

The Confirmation and Falsification of Equilibrium Displacement Models

George C. Davis*

May 23, 2001

Selected Paper
American Agricultural Economics Association Annual Meeting
Chicago, IL, August 5 – August 8, 2001

*Appreciation is expressed to Henry Kinnucan for providing some of the data used in this analysis, to Gary Brester for assistance in finding some of the elasticity estimates used in the analysis, to John Stevens for assistance with the Bayesian software used in the analysis, and to Melissa Weichert for technical assistance.

Contact Information: George C. Davis, Texas A&M University, 302 Blocker Bldg. College Station, Tx 77843-2124, Ph: (979) 845-3788. E-mail: gdavis@tamu.edu.

Copyright © 2000 by George C. Davis. All rights reserved. Readers may make verbatim copies of this document for non-commercial purposes by any means, provided that this copyright notice appears on all such copies.

The Confirmation and Falsification of Equilibrium Displacement Models

Abstract

One of the most important principles in any science is testing and consequently confirmation and falsification. In agricultural economics, the equilibrium displacement model is a popular modeling approach that presently is not testable and consequently cannot be confirmed or falsified. This paper presents four increasingly sophisticated procedures designed to overcome this limitation of equilibrium displacement models. An empirical illustration demonstrates the usefulness of these procedures in deciding between three alternative and theoretically viable equilibrium displacement models.

Key Words: Equilibrium displacement, confirmation, falsification, mixed estimation, Bayesian estimation.

The Confirmation and Falsification of Equilibrium Displacement Models

[M]easurement is science's highest court of appeal, pronouncing its final verdict for or against the meekest and loftiest ideas alike.

Fox, Gorbunov, and Hooke (p. 20)

One of the most important principles in any science is testing and consequently confirmation and falsification. With confirmation and falsification, theoretical speculations may be admitted into the elite realm of science. Without confirmation and falsification, theoretical speculations remain just that – speculation.

A popular modeling approach in agricultural economics that has received recent methodological attention is the equilibrium displacement model (EDM) (Davis and Espinoza (1998, 2000), Griffiths and Zhao, and Zhao, et al).¹ The EDM framework is appealing for three reasons: (i), it is extremely flexible in modeling diverse economic phenomena; (ii), it is easy to implement as it only involves inverting some matrices of parameters that are not wed to any particular data set; (iii), because of two, the results may be considered rather robust to econometric misspecifications. The work of Davis and Espinoza (1998, 2000), Griffiths and Zhao, and Zhao et al. has greatly improved the inferential content obtainable from EDMs. However, EDMs are still grossly inadequate when subjected to the scientific standards of confirmation and falsification because they presently are not testable as to their empirical validity. Consequently, their empirical claims are highly questionable.

The goal of this paper is to overcome this significant limitation of the EDMs by making them confirmable or falsifiable without completely destroying their major advantage, which is ease in implementation. Two conditions must be satisfied to achieve this goal:

Condition 1: The researcher must have a sincere interest in comparing the predictions of the EDM with the actual phenomenon under consideration.

Condition 2: Some data must be available on *one* endogenous variable and the exogenous variables in the EDM.

These two conditions are related. The first condition is necessary because if there is no interest in confirming the EDM, then the EDM becomes immunized from the normal scientific practices of critique, testing, and improvement. However, even if a researcher has a sincere interest in making an EDM empirically accountable, there presently exists no way to do this and this is related to the second condition. The existing argument for conducting a standard EDM analysis is that ‘EDMs are best suited for situations where data are insufficient for a complete econometric analysis and if data are sufficient for a complete econometric analysis, an EDM should not and would not be used in practice.’ This statement takes a provincial view of econometric models and EDMs and is only partially correct. While there may not be enough data to do a complete econometric analysis, there are usually enough data to test the consistency of an EDM with the phenomenon it claims to explain, as this paper will demonstrate.

In an attempt to improve the scientific standing of EDMs, this paper presents four approaches to confirming and falsifying EDMs with increasing sophistication and informational content. These approaches will simultaneously increase the confidence that may be placed in the validity of these models and will also help identify those areas of the model structure that may be deficient. In addition, the techniques will also demonstrate the importance of conducting sensitivity analysis in the manner advocated by Davis and Espinoza (1998) and Zhao, et al., and will shed light on the Griffiths and Zhao comment and the Davis and Espinoza (2000) reply. In the next section the limitation of EDMs is presented via a simple example. The following

¹ See Davis and Espinoza (1998) for documentation on the popularity of the EDM.

section cast the problem in a more general framework and presents the formal confirmation/falsification techniques. An empirical illustration is then given for the U.S. meat market where three different, but all potentially valid, theoretical model structures are investigated with the techniques. The paper closes with conclusions.

Empirical Limitations of EDMs

To demonstrate the empirical limitations of an EDM, consider a simplistic but representative situation where an analyst claims the retail beef market can be represented by the supply and demand EDM,

$$(1) \quad Q_d^* = \eta_d P^* + \eta_z Z^* \quad : \text{ Demand}$$

$$(2) \quad Q_s^* = \varepsilon_s P^* + \varepsilon_w W^* \quad : \text{ Supply}$$

$$(3) \quad Q_s^* = Q_d^* \quad : \text{ Equilibrium.}$$

For any variable $X^* = dX/X = d\ln X$ is the percentage change in X , η_d and ε_s are own price demand and supply elasticities respectively, and η_z and ε_w are elasticity scalars or vectors associated with the shift variables Z^* and W^* respectively. Solving (1) – (3) simultaneously yields the reduced forms,

$$(4) \quad P^* = \pi_{pw} W^* + \pi_{pz} Z^* \quad : \text{ Reduced Form Price}$$

$$(5) \quad Q^* = \pi_{Qw} W^* + \pi_{Qz} Z^* \quad : \text{ Reduced Form Quantity}$$

where the reduced form parameters (i.e., elasticities) are defined as $\pi_{pw} = (\eta_d - \varepsilon_s)^{-1} \varepsilon_w$, $\pi_{pz} = -(\eta_d - \varepsilon_s)^{-1} \eta_z$, $\pi_{Qw} = (\eta_d - \varepsilon_s)^{-1} \eta_d \varepsilon_w$, and $\pi_{Qz} = -(\eta_d - \varepsilon_s)^{-1} \eta_z \varepsilon_s$.²

² The term parameter and elasticity are interchangeable in this paper.

Now suppose the analyst has structural elasticity estimates of $\eta_d = -.5$, $\eta_z = .25$, $\epsilon_s = .5$, and $\epsilon_w = -.15$ but is interested only in the impact income will have on the price and quantity. The analyst substitutes the structural elasticity estimates into the reduced form parameter equations and solves the system with Z^* equal to some constant, usually $Z^* = 1$, and $W^* = 0$ to yield the solution $P^* = .25$ and $Q^* = .125$. The analyst then claims that “for a one-percent increase in income, the price of beef and quantity of beef will increase by .25 and .125 percent, respectively.” To date EDM analysis stops here or with some deterministic function of P^* and Q^* (e.g. producer surplus). However, the obvious question becomes how accurate are these estimates of the percentage change in price and quantity induced by income?

The accuracy and validity of the EDM approach clearly rest on two maintained assumptions. First, the structural parameter estimates are considered unbiased or at least reasonable. Second, the structural model is taken as being true or correct, and therefore by deduction, the reduced form model is correct. The work of Davis and Espinoza (1998, 2000), Griffiths and Zhao, and Zhao, et al. concentrates on the first maintained assumption and allows for the formal incorporation of parameter uncertainty by replacing point estimates with distributional assumptions. What results is a distribution on P^* and Q^* , so $P^* = .25$ and $Q^* = .125$, may represent means or modes of these distributions. They refer to this approach as the stochastic EDM (SEDM).

While the SEDM is certainly an improvement over previous attempts to allow for parameter uncertainty, the truth of the underlying structural model is still a maintained assumption. Consequently, even if $P^* = .25$ and $Q^* = .125$ come from a SEDM, there is still no outside validation of the ‘truth’ of the structural model. It is, therefore, difficult to place any confidence in the claim that if income increased by one-percent that the price would increase by .25 percent

or quantity by .125 percent. The central question is, how can these types of models be confirmed or falsified as being consistent with the actual phenomenon being modeled?

A General Framework for Confirming and Falsifying an EDM

As Davis and Espinoza (1998) indicate, the EDM can be couched within a standard simultaneous econometric framework. Let \mathbf{Y}^* be a $1 \times G$ vector of endogenous variables defined in terms of percentage change, \mathbf{X}^* be a $1 \times K$ vector of exogenous variables defined in terms of percentage change, $\mathbf{\Gamma}$ be a $G \times G$ matrix of parameters and \mathbf{B} be a $K \times G$ matrix of parameters.³ The structural system is then written in matrix form as $\mathbf{Y}^*\mathbf{\Gamma} + \mathbf{X}^*\mathbf{B} = 0$, which has the reduced form solution for \mathbf{Y}^* ,

$$(6) \quad \begin{aligned} \mathbf{Y}^* &= -\mathbf{X}^*\mathbf{B}\mathbf{\Gamma}^{-1} \\ &= \mathbf{X}^*\mathbf{\Pi} \\ &= \mathbf{X}^*\mathbf{\Pi}(\boldsymbol{\beta}, \boldsymbol{\gamma}) \end{aligned}$$

where $\mathbf{\Pi}$ is the $K \times G$ reduced form parameter matrix and is a function of the structural parameters with $\boldsymbol{\beta} = \text{vec}(\mathbf{B})$ and $\boldsymbol{\gamma} = \text{vec}(\mathbf{\Gamma})$. It is important to recognize that by construction the EDM claims to provide the full specification of the variables entering the structural model and therefore the reduced form model. If this were not the case, then the EDM would be internally inconsistent with its own implied reduced form. As indicated, the EDM analysis proceeds by specifying values for the structural parameters, say $\hat{\boldsymbol{\beta}}$ and $\hat{\boldsymbol{\gamma}}$, setting the elements of \mathbf{X}^* equal to a constant, usually one, to generate the values for the elements of \mathbf{Y}^* as

$$(7) \quad \mathbf{Y}^* = \mathbf{X}^*\mathbf{\Pi}_r$$

³ If the equations are repeated for T observations, as is the case in econometric estimation, then \mathbf{Y}^* is a $T \times G$ and \mathbf{X}^* is a $T \times K$.

where $\Pi_r = -\hat{\mathbf{B}}\hat{\Gamma}^{-1} = \Pi(\hat{\boldsymbol{\beta}}, \hat{\boldsymbol{\gamma}})$. It is at this point where the interpretation of (7) differs from Davis and Espinoza (1998).

In simultaneous equation models there are three classes of reduced form estimators: the unrestricted estimator, the derived or restricted estimator, and the partially restricted estimator (see e.g. Fomby, Hill, and Johnson chapter 23). Here interest centers on the first two. The *unrestricted reduced form estimator* comes from just applying ordinary least squares to the reduced form equation or system $\mathbf{Y}^* = \mathbf{X}^*\boldsymbol{\Pi} + \mathbf{V}$ without imposing any of the overidentifying restrictions and gives the estimate Π_u . The *restricted reduced form estimator* comes from estimating the structural parameters and substituting them into the overidentifying restrictions to yield the estimate $\Pi_r = \Pi(\hat{\boldsymbol{\beta}}, \hat{\boldsymbol{\gamma}})$. Davis and Espinoza (1998) interpret (7) as being an extreme version of a Bayesian estimator where the conditional (data) likelihood function plays no role in determining the posterior distribution. Griffiths and Zhao correctly point out that within a Bayesian framework this interpretation is misleading because the resulting distribution is not a posterior but just a nonlinear transformation of the prior distribution(s) of the structural parameters. However, in the Bayesian context a more accurate description is that the SEDM leads to a restricted reduced form estimate that can be considered a prior for the unrestricted reduced form estimate. This interpretation leads naturally to several ways to test the validity of the SEDM.

If the SEDM restrictions are “true” then there will be no statistical difference between the unrestricted estimate Π_u and the restricted estimate Π_r . Alternatively, if the restrictions are not “true” then the unrestricted estimate Π_u and the restricted estimate Π_r will be statistically different. The attractive feature of working with the reduced form is that the EDM can be confirmed or falsified without estimating a complete structural model. Consequently, data on all

the endogenous variables are not needed (condition two). In fact, data on one endogenous variable is sufficient and, for most commodities, the obvious candidate is the price.

The comparison between the restricted reduced form (i.e., the EDM result) and the unrestricted reduced form can be done in several ways and four increasingly sophisticated methods are pursued here: (i) an adjusted R^2 comparison between the EDM restricted reduced form and the unrestricted reduced form; (ii) an F test of the difference between the EDM restricted reduced form and the unrestricted reduced form; (iii) a mixed estimation procedure with a corresponding test of the superiority of the mixed estimator compared to the unrestricted estimator; (iii) a Bayesian procedure that leads to an odds ratio test. Before proceeding one point needs to be made clear and kept in mind. In the present context, the unrestricted reduced form model is to be interpreted only as a testing model, not necessarily a descriptive model, and is therefore analogous to an encompassing or artificial regression model in the econometrics literature, which also are only testing models. See Mizon on the encompassing approach and Davidson and MacKinnon on artificial regressions.

An adjusted R^2 and F test of the EDM

With the goal of confirming or falsifying the EDM, assume a data set is in hand and that data is only available on the first endogenous variable. The first reduced form equation is

$$(8) \quad \mathbf{y}^*_1 = \mathbf{X}^*\mathbf{\Pi}_1 + \mathbf{v}_1,$$

where \mathbf{y}^*_1 is the $T \times 1$ regressand vector, \mathbf{X}^* is the exogenous $T \times K$ regressor matrix, $\mathbf{\Pi}_1$ is the $K \times 1$ reduced form parameter vector and \mathbf{v}_1 is the $T \times 1$ disturbance term. Letting $\mathbf{\Pi}_{1u}$ represent the unrestricted reduced form estimate, the unrestricted reduced form predicted value would be $\mathbf{y}^*_{1u} = \mathbf{X}^*\mathbf{\Pi}_{1u}$. The restricted reduced form (i.e., the EDM) predicted value can be similarly

defined as $\mathbf{y}^*_{1r} = \mathbf{X}^* \boldsymbol{\Pi}_{1r}$, where $\boldsymbol{\Pi}_{1r}$ is the restricted reduced form estimate that comes from substituting the (prior) structural parameter estimates being utilized in the EDM into the overidentifying restrictions.

The R^2 can be considered the square of the correlation between a predicted value and the actual value, so a measure of fit for the unrestricted and restricted (EDM) would be $R^2_j = [\text{Cov}(y^*_{1j}, y^*_{1})]^2 / [\text{var}(y^*_{1j}) \text{var}(y^*_{1})]$, where y^*_{1} is the actual value of the endogenous variable and y^*_{1j} is its predicted value $j = u, r$. Once the R^2 s are in hand adjusted R^2 s can also be calculated. The R^2 or adjusted R^2 gives an indication of how well the EDM fits the actual data, but it is not a formal test statistic that can be used to confirm or falsified the EDM.

A simple formal test of the EDM would be an F test of the restricted reduced form parameters (EDM) versus the unrestricted reduced form parameters. Formally Hausman (p. 432) gives a Wald test of the restricted versus the unrestricted estimator, which following standard procedures can be written in its asymptotic F test form as,

$$(9) \quad f = (\boldsymbol{\Pi}_{1r} - \boldsymbol{\Pi}_{1u})' \boldsymbol{\Psi}_u (\boldsymbol{\Pi}_{1r} - \boldsymbol{\Pi}_{1u}) q^{-1}$$

where q is the number of restrictions. Under the null hypothesis that $(\boldsymbol{\Pi}_{1r} - \boldsymbol{\Pi}_{1u}) = 0$, f is distributed as an F distribution with T and q degrees of freedom.⁴ In the single equation case the weighting matrix $\boldsymbol{\Psi}_u = s^{-2}(\mathbf{X}^{*'} \mathbf{X}^*)$, with s^2 being the estimate of the variance of \mathbf{v}_1 . If the null hypothesis is rejected, then this indicates that the EDM is not consistent with actual data. The appealing nature of this test is that subsets of the EDM can be tested and used to identify individual parameter estimates that may be problematic. However, it should be noted that this test treats $\boldsymbol{\Pi}_{1r}$ as if it is a constant and effectively ignores its stochastic nature. For this reason it is natural to go to a mixed estimation and/or Bayesian procedure.

A mixed estimation approach

While the R^2 and F statistics give an idea of fit of the restricted reduced form model (i.e., the EDM), they concentrate on comparing point estimates and do not take into account variances. In the nonstochastic case, even if the restricted estimator is bias it will have a smaller variance than will the unrestricted estimator. This is not necessarily the case if the restrictions are stochastic, but it may be the case, and so the researcher may be willing to trade a smaller variance coming out of an SEDM even if the SEDM is biased when compared with the unrestricted estimator.

The prior integrated mixed estimator (PIME) of Mittelhammer and Conway is implemented here because it is designed to overcome some of the conceptual limitations of the original Theil and Goldberger mixed estimator. The first reduced form equation for the PIME would be augmented with the prior information as

$$(10) \quad \begin{bmatrix} \mathbf{y}^*_1 \\ \mathbf{\Pi}_{1r} \end{bmatrix} = \begin{bmatrix} \mathbf{X}^* \\ \mathbf{R} \end{bmatrix} \mathbf{\Pi}_1 + \begin{bmatrix} \mathbf{v}_1 \\ \mathbf{u}_1 \end{bmatrix}$$

where the new notation is \mathbf{R} , a $K \times K$ identity matrix and \mathbf{u}_1 , a $K \times 1$ disturbance vector with $E[\mathbf{u}_1] = \boldsymbol{\delta}$ and $\text{cov}(\mathbf{u}_1) = \boldsymbol{\Omega}$, a positive definite matrix. The PIME estimator is then

$$(11) \quad \mathbf{\Pi}_{1P} = (\sigma^{-2} \mathbf{X}^{*'} \mathbf{X}^* + \mathbf{R}' \boldsymbol{\Omega}^{-1} \mathbf{R})^{-1} (\sigma^{-2} \mathbf{X}^{*'} \mathbf{y}^*_1 + \mathbf{R}' \boldsymbol{\Omega}^{-1} \boldsymbol{\omega})$$

where $\text{cov}(\mathbf{v}_1) = \sigma^2 \mathbf{I}$ and $\boldsymbol{\omega}$ would be the researchers best guess as to the value of $\mathbf{R}\mathbf{\Pi}_1$. The covariance of the PIME estimator is $\boldsymbol{\Lambda}^{-1} \boldsymbol{\Psi}_u \boldsymbol{\Lambda}^{-1}$ with $\boldsymbol{\Lambda} = \boldsymbol{\Psi}_u + \mathbf{R}' \boldsymbol{\Omega}^{-1} \mathbf{R}$.

To operationalize the PIME, the first and second moments of the subjective prior distribution on $\mathbf{\Pi}_{1r}$ are needed. Consequently, the PIME is the next logical step in the stochastic EDM (SEDM) analysis since in an SEDM an entire distribution on the prior of $\mathbf{\Pi}_{1r}$ is generated. In this context the prior expected value of $\boldsymbol{\omega}$ within the PIME framework is $\boldsymbol{\omega} = \mathbf{\Pi}_{1r}$. Furthermore,

⁴ In the normal context, where the same data has been used to estimate structural parameters, this is an

because of the sampling techniques, an estimate of the covariance of the prior distribution on Π_{1r} , say $\hat{\Omega}$, is also easily generated. Once the PIME is implemented, a simple conservative test of the PIME being strong mean square error (SMSE) superior to the unrestricted least squares estimator is related to the F test given in equation (9). The test criterion is

$$\text{if } f \begin{cases} \leq \\ > \end{cases} F_{\alpha}(K, T - K; .5) \text{ then } \begin{cases} \text{do not reject} \\ \text{do reject} \end{cases} \text{ SMSE superiority}$$

of the PIME estimator. Note the appropriate F distribution is a noncentral F distribution with the noncentrality parameter equal to .5. See Mittelhammer and Conway for more discussion.

The PIME estimator is attractive because it provides a rather simple way of pooling the prior information with data to perhaps generate an estimate that has a superior mean square error compared to the unrestricted estimator. Furthermore, because actual data is being used with the SEDM, the SEDM is disciplined to be somewhat compliant with the data, a shortcoming of the SEDM as pointed out by Davis and Espinoza (1998, 2000).

The Bayesian Approach

A Bayesian approach is a more sophisticated way of pooling the prior information with data. Because the testing procedure has been couched within the context of a reduced form restriction, the standard Bayesian techniques found in several textbooks become applicable and so are just outlined here (e.g., Judge, et al. Chapter 4). In a Bayesian analysis, interest centers on estimating the entire posterior distribution for the parameter vector of interest, here Π_1 , and not just a point estimate. Let the posterior distribution be given generally as $p(\Pi_1 | \mathbf{y}, M)$, where $\mathbf{y} = (\mathbf{y}^*_1, \mathbf{X}^*)$ and M represents a specific model containing prior information.⁵ Following standard Bayesian

overidentification test.

⁵ The parameter representing the variance is omitted for simplicity.

arguments, the posterior distribution can be written as being proportional to the product of the conditional likelihood distribution of the data $l(\boldsymbol{\Pi}_1 | \mathbf{y})$ and the subjective prior distribution $p(\boldsymbol{\Pi}_1 | M)$ or $p(\boldsymbol{\Pi}_1 | \mathbf{y}, M) \propto l(\boldsymbol{\Pi}_1 | \mathbf{y}) p(\boldsymbol{\Pi}_1 | M)$. Once the posterior distribution is obtained, several summary measures are useful. For example, assuming a quadratic loss function, the posterior mean $E(\boldsymbol{\Pi}_1 | \mathbf{y}, M) = \int \boldsymbol{\Pi}_1 p(\boldsymbol{\Pi}_1 | \mathbf{y}, M) d\boldsymbol{\Pi}_1$ is optimal, which is often referred to as the Bayesian point estimate.

An appealing aspect of the Bayesian approach is that it allows one to make probability statements about one model versus another model. Let M_i denote the i th model. Using Bayes theorem, the probability of the M_i model given the data \mathbf{y} can be written as $Prob(M_i | \mathbf{y}) = [Prob(M_i) \times p(\mathbf{y} | M_i)] / p(\mathbf{y})$, where the marginal density is $p(\mathbf{y} | M_i) = \int p(\boldsymbol{\Pi}_1 | M_i) p(\mathbf{y} | \boldsymbol{\Pi}_1, M_i) d\boldsymbol{\Pi}_1$ and $p(\mathbf{y})$ is the data density. Consequently, the posterior odds ratio between models i and j is given as

$$(12) \quad K_{ij} = \frac{Prob(M_i | \mathbf{y})}{Prob(M_j | \mathbf{y})} = \frac{Prob(M_i)}{Prob(M_j)} \times \frac{p(\mathbf{y} | M_i)}{p(\mathbf{y} | M_j)}.$$

The second term in (12) is the ratio of the marginal densities and is often referred to as the ‘‘Bayes factor.’’ Note in case the subjective probability attached to each model is the same, i.e. $Prob(M_i) = Prob(M_j)$, the odds ratio is the Bayes factor. If the odds ratio is less than one then support is given for the j th model and if it is greater than one then support is given for the i th model.

Probability statements are also easily developed within the Bayesian framework by calculating a highest posterior density interval, for a particular element of $\boldsymbol{\Pi}_1$,

$$(13) \quad Prob(a < \pi_1 < b) = \int_a^b p(\pi_1 | \mathbf{y}, M) d\pi_1,$$

which, because this is a Bayesian analysis, is interpreted as giving the probability that the “true” π_1 lies between a and b . Alternatively, often (13) will be set to some predetermined value, say .95, and the values of a and b determined. For further discussion on Bayesian econometrics see for example Judge, et al. chapter four.

An Empirical Illustration with the U.S. Beef Market

The techniques outlined above are applied to three alternative SEDMs. Each SEDM is designed to determine the percentage change in the price of beef attributed to a percent change in generic beef advertising in the U.S. beef market. This market and issue is chosen for three reasons. First, several authors have used EDMs to analyze the impacts of advertising in this market (e.g., Chung and Kaiser; Kinnucan, Xiao, and Hsia; Wohlgenant). However, contrary to the conventional wisdom that EDMs are only applied where there is insufficient data to validate the model, there is more than enough data for this market to implement the procedures outlined here. Second, there exist numerous structural elasticity estimates in the literature for this industry from which the prior distributions may be formed. Finally, three alternative market structures are considered: (i) an *isolated structure* where the only variables considered endogenous are the price and quantity of beef; (ii) a *horizontal structure* where all meat prices and quantities are considered endogenous; and (iii) a *vertical structure* where the price and quantities of beef and cattle are considered endogenous. These three structures are somewhat representative of how EDMs have been implemented. For example, Lemieux and Wohlgenant; Wohlgenant; Chung and Kaiser assume a vertical structure between the beef and cattle. Piggott, Piggott, and Wright assume a horizontal structure between beef, lamb, pork, and chicken. Kinnucan, Xiao, and Hsia assume both a vertical and horizontal structure for beef, pork, and

chicken but restrict technology to be of the Leontief form. However, none of these structures have been validated so this seems an especially inviting application of the techniques discussed above.

The general EDM can be written as

$$(14.1) \quad D_b^* = \eta_{bb}p_b^* + \eta_{bp}p_p^* + \eta_{br}p_r^* + \eta_{bxd}X_d^* \quad : \text{Retail Beef Demand}$$

$$(14.2) \quad D_p^* = \eta_{pb}p_b^* + \eta_{pp}p_p^* + \eta_{pr}p_r^* + \eta_{pxd}X_d^* \quad : \text{Retail Pork Demand}$$

$$(14.3) \quad D_r^* = \eta_{rb}p_b^* + \eta_{rp}p_p^* + \eta_{rr}p_r^* + \eta_{rxd}X_d^* \quad : \text{Retail Poultry Demand}$$

$$(15.1) \quad S_b^* = \varepsilon_{bb}p_b^* + \varepsilon_{bt}w_t^* + \varepsilon_{bxs}X_s^* \quad : \text{Retail Beef Supply}$$

$$(15.2) \quad S_p^* = \varepsilon_{pp}p_p^* + \varepsilon_{pg}w_g^* + \varepsilon_{pxs}X_s^* \quad : \text{Retail Pork Supply}$$

$$(15.3) \quad S_r^* = \varepsilon_{rr}p_r^* + \varepsilon_{rn}w_n^* + \varepsilon_{rxs}X_s^* \quad : \text{Retail Poultry Supply}$$

$$(16) \quad D_t^* = \lambda_{tb}p_b^* + \lambda_{tt}w_t^* + \lambda_{txs}X_s^* \quad : \text{Farm Cattle Demand}$$

$$(17) \quad S_t^* = \theta_{tt}w_t^* + \theta_{tzs}Z_s^* \quad : \text{Farm Cattle Supply}$$

Notationally, all variables represent percentage changes. D^* and S^* are quantity demanded and supplied, respectively; p^* and w^* are retail and farm level prices, respectively. The subscripts indicate the product: b = beef, p = pork, r = poultry, t = cattle, g = hogs, and n = chicken. The capital lettered right hand side variables are considered exogenous vectors regardless of the market structure: X_d^* (retail demand), X_s^* (retail supply), and Z_s^* (farm supply). These vectors are defined precisely in the next section. The retail elasticities are denoted by η (demand) and ε (supply). The farm elasticities are denoted by λ (demand) and θ (supply).⁶

⁶ The market is assumed to be perfectly competitive because there appears little evidence in the literature for market power. See for example Muth and Wohlgenant or Paul.

Three Potential Market Structures and the Reduced Form Price for Beef

Solving different subsets of equations (14.1) – (17) is consistent with making different assumptions about the market structure. The *isolated market* structure solution is obtained by solving (14.1) and (15.1) simultaneously for the reduced form retail beef price equation,

$$(18) \quad p_b^* = (\eta_{bb} - \varepsilon_{bb})^{-1} \left[-\eta_{bp} p_p^* - \eta_{br} p_r^* + \varepsilon_{bt} w_t^* - \eta_{bxd} \mathbf{X}_d^* + \varepsilon_{bxs} \mathbf{X}_s^* \right]$$

$$= \pi_{bp} p_p^* + \pi_{br} p_r^* + \pi_{bt} w_t^* + \Pi_{bxd} \mathbf{X}_d^* + \Pi_{bxs} \mathbf{X}_s^*,$$

where Π_{bxd} and Π_{bxs} are the reduced form parameter vectors associated with the exogenous vectors of demand (\mathbf{X}_d^*) and supply (\mathbf{X}_s^*), respectively.⁷ Note in (18) that the price of pork, poultry, and cattle are all considered exogenous along with the other exogenous variables.

The *horizontal market* structure solution is obtained by solving (14.1)-(15.3) simultaneously for the reduced form price equations

$$\begin{bmatrix} p_b^* \\ p_p^* \\ p_r^* \end{bmatrix} = \begin{bmatrix} (\eta_{bb} - \varepsilon_{bb}) & \eta_{bp} & \eta_{br} \\ \eta_{bp} & (\eta_{pp} - \varepsilon_{pp}) & \eta_{pr} \\ \eta_{rb} & \eta_{rp} & (\eta_{rr} - \varepsilon_{rr}) \end{bmatrix}^{-1} \begin{bmatrix} \varepsilon_{bt} & 0 & 0 & -\eta_{bxd} & \varepsilon_{bxs} \\ 0 & \varepsilon_{pg} & 0 & -\eta_{pxd} & \varepsilon_{pxs} \\ 0 & 0 & \varepsilon_{rm} & -\eta_{rxd} & \varepsilon_{rxs} \end{bmatrix} \begin{bmatrix} w_t^* \\ w_g^* \\ w_n^* \\ \mathbf{X}_d^* \\ \mathbf{X}_s^* \end{bmatrix}$$

and the first row corresponds to the price of beef reduced form, which in reduced form notation would be,

$$(19) \quad p_b^* = \pi_{bt} w_t^* + \pi_{bg} w_g^* + \pi_{bn} w_n^* + \Pi_{bxd} \mathbf{X}_d^* + \Pi_{bxs} \mathbf{X}_s^*.$$

⁷ The focus on the price of beef is mainly to simplify the illustration but also because of the data limitations of quantities at the retail level and the analytical implications that are nicely demonstrated in Brester and Wohlgenant.

In addition to several of the arguments of the reduced form equation in (19) being different than in (18), the reduced form parameter values will be in general different even for those variables in common.

The *vertical market* structure solution is obtained by solving (14.1), (15.1), (16), and (17) simultaneously for the reduced form prices

$$\begin{bmatrix} p_b^* \\ w_t^* \end{bmatrix} = \begin{bmatrix} (\eta_{bb} - \varepsilon_{bb}) & -\varepsilon_{bt} \\ \lambda_{tb} & (\lambda_{tt} - \theta_{tt}) \end{bmatrix}^{-1} \begin{bmatrix} -\eta_{bp} & -\eta_{br} & -\eta_{bxd} & \varepsilon_{bxs} & 0 \\ 0 & 0 & 0 & -\lambda_{txs} & \theta_{tzs} \end{bmatrix} \begin{bmatrix} p_p^* \\ p_r^* \\ \mathbf{X}_d^* \\ \mathbf{X}_s^* \\ \mathbf{Z}_s^* \end{bmatrix}$$

so the first row would correspond to the price of beef reduced form, which in reduced form notation would be,

$$(20) \quad p_b^* = \pi_{bp} p_p^* + \pi_{br} p_r^* + \Pi_{bxd} \mathbf{X}_d^* + \Pi_{bxs} \mathbf{X}_s^* + \Pi_{bzs} \mathbf{Z}_s^*,$$

with Π_{bzs} being the reduced form parameter vector associated with the exogenous farm supply vector \mathbf{Z}_s^* . Once again, several of the arguments of the reduced form equation in (20) are different from those in (18) and (19) while some are the same. However, again, the reduced form parameter values will be in general different even for those variables in common.

Data and Prior Distributions

To obtain prior distributions on the structural elasticities or parameters, and therefore, reduced form parameters, the procedures outlined in Davis and Espinoza (1998), and Zhao, et al. were followed. Specifically, after reviewing the literature, nineteen published articles on different aspects of the beef industry were identified as providing insights into different important variables and enough information to obtain their corresponding elasticity estimates.

Based on the literature review, seventeen variables were identified as potentially important to be used in the empirical analysis.

For the estimation component of the analysis, quarterly data was collected on all seventeen variables for the period 1976.1-1993.4 because this period overlaps with a majority of the data sets. Henry Kinnucan was kind enough to provide a large portion of the data set and it was supplemented where needed. Table 1 gives the variables, their definitions, from which studies they were identified, the data source, and the measurement units and based on table 1,

$$\mathbf{X}_d^* = (p_{cpi}^*, m^*, a_b^*, a_p^*, h^*, f^*), \mathbf{X}_s^* = (w_k^*, w_l^*, w_e^*), \text{ and } \mathbf{Z}_s^* = (w_f^*, w_c^*, w_w^*).$$

For the prior distribution specification component of the analysis, each study's structural elasticity estimate associated with each variable in table 1 was recorded and summary statistics across the studies for each structural elasticity estimate were calculated. All retail demand elasticities were Marshallian elasticities, which were either taken directly or derived via Slutsky's equation from data available in the articles. With the exception of the retail supply elasticity provided by Brester, finding retail supply and therefore unconditional farm demand elasticities proved challenging. Though much research has been conducted on the beef processing sector, most of this work has estimated cost functions. While it is not difficult using duality theory to convert cost parameter estimates to unconditional elasticities, this usually requires additional information. The only study that provided sufficient information to calculate these elasticities was Ball and Chambers. The mathematical appendix provides the derivations for obtaining these estimates from the Ball and Chambers study. The farm supply elasticities came from Marsh.

With the summary statistics in hand, next a moment matching procedure was followed whereby a prior distribution was chosen for each elasticity. Each prior distribution was

parameterized such that the mean, standard deviation, minimum and maximum values from 1000 draws from the distribution closely matched those of the summary statistics for the corresponding elasticity. Either a Beta or uniform distribution was used for all distributions. The Beta was used whenever there was more than one estimate of an elasticity available because it is quite flexible in terms restricting the range of the distribution to lie between a minimum and maximum value. The uniform was chosen whenever there was only one estimate of an elasticity available. The endpoints for the uniform were then selected to be plus and minus twice the estimate. Table 2 gives the summary statistics from the prior distributions for the structural elasticities.

Estimation

Before presenting the results, two estimation issues need to be briefly mentioned. First, it is known that Marshallian demand functions are homogeneous of degree zero in prices and income and supply functions are homogeneous of degree zero in all prices. Consequently, imposing homogeneity by deflating variables can lead to a specification subtlety that needs to be explained. In solving for the equilibrium market price, the demand and supply functions are set equal to each other and solved. However, if the endogenous price is deflated by one price in the demand function and a different price, as it should be, in the supply function, then technically the deflated endogenous price is no longer the same in each function. This can be easily overcome with a little math as is demonstrated in the appendix, however it implies that the dependent variable in all equations estimated is the nominal price of beef and the deflators become additional regressors.

Second, while the unrestricted OLS estimation and PIME estimation is straightforward and requires no further explanation, the Bayesian estimation deserves a short discussion. One of the main criticisms of Bayesian estimation has been implementation difficulty. Though this may have been true just a few years ago, this is no longer the case. There have been great advances in the theory and implementation of Bayesian techniques using numerical methods within the last decade and several user friendly programs are now available (see Geweke 1989, 1999; Koop 1994). In this paper, the Bayesian Analysis, Computation, and Communication (BACC) program developed by John Geweke is implemented (see Koop 1999 for a review). The BACC program uses Monte Carlo importance sampling techniques in generating the prior and posterior distributions. The present analysis is a straightforward application of the normal linear model in BACC. If the reduced form price equation model is written in standard notation as $y = X\beta + u$, the errors are assumed to obey $u | X \sim N(0, H^{-1} \otimes I_T)$ and H is the $k \times k$ precision matrix. The prior distributions are assumed to be of the Normal-Gamma form such that $\beta \sim N(\underline{\beta}, \underline{H}^{-1})$ and $\underline{H} \sim W(\underline{S}^{-1}, \underline{\nu})$, with W indicating the Wishart distribution, and ν is the degrees of freedom parameter. In the present context the priors $\underline{\beta}$ come from the SEDM outlined above and, because of the sampling approach in generating these priors, this also provides an estimate of \underline{S} . For the Monte Carlo integration, 10,000 samples are drawn for the prior and posterior and the BACC software allows the estimation of all the statistics mentioned in the previous section.⁸

⁸ The BACC software and manuals are available free at <http://www.econ.umn.edu/~bacc/bacc99/>. The software is obtainable as a Gauss module and thus all of the Bayesian analysis is done in Gauss.

Results

Tables 3, 4, and 5 give the results for the three potential market structures. Each table contains the mean and standard deviation of the prior distributions of the restricted reduced form or SEDM estimates. The tables also contain the unrestricted reduced form, the PIME, and the Bayesian point estimates, along with their standard deviations, the squared correlations, and the F test statistics.

Table 3 gives the results for the isolated market structure. Comparing the restricted prior (SEDM) results with the unrestricted results reveals that all signs are in agreement with two exceptions (pork advertising and energy price). In terms of significance, 10 of the 12 variables in each model are insignificant.⁹ There are four cases of inconsistent results across the two models: the two deflators are significant in the restricted model but insignificant in the unrestricted model whereas the female participation and cattle price are insignificant in the restricted model but significant in the unrestricted model. As indicated in brackets, there are only two cases where there is a statistically significant difference between the individual restricted estimates and the unrestricted estimates (pork advertising and cattle prices). The joint F-test that all the restricted parameters estimates are not significantly different from the unrestricted estimates is rejected at any reasonable significance level, given the p-value associated with the test statistic 6.55 is $.29 \times 10^{-6}$. Thus the restricted model is rejected. However, this rejection is due to the differences with respect to pork advertising and cattle prices. If the F-test is conducted on all parameters except these two, then whether or not the models are considered significantly different depends on what is considered a reasonable level of

significance, given the p-value is .09 for the test statistic 1.75. At a minimum, the priors on the pork advertising and cattle price parameters have been identified as potentially problematic. The PIME and Bayesian results combine the prior estimates with the data. All signs are in agreement with the priors and not too surprisingly more parameters are significant. Furthermore, because the priors are combined with the data, the parameter estimates magnitudes reflect a moderation between the unrestricted and restricted estimates. As reminder, it is not true that the PIME and Bayesian parameter estimates will be bound by the prior (restricted) and unrestricted estimates, but for most parameters this is the case. The non-central F-test of the PIME being strong mean square error (SMSE) superior to the unrestricted model is rejected at any reasonable significance level, given the p-value associated with the test statistic 6.55 is $.71 \times 10^{-5}$, so the unrestricted model is preferred based on the SMSE criterion. Finally, the adjusted squared correlation statistics indicate that the restricted model is not highly correlated with the actual data (.17), whereas the unrestricted, PIME, and Bayesian have squared correlations of .63, .58, and .51, respectively.

Table 4 gives the results for the horizontal market structure. The results are qualitatively similar to those at found in table 3, with some exceptions. Once again, comparing the restricted prior (SEDM) and the unrestricted results, all signs are in agreement with the same two exceptions (pork advertising and energy price). In terms of significance, the deflators are again the only significant variables in the restricted model and cattle price is the only significant variable in the unrestricted model. Pork advertising and cattle price are again the only two variables that have significantly different parameter estimates between the restricted and unrestricted models (in brackets). The joint F-test again rejects the null that the restricted

⁹ Because of the different philosophical views of statistical significance across sampling, frequentists, and Bayesians, the terms “significance” and “insignificance” will be used here to refer to parameter estimates that are at

parameters estimates are not significantly different from the unrestricted estimates at the .01 significance level (i.e., p-value is $.86 \times 10^{-5}$ associated with test statistic 5.13). However, this rejection is due to the differences with respect to pork advertising and cattle price, as the F-test statistic of 1.25 has a p-value of .28. All signs for the PIME are in agreement with the priors, with the exception of pork advertising, and many more of the parameter estimates are significant. Again, because the priors are combined with the data in the PIME and Bayesian approaches, the parameter magnitudes reflect a moderation in general between the unrestricted and restricted estimates. The non-central F-test of the PIME being strong mean square error (SMSE) superior to the unrestricted model is again rejected at the .01 significance level, given the p-value associated with the test statistic 5.13 is $.21 \times 10^{-4}$. The Bayesian estimates all have signs in agreement with the priors with no exceptions. The significant Bayesian estimates are the same as those from the restricted and unrestricted models (i.e., the deflators and cattle price). The adjusted squared correlation statistics indicate that the restricted model is more highly correlated with the actual data than the isolated model (.47) but not too surprisingly, the unrestricted, PIME, and Bayesian estimators have higher squared correlations with the data.

Table 5 gives the results for the vertical market structure. Relative to the isolated and horizontal market structures, there are more differences between the restricted (SEDM), unrestricted, PIME, and Bayesian results based on the vertical market structure, but there are also more regressors. There are four cases of inconsistent signs between the restricted and unrestricted models (i.e., pork price, income, pork advertising, and farm supply deflator). Similar to tables 3 and 4, the only significant variables in the restricted model are the two retail deflators. Six of the 14 variables have significantly different parameter values between the

least two times their standard deviations and not at least two times their standard deviation, respectively.

restricted and unrestricted models (in brackets): pork price, poultry price, income, pork advertising, feeder cattle price, and the farm price deflator. The joint F-test again rejects the null that the restricted parameter estimates are not significantly different from the unrestricted estimates at the .01 significance level (i.e., p-value is $.29 \times 10^{-5}$ associated with test statistic 5.38). However, this rejection is again due solely to those parameter estimates that are individually significantly different. The hypothesis that the individually insignificant parameters are not jointly significantly different is not rejected at any reasonable significance level (i.e., p-value is .59 associated with test statistic .85). All signs for the PIME are in agreement with the priors, with the exception of pork price and the farm deflator, and again the PIME has many more significant parameter estimates. The non-central F-test of the PIME being strong mean square error (SMSE) superior to the unrestricted model is again rejected at the .01 significance level, given for the test statistic 5.38 the p-value is $.11 \times 10^{-4}$. The Bayesian estimates all have signs in agreement with the priors with no exceptions. The significant Bayesian estimates are the same as those from the restricted model and the magnitudes in the PIME and Bayesian estimates again reflect a moderation in general between the unrestricted and restricted estimates. The adjusted squared correlation statistics indicate that the restricted model is not highly correlated with the actual data (.05), whereas the unrestricted, PIME, and Bayesian have adjusted squared correlations of .59, .28, and .22, respectively.

As indicated, an advantage of the Bayesian approach is that odds ratios can be calculated. Table 6 gives the results corresponding to equations (12) and (13). The first row gives the marginal posterior likelihoods for each model. The second row gives the prior probability that the parameter estimate on beef advertising is greater than zero for each model. The third row gives the posterior probability that the parameter on beef advertising is greater than zero for each

model. Assuming equal priors for the three models, equation (12) implies that the posterior odds ratios for the isolated model relative to the horizontal and vertical models are $\exp(142.64 - 142.16) = 1.618$ and $\exp(142.64 - 137.55) = 162.39$, respectively. The posterior odds ratio for the horizontal model relative to the vertical model is $\exp(142.16 - 137.55) = 100.48$. Consequently, based on the posterior odds ratios, the isolated model is relatively more consistent with the data than the other two models and the horizontal model is more consistent with the data than the vertical model.

In their reply to Griffiths and Zhao, Davis and Espinoza (2000) state that probability statements about priors do not necessarily carry over to probability statements about posteriors. The results in table 6 illustrate this point. Using the prior distributions, the probability that the parameter on beef advertising is greater than zero is .91, .74, and .91 for the isolated, horizontal, and vertical models, respectively. Using the posterior distributions, the probability that the parameter on beef advertising is greater than zero is .94, .83, and .82 for the isolated, horizontal, and vertical models, respectively.

Conclusions

One of the main limitations of presently implemented equilibrium displacement models (EDMs) is their lack of empirical validation. This paper demonstrates four increasingly sophisticated procedures that remove this limitation with some minimal modeling effort. Two conditions are required for these procedures to be applicable: (i) the researcher must have a sincere interest in comparing the predictions of the EDM with the actual phenomenon under consideration; (ii) some data must be available on one endogenous variable and the exogenous variables in the EDM. If the first condition is satisfied, the second condition is often easily satisfied.

The procedures are illustrated by analyzing three potentially valid EDMs of the U.S. beef market. The results suggest that an isolated stochastic equilibrium displacement model (SEDM) that only treats beef price and quantity as endogenous is more consistent with the data relative to a horizontal SEDM that treats all meat prices and quantities as endogenous and relative to a vertical SEDM that treats beef and cattle price and quantities as endogenous. The horizontal SEDM is also more consistent with the data relative to the vertical SEDM.

The validation procedures implemented here imply two important points that are not obtainable by doing just a standard EDM or SEDM analysis. As Davis and Espinoza (1998) and Zhao, et al. discuss, the standard EDM analysis that relies on one or a few set(s) of point estimates can give the impression of significance when none exist. However, the calculation of a distribution on the prior in the SEDM analysis a la Davis and Espinoza (1998), and Zhao, et al. allows for the determination of significance, and in the present case, many of the reduced form parameter estimates are insignificant in the SEDM. This lack of significance may be considered a negative if one stops at the Davis and Espinoza and Zhao, et al, type of SEDM analysis. However, if one goes beyond their analysis and validates the model as is done here, these insignificant results turn out to be a positive, because most of the unrestricted estimates are also not significantly different from zero. Thus in general and observationally the individual parameter estimates coming from the SEDM are statistically consistent with the data. Second, the Bayesian validation procedures also demonstrate that inferences (e.g., probability statements as in Griffiths and Zhao) based on prior distributions in isolation (i.e., SEDMs) can be misleading when compared to inferences based on posterior distributions, as pointed out by Davis and Espinoza (2000).

References

- Alston, J. M. and J. A. Chalfant. "The Silence of the Lambdas: A Test of the Almost Ideal and Rotterdam Models." *Amer. J. Agr. Econ.* 75(May 1993):304-13.
- Ball, V. E. and R. G. Chambers. "An Economic Analysis of Technology in the Meat Products Industry." *Amer. J. Agr. Econ.* 64(November 1982):699-709.
- Brester, G. W. "Estimation of the U. S. Import Demand Elasticity for Beef: The Importance of Disaggregation." *Rev. Agr. Econ.* 18(January 1996):31-42.
- Brester, G. W. and T. C. Schroeder. "The Impact of Brand and Generic Advertising on Meat Demand." *Amer. J. Agr. Econ.* 77(November 1995):969-79.
- Brester, G. W. and M. K. Wohlgenant. "Correcting for Measurement Error in Food Demand Estimation." *RESTAT.* 75(May 1993):352-56.
- Capps, O., Jr. and J. D. Schmitz. "A Recognition of Health and Nutrition Factors in Food Demand Analysis." *W. J. Agr. Econ.* 16 (July 1991):21-35.
- Chambers, R. G. *Applied Production Analysis*. Cambridge: Cambridge University Press. 1988.
- Choi, S. and K. Sosin, "Testing for Structural Change: The Demand for Meat." *Amer. J. Agr. Econ.* 72(February 1990):227-36.
- Chung, C. and H. M. Kaiser. "Gains from Research and Promotion: Comment." *Amer. J. Agr. Econ.* 81(August 1999):593-97.
- Davidson, R. and J. G. MacKinnon. *Estimation and Inference in Econometrics*. Oxford: Oxford University Press. 1993.
- Davis, G. C. and M. C. Espinoza. "A Unified Approach to Sensitivity Analysis in Equilibrium Displacement Models." *Amer. J. Agr. Econ.* 80(November 1998):866-79.

- _____. "A Unified Approach to Sensitivity Analysis in Equilibrium Displacement Models: Reply." *Amer. J. Agr. Econ.* 82(February 2000):241-43.
- Eales, J. S. and L. J. Unnevehr. "Demand for Beef and Chicken Products: Separability and Structural Change." *Amer. J. Agr. Econ.* 70(May 1988):521-32,
- Eales, J. S. and L. J. Unnevehr. "Simultaneity and Structural Change in U. S. Meat Demand." *Amer. J. Agr. Econ.* 75(May 1993):259-68.
- Fomby, T. B., R.C. Hill, and S. R. Johnson. *Advanced Econometric Methods*. New York: Springer-Verlag. 1984.
- Fox, R., M. Garbuny, and R. Hooke. *The Science of Science*. New York: Walker and Company. 1963.
- Gao, X. M. and J. S. Shonkwiler. "Characterizing Taste Change in a Model of U. S. Meat Demand: Correcting for Spurious Regression and Measurement Errors." *Rev. Agr. Econ.* 15(May 1993):313-24.
- Geweke, J. "Bayesian Inference in Econometric Models Using Monte Carlo Integration." *Econometrica*. 57(November 1989):1317-1339.
- _____. "Using Simulation Methods for Bayesian Econometric Modelling: Inference, Development, and Communication." *Econometric Reviews*. 18(1999): 1-74.
- Griffiths, W.E. and X. Zhao. "A Unified Approach to Sensitivity Analysis in Equilibrium Displacement Models: Comment." *Amer. J. Agr. Econ.* 82(February 2000):236-40.
- Hahn, W. F. "A Random Coefficient Meat Demand Model." *J. Ag. Econ. Res.* 45(Fall 1994):21-30.
- Hahn, W. F. "Effects of Income-Distribution on Meat Demand." *J. Ag. Econ. Res.* 40(Spring 1988):19-24.

- Hausman, J. A. "Specification and Estimation of Simultaneous Equation Models," Chapter 7 in *Handbook of Econometrics*. Vol. 1, Eds. Z. Griliches and M. D. Intriligator. New York: North-Holland. 1983.
- Judge, G. G., W. E. Griffiths, R. C. Hill, H. Lütkepohl, and T.C. Lee. *The Theory and Practice of Econometrics*. Second Edition. New York: John Wiley and Sons. 1985.
- Kesavan, T, Z. A. Hassan, H. H. Jensen, S. R. Johnson . "Dynamics and Long-Run Structure in United States Meat Demand." *Can. J. Agr. Econ.* 41(July 1993):139-53.
- Kinnucan, H. W., H. Xiao, C.J. Hsia, and J. D. Jackson. "Effects of Health Information and Generic Advertising on U. S. Meat Demand." *Amer. J. Agr. Econ.* 79(February 1997):13-23.
- Kinnucan, H. W., H. Xiao, and C. J. Hsia. "Welfare Implications of Increased Beef Promotion." *Appl. Econ.* 28(1996):1235-1243.
- Koop, G. "Recent Progress in Applied Bayesian Econometrics." *J. Econ. Surveys.* 8(March 1994):1-34.
- _____. "Bayesian Analysis, Computation, and Communication Software." *J. Appl. Econometrics.* 14(1999):677-89.
- Lemieux, C. M. and M. K. Wohlgenant. "Ex-Ante Evaluation of the Economic Impact of Biotechnology: The Case of Porcine Somatotropine." *Amer. J. Agr. Econ.* 71(November 1989): 903-14.
- Marsh, J. M. "Estimating Intertemporal Supply Response in the Fed Beef Market." *Amer. J. Agr. Econ.* 76 (August 1994):444-453.
- McGuirk, A., P. Driscoll, J. Alwang, H. L. Huang. "System Misspecification Testing and Structural-Change in the Demand for Meats." *J. Agr. Res. Econ* 20(July 1995):1-21.

- Mittelhammer, R. C. and R. K. Conway. "Applying Mixed Estimation in Econometric Research." *Amer. J. Agr. Econ.* 70(November 1988):859-65.
- Mizon, G. E. "The Encompassing Approach in Econometrics." in *Econometrics and Quantitative Economics*, D. F. Hendry and K.F. Wallis, Eds. Oxford: Basil Blackwell. 1984.
- Moschini, G., D. Moro, and R. D. Green. "Maintaining and Testing Separability in Demand Systems." *Amer. J. Agr. Econ.* 76(February 1994):61-73.
- Moschini, G. and K. D. Meilke. "Modeling the Pattern of Structural Change in U. S. Meat Demand." *Amer. J. Agr. Econ.* 71(May 1989):253-61.
- Muth, M. and M. K. Wohlgenant. "Measuring the Degree of Oligopsony Power in the Beef Packing Industry in the Absence of Marketing Input Data." *Journal of Agricultural and Resource Economics*. Vol. 24. No. 2. (December, 1999):299-312.
- Paul, C. J. M. "Market and Cost Structure in the U.S. Beef Packing Industry: A Plant Level Analysis." *American Journal of Agricultural Economics*. Vol. 83.1(Feb. 2001):64-76.
- Piggott, R. R., N. E. Piggott, and V. E. Wright. "Approximating Farm-Level Returns to Incremental Advertising Expenditure: Methods and an Application to the Australian meat Industry." *Amer. J. Agri. Econ.* 77(August 1995):497-511.
- Thurman, W. N. "The Poultry market: Demand Stability and Industry Structure." *Amer. J. Agri. Econ.* 69(February 1987):30-37.
- Wohlgenant, M. K. "Distribution of Gains from Research and Promotion in Multi-Stage Production Systems: The Case of the U.S. Beef and Pork Industries." *Amer. J. Agr. Econ.* 75(August 1993): 642-651.
- Zhao, X., W. E. Griffiths, G. R. Griffith and J. D. Mullen. "Probability Distributions for Economic Surplus Changes." *Aust. J. Agr. Res. Econ.* 44(March 2000):83-106.

Table 1. Variable Definitions, Study Utilization, Data, Sources, and Units

Variable and Definition ^a	Prior Variable Identification Source ^b	Empirical Analysis	
		Data Source ^c	Original Units
<i>Retail Sector</i>			
p^*_b = beef price	All Retail Demand Studies	Kinnucan, et al.	¢/lb per pound
p^*_p = pork price	All Retail Demand Studies	Kinnucan, et al.	¢/lb per pound
p^*_r = poultry price	All Retail Demand Studies	Kinnucan, et al.	¢/lb per pound
p^*_{cpi} = consumer price index	All Retail Demand Studies	FRED	consumer price index
m^* = income	All Retail Demand Studies	FRED	per capita disposable income \$1000
a^*_b = generic beef advertising	Brester and Schroeder, Kinnucan, et al.	Kinnucan, et al.	\$1000
a^*_p = generic pork advertising	Brester and Schroeder, Kinnucan, et al.	Kinnucan, et al.	\$1000
h^* = health information index	Capps, Kinnucan, et al., McGuirk, et al.	Kinnucan, et al.	weighted average number of articles on cholesterol
f^* = female labor participation	McGuirk, et al.	BLS	Women overage of 20 in labor force
w^*_k = processing capital price	Ball and Chambers	FRED	Producer Price index for capital goods (1982-84 base)
w^*_l = processing labor price	Ball and Chambers, Kinnucan et al.	Kinnucan, et al.	Wage rate in meat packing \$/hr.
w^*_e = energy price	Ball and Chambers	Kinnucan, et al.	Energy price index (1982-84 base)

Table 1. Continued

Variable and Definition ^a	Prior Variable Identification Source ^b	Empirical Analysis	
		Data Source ^c	Original Units
<i>Farm Sector</i>			
w^*_t = cattle price	Brester, Marsh	NASS	Prices received by farmers, \$/cwt.
w^*_g = hog price	Theory	NASS	Prices received by farmers, \$/cwt.
w^*_n = chicken/turkey price	Theory	NASS	Prices received by farmers, \$/lb.
w^*_f = feeder cattle	Brester, Marsh	USDA Red Meat Yearbook	Slaughter Steers Nebraska Direct, \$/cwt.
w^*_c = corn price	Marsh	NASS	Prices received by farmers, \$/bu.
w^*_w = farm labor price	Theory	NASS	Farm wage index (1982-84 base)

^a All variables are expressed as percentage change in the empirical analysis. ^b **Retail Demand Studies:** Alston and Chalfant, Brester and Schroeder, Brester and Wollhgenant, Capps and Schmitz, Choi and Sosin, Eales and Unnevehr (1988,1993), Gao and Shonkwiler, Hahn (1994, 1988), Kesavan, et al., Kinnucan, et al., McGuirk, et al., Moschini, Moro, and Green, Moschini and Meilke, Thurman. **Retail Supply Studies:** Ball and Chambers, Brester. **Farm Demand Studies:** Ball and Chambers. **Farm Supply Studies:** Marsh. ^c Federal Reserve Economic Data (FRED), Bureau of Labor Statistics (BLS), National Agricultural Statistical Service (NASS).

Table 2. Summary Statistics on Prior Distributions of Structural Parameters

Retail Demand		Price			Advertisement			<u>Income^a</u>	<u>Health</u>	<u>Female</u>
		<u>Beef</u>	<u>Pork</u>	<u>Poultry</u>	<u>Beef</u>	<u>Pork</u>				
Beef	η_{bb}	η_{bp}	η_{br}	η_{bba}	η_{bpa}	η_{bm}	η_{bh}	η_{bf}		
mean	-.846	.05	.013	.0028	.012	.98	-.19	-.39		
variance	(.072)	(.925)	(.013)	(.32E-5)	(.25E-6)	(.55)	(.04)	(.05)		
range	[-1.27, -.45]	[-.12, .54]	[-.13, .36]	[.0003, .006]	[.003, .002]	[.13, 2.09]	[-.58, -.0005]	[-.78, -.0006]		
Pork	η_{pb}	η_{pp}	η_{pr}	η_{pba}	η_{ppa}	η_{pm}	η_{ph}	η_{pf}		
mean	.05	-.83	-.05	-.004	-.0002	.59	-.07	.37		
variance	(.025)	(.11)	(.02)	(.7E-6)	(.7E-6)	(.28)	(.008)	(.042)		
range	[-.12, .54]	[-1.23, .17]	[-.38, .15]	[-.009, .0006]	[-.0005, .0001]	[.02, 1.88]	[-.23, .014]	[.0005, .72]		
Poultry	η_{rb}	η_{rp}	η_{rr}	η_{rba}	η_{rpa}	η_{rm}	η_{rh}	η_{rf}		
mean	.08	.02	-.46	.006	-.005	.51	.52	1.41		
variance	(.04)	(.02)	(.15)	(.6E-6)	(.6E-6)	(.64)	(.22)	(.66)		
range	[-.29, .38]	[-.25, .34]	[-1.25, -.01]	[-.01, -.002]	[-.01, -.001]	[.57, 1.84]	[.004, 1.54]	[.003, 2.81]		
Retail Supply		Price								
	<u>Beef</u>	<u>Pork</u>	<u>Poultry</u>	<u>Cattle</u>	<u>Hogs</u>	<u>Chickens</u>	<u>Labor</u>	<u>Energy</u>	<u>Capital</u>	
Beef	ϵ_{bb}	-----	-----	ϵ_{bt}	-----	-----	ϵ_{bl}	ϵ_{be}	ϵ_{bk}	
mean	.49			-.09			-.013	.0004	-.01	
variance	(.04)			(.003)			(.0001)	(.06E-6)	(.37E-4)	
range	[.12, .86]			[-.19, 0.00]			[-.03, 0.00]	[0.00, .0008]	[-.02, 0.00]	
Pork	-----	ϵ_{pp}	-----	-----	ϵ_{pg}	-----	ϵ_{pl}	ϵ_{pe}	ϵ_{pk}	
mean		.49			-.09					
variance		(.04)			(.003)					
range		[.12, .86]			[-.19, 0.00]					
								-----Same as Beef-----		

Table 2. Continued

Retail Supply		Price								
	<u>Beef</u>	<u>Pork</u>	<u>Poultry</u>	<u>Cattle</u>	<u>Hogs</u>	<u>Chickens</u>	<u>Labor</u>	<u>Energy</u>	<u>Capital</u>	
Poultry	-----	-----	ϵ_{rr}	-----	-----	ϵ_{rk}	ϵ_{rl}	ϵ_{re}	ϵ_{rk}	
mean			.99			-.09				
variance			(.04)			(.003)	-----Same as Beef-----			
range			[.62, 1.36]			[-.19, 0.00]				
Farm Demand		Price								
	<u>Beef</u>	<u>Cattle</u>	<u>Labor</u>	<u>Energy</u>	<u>Capital</u>					
Cattle	λ_{tb}	λ_{tt}	λ_{tl}	λ_{te}	λ_{tk}					
mean	.026	-.03	.02	-.002	-.06					
variance	(.0002)	(.0003)	(.0002)	(.14E-5)	(.0011)					
range	[.0001, .05]	[-.06, 0.00]	[0.00, .04]	[-.004, 0.00]	[-.12, -.0003]					
Farm Supply		Price								
	<u>Cattle</u>	<u>Feeder</u>	<u>Corn</u>	<u>Labor</u>						
Cattle	θ_{tt}	θ_{tf}	θ_{tc}	θ_{tl}						
mean	.17	-.71	-.11	.002						
variance	(.009)	(.16)	(.004)	(.14E-5)						
range	[0.00, .34]	[-1.4, -.0001]	[-.23, -.0004]	[0.00, .004]						

^a Based on expenditure and income elasticities.

Table 3. Results from Isolated Market Structure^a

	(SEDM)			
	Restricted Prior	Unrestricted	PIME	Bayesian
Pork Price (p^*_p)	.04 (.13)	.10 (.06) [1.01]	.09 ^b (.05)	.08 (.07)
Poultry Price (p^*_r)	.01 (.09)	.09 (.06) [1.36]	.06 (.04)	.05 (.06)
Beef Advertising (a^*_b)	.002 (.002)	.001 (.001) [-1.36]	.001 (.001)	.002 (.001)
Pork Advertising (a^*_p)	.0009 (.0005)	-.001 (.001) [-3.13]	.0003 (.0002)	.0006 (.0004)
Income (m^*)	.80 (.67)	.46 (.27) [-1.26]	.28 (.21)	.37 (.35)
Cholesterol (h^*)	-.16 (.18)	-.29 (.21) [-.66]	-.09 (.08)	-.12 (.13)
Female (f^*)	-.32 (.21)	-.74 ^b (.35) [-1.22]	-.47 ^b (.09)	-.42 ^b (.18)
Cattle Price (w^*_t)	.07 (.05)	.31 ^b (.04) [6.66]	.22 ^b (.02)	.16 ^b (.04)
Labor Price (w^*_l)	.01 (.007)	.07 (.07) [.87]	.01 ^b (.001)	.01 (.006)
Energy Price (w^*_e)	-.0003 (.0002)	.04 (.09) [.48]	-.0003 ^b (.00002)	-.0003 ^b (.0001)
Retail Demand Deflator (p^*_{cpi})	.63 ^b (.13)	.95 (.69) [.44]	.71 ^b (.03)	.67 ^b (.13)
Retail Supply Deflator (w^*_k)	.36 ^b (.13)	.58 (.67) [.32]	.29 ^b (.03)	.33 ^b (.13)

Table 3 Continued

	(SEDM)			
	Restricted Prior	Unrestricted	PIME	Bayesian
Squared Correlation (R^2)	.30	.69	.65	.59
Adjusted Square Correlations (\bar{R}^2)	.17	.63	.58	.51
H_0 : Full difference F		6.55		
H_1 : Insignificant difference F		1.75		

^a The standard deviation is in parenthesis. The t-test value of the difference between unrestricted and restricted parameter estimates is in square brackets.

^b The parameter estimate is at least twice as large as the standard deviation.

Table 4. Results from Horizontal Market Structure^a

	(SEDM)			
	Restricted Prior	Unrestricted	PIME	Bayesian
Income (m*)	.89 (.74)	.55 (.29) [-1.19]	.42 (.22)	.46 (.36)
Beef Advertising (a* _b)	.002 (.002)	.0007 (.0008) [-.89]	.0008 (.0007)	.001 (.001)
Pork Advertising (a* _p)	.0006 (.001)	-.001 (.007) [-2.37]	-.0004 (.0004)	.00002 (.0007)
Cholesterol (h*)	-.14 (.22)	-.34 (.22) [-.90]	-.23 ^b (.09)	-.19 (.15)
Female (f*)	-.21 (.33)	-.71 (.40) [-1.26]	-.44 ^b (.14)	-.37 (.24)
Cattle Price (w* _t)	.07 (.05)	.31 ^b (.04) [5.96]	.22 ^b (.02)	.17 ^b (.04)
Hog Price (w* _g)	.008 (.03)	.03 (.03) [.57]	.03 ^b (.01)	.02 (.02)
Chicken Price (w* _n)	.005 (.02)	.008 (.03) [.10]	.014 ^b (.006)	.01 (.01)
Labor Price (w* _l)	.013 (.009)	.06 (.07) [.83]	.016 ^b (.002)	.01 (.01)
Energy Price (w* _e)	-.0004 (.0003)	.02 (.09) [.24]	-.0005 ^b (.00004)	-.0005 (.0002)
Retail Demand Deflator (p* _{cpi})	.73 ^b (.26)	.97 (.76) [.32]	.86 ^b (.09)	.81 ^b (.20)
Retail Supply Deflator (w* _k)	.46 ^b (.23)	.49 (.75) [.05]	.44 ^b (.06)	.44 ^b (.18)

Table 4 Continued

	(SEDM)			
	Restricted Prior	Unrestricted	PIME	Bayesian
Squared Correlation (R^2)	.56	.65	.63	.60
Adjusted Squared Correlation (\bar{R}^2)	.47	.58	.56	.52
H_0 : Full difference F		5.13		
H_1 : Insignificant difference F		1.25		

^a The standard deviation is in parenthesis. The t-test value of the difference between unrestricted and restricted parameter estimates is in square brackets.

^b The parameter estimate is at least twice as large as the standard deviation.

Table 5. Results from Vertical Market Structure^a

	(SEDM)			
	Restricted Prior	Unrestricted	PIME	Bayesian
Pork Price (p^*_p)	.04 (.13)	-.14 (.07) [-2.46]	-.01 (.05)	.02 (.08)
Poultry Price (p^*_r)	.01 (.09)	.16 ^b (.06) [2.41]	.07 (.04)	.04 (.07)
Income (m^*)	.82 (.69)	-.09 (.29) [-3.04]	.10 (.22)	.23 (.37)
Beef Advertising (a^*_b)	.002 (.002)	.001 (.001) [-1.19]	.001 (.001)	.001 (.001)
Pork Advertising (a^*_p)	.001 (.001)	-.001 (.001) [-2.63]	.0002 (.0002)	.001 (.0004)
Cholesterol (h^*)	-.16 (.17)	-.34 (.22) [-.81]	-.08 (.08)	-.12 (.14)
Female (f^*)	-.32 (.22)	-.74 (.42) [-1.02]	-.50 ^b (.10)	-.38 ^b (.19)
Labor Price (w^*_l)	.01 (.009)	.12 (.07) [1.48]	.0007 (.002)	.01 (.008)
Energy Price (w^*_e)	-.0006 (.0008)	-.13 (.079) [-1.34]	-.0005 ^b (.0001)	-.0005 (.0005)
Retail Demand Deflator (p^*_{cpi})	.64 ^b (.13)	1.04 (.74) [.53]	.65 ^b (.03)	.64 ^b (.13)
Retail Supply/Farm Demand Deflator (w^*_k)	.37 ^b (.13)	.22 (.72) [-.21]	.35 ^b (.03)	.37 ^b (.13)
Feeder Cattle Price (w^*_f)	.12 (.34)	.35 ^b (.05) [4.82]	.20 ^b (.04)	.19 ^b (.06)
Corn Price (w^*_c)	.02 (.03)	.02 (.03) [.07]	.01 (.02)	.02 (.03)

Table 5 Continued

	(SEDM)			
	Restricted Prior	Unrestricted	PIME	Bayesian
Farm Supply Deflator (w^*_w)	-.02 (.01)	.44 ^b (.08) [5.66]	.0005 (.002)	-.01 (.01)
Squared Correlation (R^2)	.23	.67	.42	.37
Adjusted Squared Correlation (\bar{R}^2)	.05	.59	.28	.22
H ₀ : Full Difference F		5.38		
H ₁ : Insignificant Difference F		.85		

^a The standard deviation is in parenthesis. The t-test value of the difference between unrestricted and restricted parameter estimates is in square brackets.

^b The parameter estimate is at least twice as large as the standard deviation.

Table 6. Bayesian Statistics for Different Models.

	<u>Isolated</u>	<u>Horizontal</u>	<u>Vertical</u>
Marginal Posterior log likelihoods	142.64	142.16	137.55
Prior Prob ($0 <$ Beef Advertising parameter)	.91	.74	.91
Posterior Prob ($0 <$ Beef Advertising parameter)	.94	.83	.82

Mathematical Appendix

Retail Supply Elasticity Derivations

From Chambers (pages 169-170), the cost function can be written as the primal/dual problem

$$(A.1) \quad C(w,y) = \text{MAX}_{p>0} [py - \Pi(p,w)] \\ = p^*y - \Pi(p^*,w)$$

so

$$(A.2) \quad \frac{\partial C(w,y)}{\partial y} = p^*$$

$$(A.3) \quad \frac{\partial C(w,y)}{\partial w_i} = \frac{-\partial \Pi(p^*,w)}{\partial w_i} \quad \forall i$$

The first order conditions for (A.1) imply Hotelling's Lemma

$$(A.4) \quad y = \frac{\partial \Pi(p^*,w)}{\partial p}$$

so by the implicit function theorem from (A.4) and also (A.2)

$$(A.5) \quad \frac{\partial p^*}{\partial y} = \left(\frac{\partial^2 \Pi}{\partial p^2} \right)^{-1} = \frac{\partial^2 C}{\partial y^2}$$

$$(A.6) \quad \frac{\partial p}{\partial w_j} = - \left(\frac{\partial^2 \Pi}{\partial p \partial w_j} \right) \left(\frac{\partial^2 \Pi}{\partial p^2} \right)^{-1} \\ = - \left(\frac{\partial y}{\partial w_j} \right) \left(\frac{\partial y}{\partial p} \right)^{-1} \\ = \frac{\partial^2 C}{\partial y \partial w_j}$$

where the second line in (A.6) just uses Hotelling's lemma. Consequently, under perfect competition marginal cost (MC) equals price (p), so the supply output price elasticity (ϵ_{yj}) and the j^{th} input price elasticities (ϵ_{yp}) are, with some simple algebra

$$(A.7) \quad \epsilon_{yp} = \left(\frac{\partial \ln MC}{\partial \ln y} \right)^{-1}$$

$$(A.8) \quad \epsilon_{yj} = - \frac{\partial \ln MC}{\partial \ln w_j} \times \epsilon_{yp}$$

Now Ball and Chambers use a translog cost specification of the form

$$(A.9) \quad C = \exp[\alpha_0 + \alpha_y \ln y + \sum_i \alpha_i \ln w_i + .5\beta_{yy}(\ln y)^2 + .5\sum_i \sum_j \beta_{ij} \ln w_i \ln w_j \\ + \sum_i \gamma_{yi} \ln y \ln w_i + \phi_T T + .5\phi_{TT} T^2 + \phi_{TY} T \ln y + \sum_i \phi_{Ti} T \ln w_i]$$

Noting that

$$\frac{\partial \ln C}{\partial \ln y} = \frac{MC}{AC} = \epsilon_{cy}$$

then with some straight forward calculus it can be shown that for the translog

$$(A.7.1) \quad \epsilon_{yp} = [\beta_{yy} \epsilon_{cy}^{-1} + \epsilon_{cy} - 1] = \left[\frac{\partial \ln MC}{\partial \ln y} \right]^{-1}.$$

Similarly, it can be shown that

$$\frac{\partial \ln MC}{\partial \ln w_j} = \gamma_{yj} \epsilon_{cy}^{-1} + s_j$$

so for the translog

$$(A.8.1) \quad \epsilon_{yj} = -[\gamma_{yj} \epsilon_{cy}^{-1} + s_j] \epsilon_{yp}.$$

Ball and Chambers report all of values necessary to implement (A.7.1) and (A.8.1).

Retail Demand Elasticity Derivations from the Cost Function

From the cost minimization problem the conditional demand is $D_i^C(w, y)$. The unconditional demand is obtained by substituting the supply function $y(p, w)$ into the conditional demand or

$$(A.10) \quad D_i^u = D_i^C(w, y(p, w)).$$

Consequently by the chain rule, the i^{th} input output price elasticity is

$$(A.11) \quad \lambda_{ip}^u = \frac{\partial \ln D_i^u}{\partial \ln p} = \frac{\partial \ln D_i^C}{\partial \ln y} \frac{\partial \ln y}{\partial \ln p}$$

$$= \lambda_{iy}^C \epsilon_{yp}$$

and the i^{th} input input price elasticity is

$$(A.12) \quad \lambda_{ij}^u = \frac{\partial \ln D_i^u}{\partial \ln w_j} = \frac{\partial \ln D_i^C}{\partial \ln w_j} + \frac{\partial \ln D_i^C}{\partial \ln y} \frac{\partial \ln y}{\partial \ln w_j}$$

$$= \lambda_{ij}^C + \lambda_{iy}^C \epsilon_{yj}$$

These conditional elasticities λ_{ij}^C and λ_{iy}^C are reported in Ball and Chambers and are then coupled with the estimates of ϵ_{yp} and ϵ_{yj} from equations (A.7.1) and (A.8.1).

Homogeneity, Deflation, and the Estimating Equations

According to consumer theory, the Marshallian demand function $D(P, m)$ is homogeneous of degree zero in prices (P) and income (m). According to producer theory the supply function $S(p, W)$ is homogeneous of degree zero in p and W . Homogeneity in D can be imposed by deflating all arguments by a single price, and usually this is assumed to be an aggregate of all other goods whose price is represented by the cpi. Let this price be denoted as p_{cpi} , so the demand function can be written as $D(\tilde{P}, \tilde{m})$, where \tilde{P} is the vector of deflated prices $\tilde{P} = P \bullet p_{\text{cpi}}^{-1}$ and $\tilde{m} = m \bullet p_{\text{cpi}}^{-1}$ is the deflated income. On the supply side a similar argument can be made for imposing homogeneity but the deflator will be different, say w_k . Now the supply function can be written as $S(\bar{p}, \bar{W}_{-1})$, where \bar{p} is the deflated output price $\bar{p} = p \bullet w_k^{-1}$ and $\bar{W}_{-1} = W_{-1} \bullet w_k^{-1}$

vector of deflated $n - 1$ input prices. In equilibrium we want to solve for the endogenous market price p , and if the demand and supply functions are in their regular form then $D(P,m) = S(p,W)$ implies via the implicit function theorem that there exist a reduced form solution $p = f(P_{-1}, m, W)$, where P_{-1} is the vector of exogenous prices in demand. Alternatively, if homogeneity is imposed then setting demand equal to supply yields $D(\tilde{p}, \tilde{P}_{-1}, \tilde{m}) = S(\bar{p}, \bar{W}_{-1})$. Consequently, because $\tilde{p} \neq \bar{p}$ due to different deflators, this equation must be solved for the nominal price. This is very simple in the present setting because the equilibrium displacement model is expressed in log differentials. Taking total log differentials of both sides of $D(\tilde{p}, \tilde{X}_d) = S(\bar{p}, \bar{W}_{-1})$ where for simplicity $\tilde{X}_d = (\tilde{P}_{-1}, \tilde{m})$ yields $\eta_p \tilde{p}^* + \eta_{xd} \tilde{X}_d^* = \varepsilon_p \bar{p}^* + \varepsilon_w \bar{W}_{-1}^*$. Now in empirical work for any variable z , $z_t^* = \ln z_t - \ln z_{t-1} = \ln(z_t / z_{t-1})$. Consequently,

$\eta_p [\ln(p_t / p_{cpit}) - \ln(p_{t-1} / p_{cpit-1})] = \eta_p p_t^* - \eta_p p_{cpit}^*$. A similar result can be obtained on the supply side. The equilibrium condition can then be written as

$\eta_p p_t^* - \eta_p p_{cpit}^* + \eta_{xd} \tilde{X}_{dt}^* = \varepsilon_p p_t^* - \varepsilon_p w_{kt}^* + \varepsilon_w \bar{W}_{-1t}^*$ which leads to the reduced form price equation

$$(A.13) \quad p_t^* = [\eta_p - \varepsilon_p]^{-1} \left(-\eta_{xd} \tilde{X}_{dt}^* + \varepsilon_w \bar{W}_{-1t}^* + \eta_p p_{cpit}^* - \varepsilon_p w_{kt}^* \right).$$

As seen in equation (A.13), both deflators are then included as right hand side variables.

An important final question that needs to be addressed is how should EDMs or SEDMs be interpreted if they are not tested or if they are falsified? Not testing an EDM or SEDM is not necessarily fatal. It depends on why they are not tested. EDMs or SEDMs are still very appealing analytical tools when there is insufficient data to do estimation and this would be the case when there is some *ex ante* factor that is expected to affect a market that has not been in effect long enough to support an econometric type analysis. For example, Lemieux and Wolghenant use an EDM to analyze the impact of PST on the hog market, and at the time this analysis was conducted there simply was not enough data available to implement standard econometric procedures. EDMs or SEDMs would seem to be less appealing in an *ex post* setting where there is sufficient data to conduct a standard or prior incorporating econometric procedure. If an EDM or SEDM is tested and falsified one can always interpret the results within a *ceteris paribus* comparative static framework. That is, an alternative interpretation of EDMs is that they are a useful tool for signing comparative static relationships when these relationships cannot be signed analytically. In this context the theoretician is taking what are considered reasonable values for key parameters and trying to sign the comparative static results, *ceteris paribus*. However, in this interpretation, the quantitative results are an illusion and the analyst should not take these results as being quantitatively accurate but only as being qualitatively suggestive. If the analyst takes refuge in this interpretation, then it would seem more appropriate to only report the signs and not the magnitudes coming from the model.