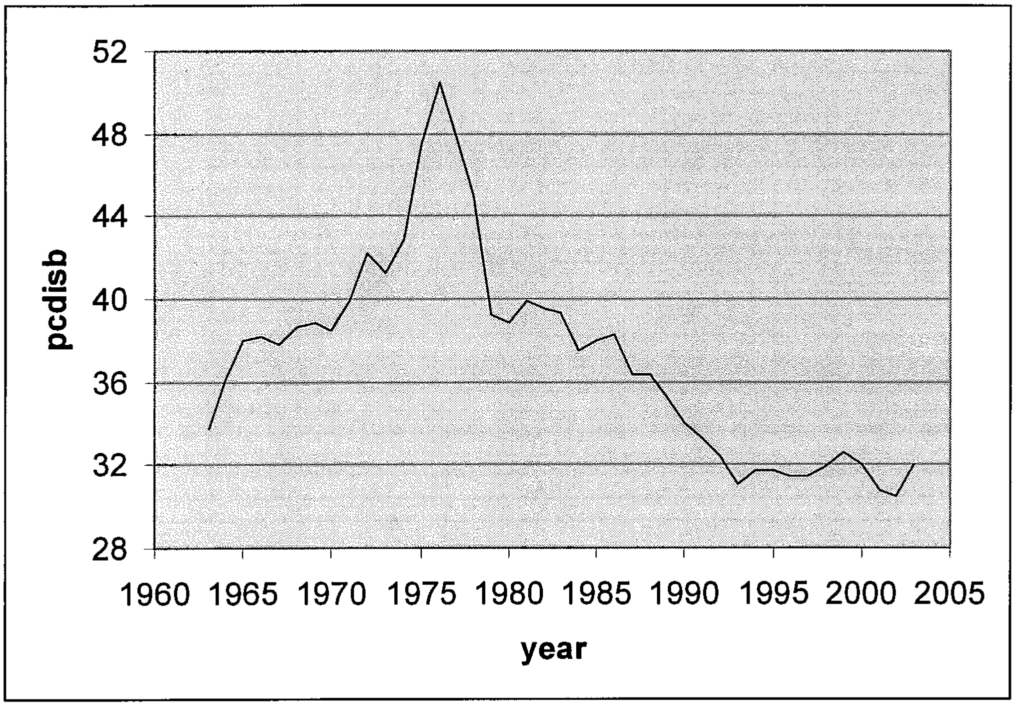
Thurman, Walter N. (1986) "Endogeneity Testing in a Supply and Demand Framework." *The Review of Economics and Statistics*, Vol. 68, No. 4, 638-646.

Trant, Michael (2005) "Economic Impacts of U.S. Countervail Duties and Disease Controls on the Canadian Cattle and Swine Industry." Presented on the conference.

Tryfos, P., and N. Tryphonopoulos (1973) "Consumer Demand for Meat in Canada." *American Journal of Agricultural Economics*, Vol. 55, No. 4, 647-652.

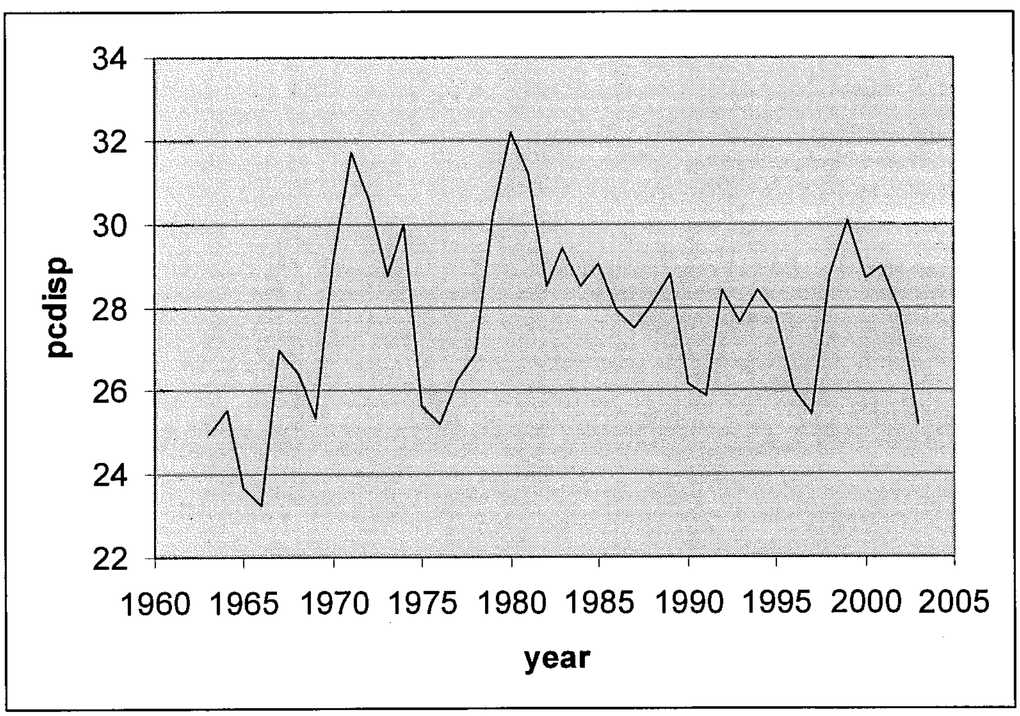
World Health Organization (2006a) Bovine Spongiform Encephalopathy, Fact Sheet no. 113, http://www.who.int/mediacentre/factsheets/fs113/en.

Figure 1. Plot of consumption of beef, 1963-2003



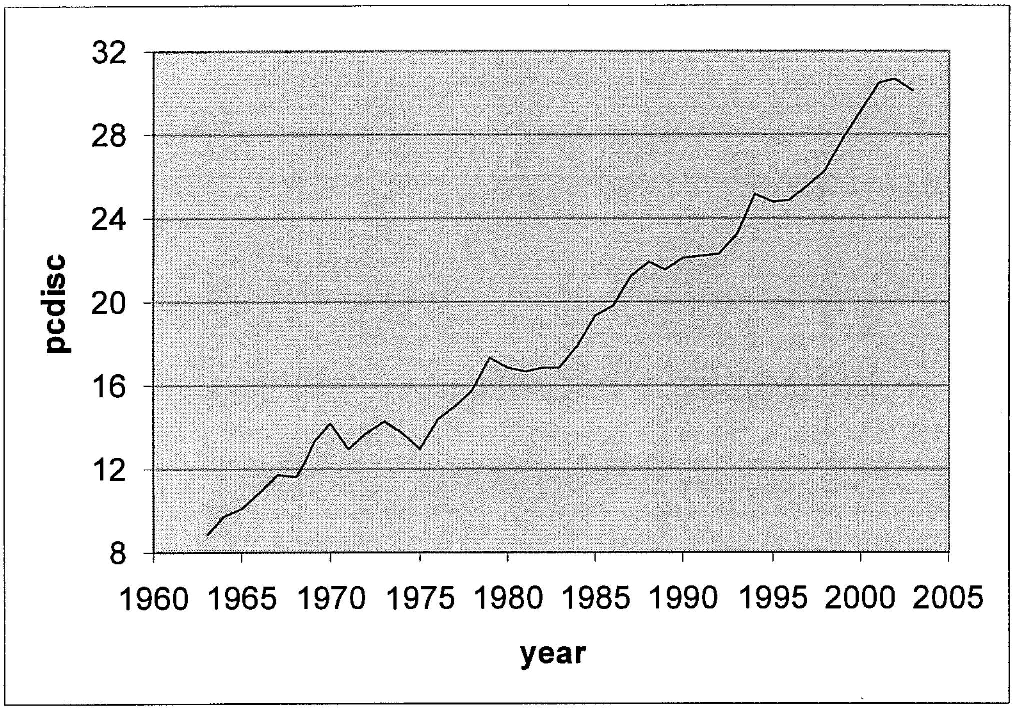
Source: See table 1.

Figure 2. Plot of consumption of pork, 1963-2003



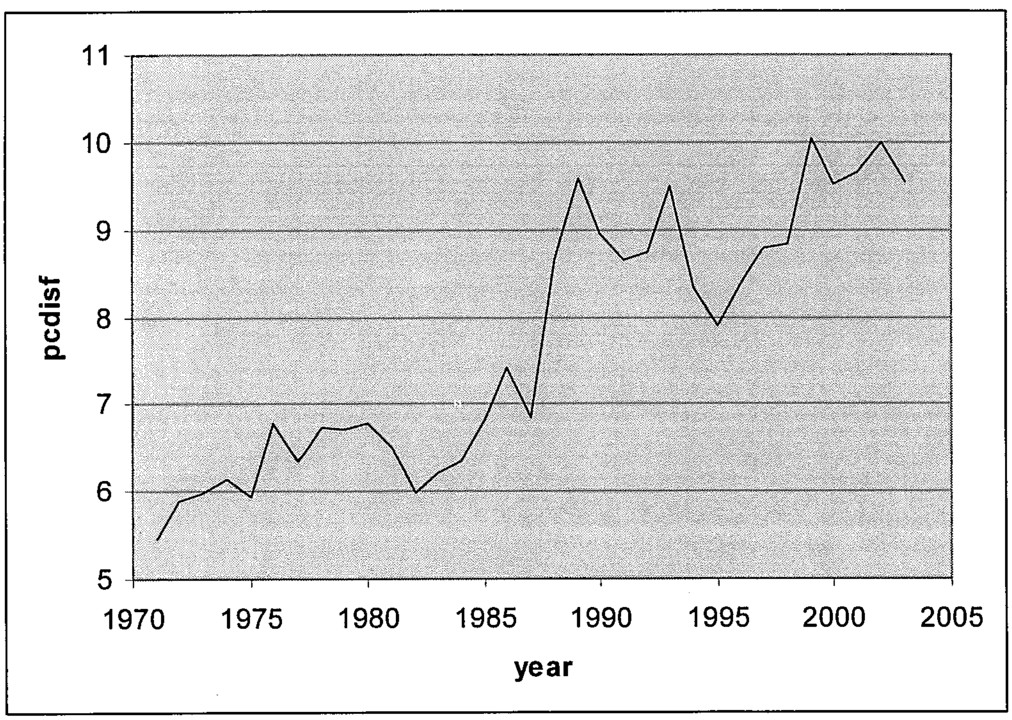
Source: See table 1.

Figure 3. Plot of consumption of chicken, 1963-2003



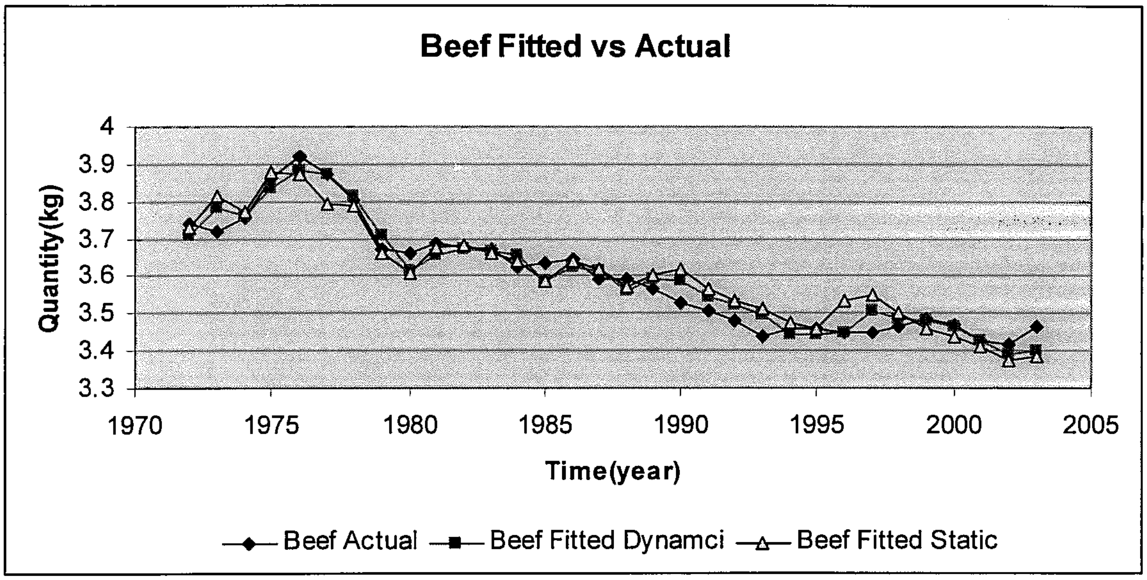
Source: See table 1.

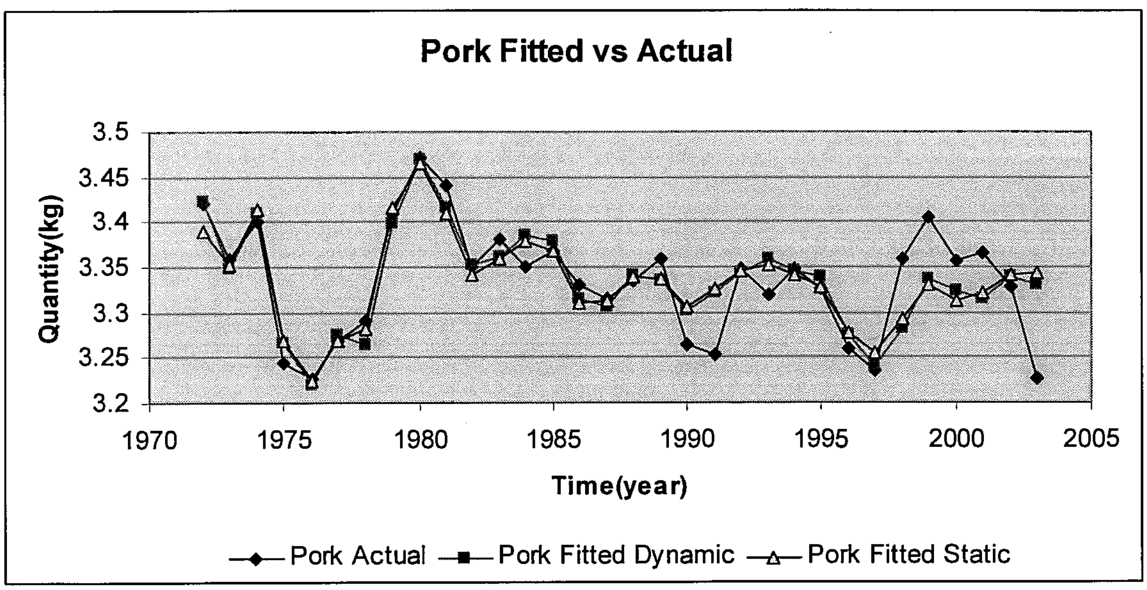
Figure 4. Plot of consumption of fish, 1971-2003



Source: See Table 1.

Figure 5. Fitted value versus actual value





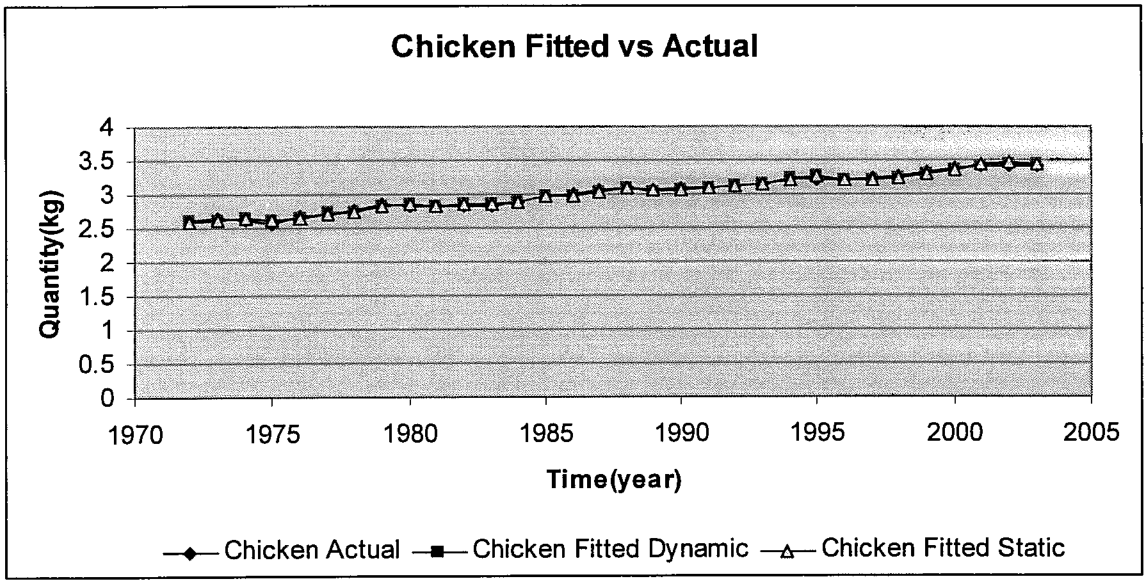

Chicken Fitted vs Actual
Quantity(kg)
4
3.5
3
2.5
2
1.5
1
0.5
0
1970
1975
1980
1985
1990
1995
2000
2005
Time(year)
Chicken Actual
Chicken Fitted Dynamic
Chicken Fitted Static

Table 1. Data Sources

Variables	Sources
Consumption	
Beef	1971-2003, CANSIM II v62316-Table 0030035
Pork	1971-2003, CANSIM II v62319-Table 0030035
Chicken	1971-2003, CANSIM II v60465-Table 0030017
Fish	1971-1987, Table 170 of *Handbook of Food, Expenditures, Prices and Consumption*, Agriculture Canada (1991), p. 240
	1988-2003, CANSIM II v1312689-Table 002-0019
Prices[1]	
Beef CPI	1971-2003, CANSIM II v735324-Table 326-0001 (1992=100)
Pork CPI	1971-1978, Catalogue 62-010, Statistics Canada, (1986=100)
	1979-2003, CANSIM II v735325-Table 326-0001 (1992=100)
Chicken CPI	1971-2003, CANSIM II v735328-Table 326-0001 (1992=100)
Fish CPI	1971-1978, Table 35 of *Handbook of Food, Expenditures, Prices and Consumption*, Agriculture Canada (1991), p. 73 (1986=100)
	1979-2003, CANSIM II v735334-Table 326-0001 (1992=100)
All items	1971-2003, CANSIM II v735319-Table 0030017 (1992=100)
Farm Product Prices	
Cattle FPPI	1971-2003, CANSIM II v1811734-Table 002-0022 (1997=100)
Hogs FPPI	1971-2003, CANSIM II v1811725-Table 002-0022 (1997=100)
Poultry FPPI	1971-2003, CANSIM II v1811726-Table 002-0022 (1997=100)
Per capita disposable income[2]	Computed by Statistics Canada (obtained by email)

Note: 1. The price data were provided to me by Andy Baldwin, who also rebased them to 1997 = 100

2. Per capita disposable income is computed by dividing CANSIM II v647037-Table 380-0019 by CANSIM II v466668-Table 051-0001.

Table 2. Variable Definitions		
Variable	Definition	Units
Qb	Annual Canadian per capita disappearance of beef	Retail weight, kg
Qp	Annual Canadian per capita disappearance of pork	Retail weight, kg
Qc	Annual Canadian per capita disappearance of chicken	Eviscerated weight, kg
Pb	Canadian real consumer price index of beef, 1997=100	
Pp	Canadian real consumer price index of pork, 1997=100	
Pc	Canadian real consumer price index of chicken, 1997=100	
Pf	Canadian real consumer price index of fish, 1997=100	
Y	Annual Canadian real per capita disposable income	$ / per person
t	Time trend	Period 1971-2003
BSE	Dummy variable denotes food scares due to BSE	1 = year 1996 0 = otherwise
FPB	Canadian farm product price index for beef, 1997=100	
FPP	Canadian farm product price index for pork, 1997=100	
FPC	Canadian farm product price index for poultry, 1997=100	
BANSB	Dummy variable represents the ban on Canadian beef export due to BSE	1 = year 2003 0 = otherwise
CDB	U.S. countervail duty on Canadian cattle and beef exports	1 = year 1998 0 = otherwise
CDP	U.S. countervail duty on Canadian hog exports	1 = 1985 or 1 = 1989, 1990 and 1991 0 = otherwise
Qb(-1)	Lagged value of per capita disappearance of beef	Retail weight, kg
Qp(-1)	Lagged value of per capita disappearance of pork	Retail weight, kg
Qc(-1)	Lagged value of per capita disappearance of chicken	Eviscerated weight, kg

Note: The definitions of CDB and CDP are from Trant (2005).

Table 3. Summary of Results of Order Condition

No. of endogenous variables in complete model = M = 6
No. of endogenous variables in each equation = m= 4
No. of exogenous and predetermined variables in dynamic and static systems= K
No. of exogenous and predetermined variables in each equations = k

Equation	K	k	K-k	m-1	(K-k)-(m-1)
Beef-static	11	5	6	3	3
Pork-static	11	4	7	3	4
Chicken-static	11	4	7	3	4
Beef-dynamic	14	6	8	3	5
Pork-dynamic	14	5	9	3	6
Chicken-dynamic	14	5	9	3	6

Table 4. Results of Normality, Heteroscedasticity, Autocorrelation and Wu-Hausman Tests

	Jarque-Bera Test	Goodness of Fit Test	BPG Test	BG Test	WH Test
Static model					
Beef	0.0623 (0.969)	12.6089 (0.002)	7.047 (0.4240)	9.3201 (0.0095)	2.3514 (0.0999)
Pork	5.4156 (0.067)	8.4315 (0.004)	11.6410 (0.0705)	2.6046 (0.0947)	0.6129 (0.6135)
Chicken	1.6632 (0.435)	5.8950 (0.015)	6.897 (0.3305)	2.5854 (0.2745)	6.2780 (0.0029)
Dynamic model					
Beef	0.4053 (0.817)	8.8560 (0.003)	6.048 (0.6419)	0.6046 (0.5555)	1.1152 (0.3664)
Pork	3.8094 (0.149)	11.1267 (0.004)	12.867 (0.0755)	2.1518 (0.1401)	0.5482 (0.6493)
Chicken	1.5995 (0.449)	6.0313 (0.049)	6.107 (0.5273)	2.9364 (0.2303)	2.9516 (0.0562)

Notes: 1. The numbers in parentheses underneath the test statistics are p-values.
2. The BPG test is the Breusch-Pagan-Godfrey test.
3. The BG test is the Breusch-Godfrey test.
4. The WH test is the Wu-Hausman test.

Table 5. Auxiliary R^2s				
	Static		Dynamic	
Beef model	lnPb	0.5793	lnQb(-1)	0.9079
	lnPp	0.8243	lnPb	0.5904
	lnPc	0.7841	lnPp	0.8806
	lnPf	0.6743	lnPc	0.7618
	lnY	0.8847	lnPf	0.6669
	t	0.9014	lnY	0.9149
	BSE	0.1281	t	0.9603
	Constant	0.0000	BSE	0.1343
			Constant	0.0000
Pork model	lnPb	0.5663	lnQp(-1)	0.3402
	lnPp	0.8227	lnPb	0.6291
	lnPc	0.7811	lnPp	0.8510
	lnPf	0.6555	lnPc	0.7541
	lnY	0.8793	lnPf	0.6502
	t	0.8966	lnY	0.8706
	Constant	0.0000	t	0.8897
			Constant	0.0000
Chicken model	lnPb	0.5663	lnQc(-1)	0.9912
	lnPp	0.8227	lnPb	0.7876
	lnPc	0.7811	lnPp	0.8418
	lnPf	0.6555	lnPc	0.7684
	lnY	0.8793	lnPf	0.7502
	t	0.8966	lnY	0.8590
	Constant	0.0000	t	0.9925
			Constant	0.0000

Table 6. Results of Tests for Specification Error

	RESET	FRESETL	FRESETS
Dynamic beef model	0.003	0.004	0.001
Static beef model	0.000	0.000	0.000
Dynamic pork model	0.982	0.989	0.999
Static pork model	0.871	0.777	0.803
Dynamic chicken model	0.169	0.006	0.002
Static chicken model	0.169	0.042	0.205

Notes: 1.The RESET test proposed by Ramsey (1969) is a simple test for errors in functional form. Three powers of the fitted values were included in the test equations.
2.DeBenedictis and Giles (1998) proposed the FRESETS and FRESETL tests, which are modifications of the original RESET test. For each test, the test equation includes six functions of the fitted values.
3.The third versions of the RESET, FRESETL and FRESETS test statistics are reported.
4. The results are obtained using SHAZAM version 10.0

Table 7. 2SLS and OLS Estimation Results

		Static			Dynamic		
	Variable	Coefficient Estimates	t-statistic	p-value	Coefficient Estimates	t-statistic	p-value
Beef	constant	2.8639	0.9874	0.3333	1.4190	0.7804	0.4431
	LnPb	-0.3968	-2.8467	0.0089	-0.1899	-2.0869	0.0482
	lnPp	0.2767	2.5299	0.0184	0.0483	0.3667	0.7172
	lnPc	0.5589	2.2315	0.0352	0.1561	0.7921	0.4364
	lnPf	-0.2002	-1.7293	0.0966	0.0552	0.4861	0.6315
	lnY	0.1009	0.0.3282	0.7456	0.0174	0.0789	0.9378
	t	-0.0113	-2.0897	0.0474	-0.0052	-1.4501	0.1605
	BSE	-0.0864	-3.2484	0.0034	-0.0313	-0.7664	0.4512
	lnQb(-1)				0.5870	3.8031	0.0009
	r^2	0.9460			0.9749		
Pork	constant	5.3280	4.0833	0.0004	4.9125	2.4360	0.0226
	lnPb	0.3264	4.1324	0.0003	0.2846	2.8025	0.0099
	lnPp	-0.4680	-4.4880	0.0001	-0.4745	-3.7896	0.0009
	lnPc	-0.0198	-0.1087	0.9143	-0.0806	-0.3915	0.6989
	lnPf	0.1645	2.6286	0.0142	0.1565	1.3307	0.1958
	lnY	-0.2037	-1.4883	0.1487	-0.2101	-1.1083	0.2787
	t	-0.0029	-1.2471	0.2235	-0.0033	-1.5254	0.1402
	lnQp(-1)				0.1487	1.0805	0.2907
	r^2	0.8220			0.8346		
Chicken	constant	-0.8167	-0.6078	0.5488	-0.6146	-0.4242	0.6754
	lnPb	0.4303	5.3596	0.0000	0.4520	3.5669	0.0016
	lnPp	0.1370	1.3914	0.1012	0.1102	1.0363	0.3108
	lnPc	-0.7193	-3.8286	0.0008	-0.8149	-3.7933	0.0009
	lnPf	0.3187	3.2417	0.0034	0.3572	2.6577	0.0141
	lnY	0.3377	2.4182	0.0232	0.3545	2.3052	0.0305
	t	0.0264	14.2329	0.0000	0.0296	4.1601	0.0004
	lnQc(-1)				-0.1424	-0.5862	0.5635
	r^2	0.9951			0.9948		

Notes:1. Values reported for dynamic and static chicken models are the 2SLS results.
2. Values reported for dynamic and static pork models are the OLS results The Newey-West autocorrelation correction is applied to the standard errors of the static version.
3. Values reported for dynamic beef model are OLS results, while the results for the static beef model are the 2SLS results with the Newey-West autocorrelation correction.
4. r^2 is the squared-correlation between actual and fitted values.

Table 8. 2SLS and OLS estimates before and after autocorrelation correction (static model)

	Variable	2SLS			2SLS (Newey-West correction)		
		Coefficient	t-stats	p-value	Coefficient	t-stats	p-value
Beef	constant	2.8639	1.1234	0.2711	2.8639	0.9874	0.3333
	lnPb	-0.3968	-2.6581	0.0138	-0.3968	-2.8467	0.0089
	lnPp	0.2767	1.5631	0.1311	0.2767	2.5299	0.0184
	lnPc	0.558881	1.6225	0.1178	0.558881	2.2315	0.0352
	lnPf	-0.2002	-1.0602	0.2996	-0.2002	-1.7293	0.0966
	lnY	0.1009	0.3822	0.7057	0.1009	0.3282	0.7456
	t	-0.0113	-3.2332	0.0035	-0.0113	-2.0897	0.0474
	BSE	-0.0864	-1.4879	0.1498	-0.0864	-3.2484	0.0034
	Variable	OLS			OLS (Newey-West correction)		
Pork	constant	5.3280	3.3484	0.0025	5.3280	4.0833	0.0004
	lnPb	0.3264	3.4725	0.0018	0.3264	4.1324	0.0003
	lnPp	-0.4680	-4.0690	0.0004	-0.4680	-4.4880	0.0001
	lnPc	-0.0198	-0.0985	0.9223	-0.0198	-0.1087	0.9143
	lnPf	0.1645	1.4012	0.1730	0.1645	2.6286	0.0142
	lnY	-0.2037	-1.2291	0.2300	-0.2037	-1.4883	0.1487
	t	-0.0030	-1.3039	0.2037	-0.0030	-1.2471	0.2235

Table 9. Decomposition of Change in Consumption between 1976 and 2003

Variables	$\Delta \ln \hat{Q}b$ Static	$\Delta \ln \hat{Q}p$ Static	$\Delta \ln \hat{Q}c$ Static	$\Delta \ln \hat{Q}b$ Dynamic	$\Delta \ln \hat{Q}p$ Dynamic	$\Delta \ln \hat{Q}c$ Dynamic
$\Delta \ln \hat{Q}$	-0.4869	0.1043	0.7960	-0.4871	0.1044	0.7793
$\hat{\alpha}_1 * \Delta \ln Pb$	-0.0075	0.0617	0.0813	-0.0359	0.0538	0.0854
$\hat{\alpha}_2 * \Delta \ln Pp$	-0.1268	0.2150	-0.0629	-0.0022	0.2180	-0.0506
$\hat{\alpha}_3 * \Delta \ln Pc$	-0.0595	0.0021	0.0765	-0.0166	0.0086	0.0867
$\hat{\alpha}_4 * \Delta \ln Pf$	0.0570	-0.0468	-0.0907	-0.0157	-0.0445	-0.1017
$\hat{\alpha}_5 * \Delta \ln Y$	0.0237	-0.0479	0.0793	0.0041	-0.0494	0.0834
Subtotal (rows 2-6)	-0.1131 (23.23%)	0.1841 (176.51%)	0.0835 (10.49%)	-0.0865 (17.76%)	0.1865 (178.64%)	0.1032 (13.24%)
$\hat{\alpha}_6 * \Delta t$	-0.3051 (62.66%)	-0.0783 (-75.07%)	0.7128 (89.55%)	-0.1404 (28.82%)	-0.0891 (-85.34%)	0.7992 (102.55%)
$\hat{\alpha}_7 * \Delta BSE$	-0.0864 (17.74%)			-0.0313 (6.43%)		
$\hat{\alpha}_8 * \Delta \ln Qi(-1)$				-0.2415 (49.58%)	0.0100 (9.58%)	-0.1207 (-15.49%)

Notes: 1.The entries in each row are of the form $\hat{\alpha}_j * \Delta X_j$, where ΔX_j is the change in variable X_j and $\hat{\alpha}_j$ is the estimated of coefficients of X_j.

2. The values in the parentheses are the percentage share of the total change in $\ln \hat{Q}$. The percentage share is positive if the change in the component is of the same sign as the total change, and negative otherwise.