A Random Coefficient Meat Demand Model

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Abstract. *The stability of the U S consumer demand for meat has been a popular topic for journal articles I show that econometric models imply that demand is fundamentally unstable A good way to build taste instability into econometric demand equations is to specify them as random coefficient models I estimate a random coefficient model of meat demand and find significant evidence that taste instability has caused fluctuations in the elasticities of demand for beef, pork, chicken, and turkey*

Keywords. *random coefficients, demand systems, meat demand, taste stability*

The U S consumer demand for meat has been a popular topic for journal articles For example, there were three articles on this topic in the May 1993 issue of the *American Journal of Agricultural Economics (AJAE)* alone (Alston and Chalfant (1993), Eales and Unnevehr, and Yong and Hayes) Much of the interest in meat demand has been driven by the controversy over the stability of consumer tastes for red meat Beef consumption has dropped since the 1970's while poultry consumption has steadily risen Some have attributed this drop in beef consumption to consumer health concerns while others have attributed it to the increase in beef prices relative to poultry prices Each of the three articles just mentioned addressed the issue of the stability of consumer tastes for meats Alston and Chalfant and Eales and Unnevehr concluded that the demand for meats has been stable while Yong and Hayes concluded that it has not

I take the view that the U S demand for meat has been fundamentally unstable and estimate a random coefficient model of meat demand In this, I am actually being consistent with Alston and Chalfant, Eales and Unnevehr, and Young and Hayes, even though only Yong and Hayes actually conclude that tastes have been unstable The debate over the stability of meat demand is muddled by the fact that there are actually two different definitions of stability, although everyone seems to act as if there were only one The first definition of stability requires stable consumer tastes The second definition is that consumer demands can be represented using econometric demand functions with stable parameters Alston and Chalfant and Eales and Unnevehr used the stable parameter definition of demand stability while Yong and Hayes used the stable taste definition The random coefficient meat demand model is based on the stable (or at least stationary) parameter definition but implies unstable tastes In fact, all econometric specifications of demand imply unstable tastes Alston and Chafant and Eales and Unnevehr tested econometric models of meat demand and found that their models' parameters were stable However, the random components of their models imply that tastes are unstable

Given a set of tastes (meeting certain regularity conditions), there will exist a set of demand functions that relate what consumers want to buy to the prices of goods and total expenditure Econometric demand functions depend on prices and expenditures, but have random components as well The random components imply that demand reacts to factors other than prices and expenditure In theory, the only other factors left to explain demand are tastes Econometric specifications of demand functions imply that tastes are not stable

It is not too hard to come up with reasons why tastes might fluctuate somewhat randomly Tastes may be influenced by more or less random factors in the consumer's environment such as weather There could be a stable demand relationship between prices, expenditures, and random "environmental" factors, a "meta-utility" relationship The econometric demand specification could be random with stable parameters and consistent with utility maximization, but not consistent with stable tastes

Data, Model Specification, and Estimation Procedure

This study uses monthly data from USDA-ERS on the U S disappearance of beef, pork, chicken, and turkey, the four major meats consumed within the United States The quantities are the estimated, per-capita, monthly disappearances of beef, pork, chicken, and turkey Beef and pork disappearances are measured on a retail weight basis, while chicken and turkey consumption is measured on the ready-to-cook basis The beef price is the retail Choice beef price as reported in ERS price spreads and the pork price is also the retail price

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calculated for prices spreads Chicken and turkey prices are national average prices for whole birds The time period used consists of the years from 1980 to 1992 inclusive, 156 observations

I have assumed that the demand for these four meats is weakly separable from the demands for other goods This assumption allows one to model meat demand conditional only on meat prices and meat expenditures The assumption of separability is common in the analysis of meat demand Moschini, Mora, and Green (1994) have presented evidence that meat demand is separable from the demand for other goods

The Demand System

I specified meat demand using Keller and Van Driel's CBS system (CBS stands for the Central Bureau of Statistics of the Netherlands, then Keller and Van Driel's employer) The CBS system has a number of advantages The system is linear in its parameters, which greatly simplifies its estimation The CBS system can be aggregated across consumers to a market level demand The fixed coefficient CBS model can be seen as a special case of the random coefficient model, and this allows testing of the random coefficient version It is possible to impose all the restrictions of demand theory on the coefficients

The CBS model resembles the Rotterdam model In their 1991b and 1993 papers, Alston and Chalfant found that U S meat demand estimated with the Rotterdam model had stable coefficients Other researchers that have used the Rotterdam model for meat or food demand include Gao and Shonkwiler (1993) and Moschini, Mora, and Green

The primary difference between the Rotterdam and CBS model is that the CBS model has non-linear Engle curves The CBS's expenditure response is identical to that of Deaton and Muellbauer's Almost Ideal Demand System (AIDS) in that the budget shares are a function of the logarithm of expenditures Deaton and Muellbauer noted that cross sectional studies of consumer purchases demonstrate that this type of expenditure response provides a superior fit

Prior to the estimation of the random coefficient system, I compared the performance of the Rotterdam and CBS model by specifying a model that was a mixture of the CBS and Rotterdam models and estimating it using the meat data (Alston and Chalfant made a similar comparison of the AIDS and Rotterdam model in their 1993 paper) The model had a parameter that was 1 for the CBS specification, zero for the Rotterdam specification, and between zero and 1 for a mix of the two The estimated coefficient was almost exactly 1 supporting the CBS mode The calculated test statistic for this coefficient was not significantly different than 1 and significantly different from zero However, the test statistic is based on the assumption that only the intercepts of the meat demand models are random, and the true distribution of the test may not conform to the hypothetical one

Like the Rotterdam model, the CBS model is based on a set of partial differential equations The CBS's partial differential equations can be written as

$$W_i \left(\partial Ln(q_i) - \sum_j W_j \partial Ln(q_j)\right) = A_i + \sum_j C_{ij} \partial Ln(p_n) + B_i \left(\partial Ln(X) - \sum_j W_j \partial Ln(p_j)\right) \quad (1)$$

where p_i, q_i, and X are the price of the i'th good, the quantity demanded of the i'th good, and total expenditure In the tables of this report where estimates are presented, those variables subscripted by b refer to beef, p is for pork, c is for chicken and t is for turkey The term W_i is the budget share defined by the following equation

$$W_i = \frac{p_i q_i}{X} \quad (2)$$

The terms A_i, B_i, and C_{ij} are parameters of the model Prices and expenditures affect demand through the B_i and C_{ij} coefficients The A_i represent those changes in demand caused by changes in tastes A positive value of A_i implies that the demand for good i will increase even if all prices and expenditures do not change

The partial differential equation, (1), defines the CBS model However, one does not observe the derivatives of the demand function One observes prices, quantities, and expenditures The CBS model, like the Rotterdam model, is estimated by using the differential equation as the basis for specifying a set of difference equations Usually, these models are estimated in first difference form However, the data used here is monthly data and there is considerable seasonality in the demands for meats To correct for this seasonality, the model was estimated in twelfth differences Data for one month were compared with those from a year earlier

I also allow the model's parameters to vary randomly over time The typical CBS formulation has fixed coefficients and an error term The error term effectively makes the intercepts, the A_i, random In the typical CBS model, taste changes cause fluctuations in the level of demand The Random Coefficient CBS, (RCCBS) used in this paper will have random B_i and C_{ij} as well In the RCCBS taste changes will cause fluctuations in the elasticities of demand as well as in the level of demand

The RCCBS's difference equations are specified

$$y_{i,n} = A_{i,n} + \sum_j C_{ij,n}\Delta^{12}Ln(p_{j,n}) + B_{i,n}(\Delta^{12}Ln(X_n) - \Delta^{12}P_n) \tag{3}$$

Note that all the coefficients in the RCCBS have an additional subscript so that their values can vary over time period The terms $A_{i,n}$, $B_{i,n}$, and $C_{ij,n}$ are the time varying values of A_i, B_i, and C_{ij} The term P_n is a price index, and there is a quantity index Q_n in the formula for $y_{i,n}$ The terms not yet fully defined are generated using the following equations

$$\Delta^{12}P_n = \sum_j W_{j,n-12}\,\Delta^{12}Ln(p_{j,n}), \tag{4}$$

$$\Delta^{12}Q_n = \sum_j \left(\frac{W_{j,n-12} + W_{j,n}}{2}\right)\Delta^{12}Ln(q_{j,n}), \tag{5}$$

$$y_{i,n} = \left(\frac{W_{i,n-12} + W_{i,n}}{2}\right)(\Delta^{12}Ln(q_{i,n}) - \Delta^{12}Q_n), \tag{6}$$

Note that (5) and (6) use the average of current and lagged budget shares, while (4) uses lagged budget shares only The use of average budget shares should make the difference equation in (3) better approximate the differential equation, (1) However, the use of average budget shares introduces the possibility of simultaneity bias in making the price index P_n a function of current endogenous variables As a compromise, the lagged budget shares appear on the right-hand side while average shares appear on the left

The economic theory of consumer demand implies four sets of restrictions on consumer demand functions Keller and Van Driel demonstrate how these restrictions can be applied to the CBS Their results are extended to the RCCBS and summarized below

Three of these sets are equality restrictions One set of equality constraints is the adding-up or aggregation constraints Consumer demand functions need to be constructed so the sum of the money spent all goods adds up to total expenditures Adding-up implies the following restrictions on the demand system's parameters

$$\sum_i A_{i,n} = 0, \forall\, n, \tag{7}$$

$$\sum_i B_{i,n} = 0, \forall\, n, \text{ and} \tag{8}$$

$$\sum_i C_{ij,n} = 0, \forall\, j,\, n \tag{9}$$

As is the case with many demand systems, the adding up restrictions for the RCCBS model hold automatically When the $y_{i,n}$ of the CBS are summed over all "i", that sum is zero The adding-up constraints (7-9) cause the right-hand side of (3) to sum to zero when summed across meats

Demand functions are also required to be homogeneous of degree 0 in prices and expenditures This condition is met through the set of restrictions defined by

$$\sum_j C_{ij,n} = 0, \forall\, i,\, n \tag{10}$$

The last equality conditions are the symmetry conditions on the compensated demand derivatives The symmetry conditions imply

$$C_{ij,n} = C_{ji,n}, \ \forall\, i, j, n \tag{11}$$

Note that given the symmetry conditions, the restrictions implied by (9) and (10) are identical, so that one set of these equations becomes irrelevant

The inequality restrictions come into play through the requirement that the matrix of compensated demands be negative semi-definite Keller and Van Driel demonstrate that these sign conditions imply that each time period's matrix of $C_{ij,n}$ terms must be negative semi-definite One implication of the inequality restrictions is that the $C_{ii,n}$ coefficients cannot be positive

Stochastic Specification of the Random Coefficient Demand System

At this point, I am going to switch the notation that I use to specify the RCCBS The RCCBS can be specified as a linear model with time-varying coefficients

$$y_{i,n} = z_{i,n}\,\theta_n \tag{12}$$

In (12) $z_{i,n}$ is an appropriately configured vector of price and expenditure terms, the predetermined variables of the model

Equation (12) could be any model with coefficients that vary over time I had to specify the process generating the coefficients prior to estimation I assumed that the coefficients are identically and independently distributed over time I denote the expected value of θ_n by θ and the covariance matrix of the coefficients by Σ_θ The expected values and variances of $A_{i,n}$, $B_{i,n}$, and $C_{ij,n}$ will be denoted by A_i, B_i, C_{ij}, σ_{Ai}, σ_{Bi}, σ_{Cij}

The restrictions that apply to the time-varying coefficients also apply to their mean values These restrictions also have implications for the covariance matrix, Σ_θ While there are 24 total coefficients in the RCCBS for the four meats, the equality restrictions allows one to eliminate 12 of the coefficients from the model one of the four $A_{i,n}$, one of the four $B_{i,n}$, and ten of the sixteen $C_{ij,n}$ Because of the equality restrictions, the covariance matrix, Σ_θ has a rank of 12 at most If only the intercepts are random, the covariance matrix has a rank of 3 I have assumed that the A_i must be stochastic If not, then if prices and expenditures do not change, demand changes will be perfectly predictable

The Three-Stage Estimation Procedure

I estimated the model in three stages I used the first two stages to estimate Σ_θ and the last to estimate θ This type of model is difficult to estimate with standard econometric packages, so I estimated the model using the mathematical programming software, GAMS (Brooke, Kendrick, Meeraus, 1988)

Note that the random coefficient model specified in (12) can be rewritten as fixed coefficient model with heteroskedastic error terms as follows

$$y_{i,n} = z_{i,n}\theta + e_{i,n}, \tag{13}$$

where

$$e_{i,n} = z_{i,n}(\theta_n - \theta), \tag{14}$$

and

$$E(e_{i,n}e_{j,n}) = z_{i,n}\Sigma_\theta z_{j,n}' \tag{15}$$

When only the intercepts are random, the variances and covariance implied by (15) will be fixed over all observations If other coefficients are random, the (co)variances will be functions of the prices and/or expenditures Because of the adding up properties of the CBS model, the full covariance matrices of the $e_{i,n}$ terms is singular for both the RCCBS and the CBS

For all three stages, I imposed the equality restrictions directly estimating only the 12 of the 24 elements of the θ vector I also only directly estimated the parts of the Σ_θ associated with the 12 estimated coefficients

In the first stage, I used the specification in (13) and estimated θ without correcting for the heteroskedasticity implied by random elasticities of demand The estimated values of θ were those that minimized the determinant of a three-by-three sub-matrix of the $e_{i,n}$ covariance matrix Barten (1969) has shown that using this procedure for demand systems that add up produces estimates that are independent of the excluded good The excluded variable was turkey The first stage estimates will produce consistent, though possibly inefficient, estimates of the mean parameter vector Given the consistency of the θ estimate, I then have consistent estimates of the $e_{i,n}$ Call those estimates $\hat{e}_{i,n}$

I used the error terms from the first stage to estimate the covariance matrix in the second stage The second stage is the most important of the three, because as (13-15) show, the only difference between the RCCBS and CBS is that the RCCBS has heteroskedastic error terms

I estimated Σ_θ by finding the estimate, call it s_θ, that minimized the following relative sum of squared errors (SSE)

$$SSE = \frac{\sum_i \sum_j \sum_n D_{ij}\left(\overline{e_{i,n}}\;\;\overline{e_{j,n}} - Z_{i,n}\, s_\theta\, Z_{j,n}'\right)^2}{SST} \tag{16}$$

where

$$SST = \sum_n \sum_i \sum_j D_{ij}\left(\hat{e}_{i,n}\hat{e}_{j,n} - \frac{\sum_n \hat{e}_{i,n}\hat{e}_{j,n}}{144}\right)^2 \tag{17}$$

In (16) and (17), D_{ij} is a dummy variable that allows each covariance term to be used only once For instance, it is 1 when i is b and j is p and zero when i is p and j is b The estimates of the Σ_θ matrix from the second stage will be consistent

The objective in (16) is the equivalent of 1 minus the R square of the regression implied by (17) This objective lies between zero and 1 The more the heteroskedasticity, the lower the objective function The objective in equation (16) could be used as a test statistic if one knew its distribution

To evaluate this test statistic, I used a Monte Carlo technique I used the estimates of θ and covariance matrix for homoskedastic errors from the first stage along with the data on the predetermined variables to generate new observations of the $y_{i,n}$ that were homoskedastic. I then ran these new $y_{i,n}$ through the first two stages to evaluate the distribution of the objective of equation (17).

It was in the second stage that I ran into some anticipated and unanticipated problems. The anticipated problem was the need to force the estimate s_θ to be symmetric and positive definite. Left unrestricted, the estimated s_θ was not. This problem was easily handled by specifying the matrix s_θ as the product of a matrix, K, and its transpose.

$$s_\theta = K'K \tag{18}$$

The unanticipated problem was that my first estimated K matrix had a rank of only 6. For the third stage of the estimation, it would have been helpful, but not necessary, for the s_θ to have its full rank of 12. To make the estimated matrix have its full rank, I resorted to a version of ridge regression. I restricted the K matrix to be a six by twelve matrix and then specified s_θ as follows.

$$s_\theta = K'K + rM \tag{19}$$

where r is a small positive weight and M a positive, semi-definite matrix. The usual procedure in ridge regression is to specify M as the identity matrix or some other diagonal matrix. However, because of the equality constraints, the Σ_θ can not be a diagonal matrix. I used an M matrix that could be a Σ_θ, consequently, M was also consistent with the equality constraints. The M matrix is block diagonal in the A, B and C coefficients. Its values can be seen in table 1. The M matrix actually used in the program was taken from Table 1, but reduced to a 12 by 12 matrix. The value of r I used was 10^{-8}.

In stage 3, I estimated the mean value parameter. Swamy and Tinsley (1980) developed a procedure that is useful for estimating linear, random-coefficient regression models such as specified by

Table 1—The non-zero elements of the "M" matrix, times 3[1]

	A_b	A_p	A_c	A_t
A_b	3	–1	–1	–1
A_p	–1	3	–1	–1
A_c	–1	–1	3	–1
A_t	–1	–1	–1	3

	B_b	B_p	B_c	B_t
B_b	3	–1	–1	–1
B_p	–1	3	–1	–1
B_c	–1	–1	3	–1
B_t	–1	–1	–1	3

	C_{bb}	C_{bp}	C_{bc}	C_{bt}	C_{pp}	C_{pc}	C_{pt}	C_{cc}	C_{ct}	C_{tt}
C_{bb}	3	–1	–1	–1	–1	1	1	–1	1	–1
C_{bp}	–1	3	–1	–1	–1	–1	–1	1	1	1
C_{bc}	–1	–1	3	–1	1	–1	1	–1	–1	1
C_{bt}	–1	–1	–1	3	1	1	–1	1	–1	–1
C_{pp}	–1	–1	1	1	3	–1	–1	–1	1	–1
C_{pc}	1	–1	–1	1	–1	3	–1	–1	–1	1
C_{pt}	1	–1	1	–1	–1	–1	3	1	–1	–1
C_{cc}	–1	1	–1	1	–1	–1	1	3	–1	–1
C_{ct}	1	1	–1	–1	1	–1	–1	–1	3	–1
C_{tt}	–1	1	1	–1	–1	1	–1	–1	–1	3

[1]Symmetry conditions have been used to eliminate non-unique C_{ij}

(12) They presented their technique for a single equation model, but the generalization to a system specified as in (12) is trivial Their model also allows one to specify the error terms as an integrated autoregressive/moving average (ARIMA) process, so the RCCBS is a rather simple random coefficient model Given an estimate of Σ_θ, which I had from the second step, their technique will produce estimates of the time path of θ_n and an estimate of the mean value of the coefficient vector, θ

Basically, their procedure is to find estimates of θ_n and θ, call them T_n and T, that solve the following problem

$$\text{Minimize} \quad \sum_n (T_n - T) \; s_\theta^{-1} \; (T_n - T) \tag{20}$$

$$\text{subject to} \quad y_{i\,n} = z_{i\,n} T_n, \quad \forall \; i,n$$

Up to this point I have not addressed the problem of insuring that the $C_{ij\,n}$ estimates are negative definite These inequality constraints can be imposed in general by adding a set of non-linear inequalities to the minimization problem in (20) A less complex method is to force all the off-diagonal $C_{ij\,n}$ to be positive Given the homogeneity and symmetry constraints, this simple sign constraint is enough to insure that all the $C_{ij,n}$ matrices are negative, semi-definite The sign constraint also forces all the meats to be substitutes for one another, which is consistent with my prior expectations

I tried the Swamy-Tinsley specification, but it did not converge even after 50,000 iterations I therefore decided to use the specification implicit in equation (13) and estimate the value of θ using generalized least squares I estimated the covariance matrix of the error terms using equation (15), replacing Σ_θ with its estimate, s_θ

The GLS type specification does not allow me to directly estimate the time path of the random coefficients However, the primary variables of interest are their means and covariance matrix Also, as Swamy and Tinsley demonstrated, the estimated time path of the coefficients will not be accurate They demonstrated that specification of the problem in (20) insures that the estimated time path of the coefficients will tend to be "smoother" than the actual, unobserved time path Further, it is possible to show, that without the inequality restrictions imposed on the $C_{ij,n}$ estimates, the estimated mean vector for the GLS and for the Swamy-Tinsley procedures will be identical See the appendix

As noted above, because of the adding-up features of the CBS model, the error term covariance matrix for all four meats will be singular To get estimates of the coefficients, I performed GLS on a three-meat group The excluded meat was turkey

Evaluating the Properties of the Estimates

The three-stage procedure will produce consistent estimates of Σ_θ and θ, given the usual conditions for consistency However, an evaluation of the model requires estimates of the "accuracy" of the estimates in small samples The three-stage procedure is nonlinear, and asymptotic approximations may be inaccurate given the sample size

To estimate standard errors for the estimates, I used the nonparametric procedure called jackknifing Efron and Gong (1983) discussed jackknifing in their review article This procedure is straightforward I created 144 alternative subsamples of the data by dropping a different observation from each I ran the three-stage procedure on each of the subsamples, and used the s_θ and T from each subsample to calculate standard errors for the estimates using the full sample

Following Efron and Gong, suppose that X is some statistic generated from a sample of size N and that $X_{(n)}$ is the same statistic generated from the sample with observation n dropped The jackknife standard error of X, denoted s_x, is

$$s_x = \left(\frac{N-1}{N} \sum_{n=1}^{N} \left(X_{(n)} - \frac{\sum_{n=1}^{n} X_{(n)}}{N} \right)^2 \right)^{1/2} \tag{21}$$

One of the interesting features of the jackknife and related nonparametric methods that Efron and Gong note is that they can give accurate estimates of the distribution of estimators even when the estimators come from misspecified models

Results

The objective value from the second stage was 81 4 percent, and R squared of just under 19 percent At first glance, this is not a great fit However, I ran 200 Monte Carlo iterations of a homoskedastic model with the parameter and covariance matrix estimates from the first stage The smallest objective from the Monte Carlo trials was 85 2 percent

If 81 4 percent were in fact not significant at the 5 percent level, it would be extremely unlikely that none of the 200 iterations would come up with an objective value less than 81 4 Also, the estimated fifth percentile from the Monte Carlo trial is 89 1, and the jackknife standard error of the fifth percentile estimate is 0 03 The objective value from the second stage is more than 200 standard deviations below the estimated fifth percentile, further proof that the objective is significant at the 5 percent level Consequently, I reject the CBS model in favor of the RCCBS model Fluctuations in tastes have caused fluctuations in the elasticities of demand for meats

Table 2 has the estimates of the mean values of the parameters and estimates of the standard deviations of the random coefficients implied by the s_θ from the second stage along with the jackknife standard errors of the estimates Table 3

Table 2—Selected parameter estimates and their jackknife standard errors

	Estimate of mean of coefficient (1)	Jackknife standard error estimate for mean (2)	Estimate divided by jackknife standard error (1)/(2)	Estimate of standard error of coefficient (3)	Jackknife standard error estimate for standard error (4)	Estimate divided by jackknife standard error (3)/(4)
A_b	-0 006	0 002	-2 775	0 004	0 002	1 704
A_p	-0 001	0 002	-0 477	0 005	0 002	2 589
A_c	0 005	0 001	5 703	0 005	0 001	6 929
A_t	0 002	0 001	3 093	0 003	0 001	3 186
B_b	0 053	0 038	1 381	0 154	0 036	4 232
B_p	-0 017	0 027	-0 612	0 108	0 033	3 282
B_c	-0 014	0 024	-0 579	0 068	0 015	4 541
B_t	-0 022	0 012	-1 841	0 024	0 015	1 593
C_{bb}	-0 154	0 025	-6 165	0 054	0 019	2 844
C_{bp}	0 114	0 021	5 407	0 078	0 022	3 498
C_{bc}	0 027	0 012	2 211	0 036	0 015	2 348
C_{bt}	0 013	0 014	0 922	0 049	0 011	4 500
C_{pp}	-0 123	0 024	-5 054	0 088	0 021	4 263
C_{pc}	0 001	0 009	0 061	0 022	0 007	3 201
C_{pt}	0 008	0 011	0 738	0 036	0 009	3 798
C_{cc}	-0 024	0 009	-2 683	0 025	0 007	3 432
C_{ct}	-0 003	0 008	-0 395	0 011	0 005	2 293
C_{tt}	-0 018	0 010	-1 751	0 022	0 007	3 043

Table 3—Conditional[1] elasticities (and standard errors) implied by mean coefficient estimates and mean budget shares

	Beef price	Pork price	Chicken price	Turkey price	Meat expenditure
	Regular elasticities of demand				
Beef quantity	-0 869	-0 095	-0 117	-0 020	1 101
	(0 264)	(0 123)	(0 043)	(0 103)	(0 301)
Pork quantity	-0 090	-0 699	-0 143	-0 010	0 941
	(0 470)	(0 224)	(0 040)	(0 128)	(0 396)
Chicken quantity	-0 298	-0 256	-0 299	-0 058	0 911
	(0 468)	(0 075)	(0 123)	(0 049)	(0 433)
Turkey quantity	0 080	0 070	-0 147	-0 459	0 456
	(1 511)	(0 651)	(0 176)	(0 548)	(0 832)
	Compensated elasticities of demand				
Beef quantity	-0 296	0 219	0 052	0 025	
	(0 120)	(0 158)	(0 072)	(0 094)	
Pork quantity	0 400	-0 431	0 002	0 029	
	(0 289)	(0 309)	(0 074)	(0 115)	
Chicken quantity	0 177	0 003	-0 159	-0 021	
	(0 246)	(0 137)	(0 159)	(0 051)	
Turkey quantity	0 317	0 199	-0 077	-0 440	
	(1 198)	(0 794)	(0 189)	(0 554)	

[1]Elasticities are conditional on a given level of meat expenditure

shows the elasticities of demand implied by the mean coefficient estimates Because the B_i and C_{ij} are random, these elasticities will vary randomly over time Table 3 also shows the standard deviations of the elasticities of demand implied by s_θ estimates

The estimated mean A_i values for beef, chicken, and turkey are statistically significant The mean A_i measure the general drift in tastes over time The estimated A_i for beef is negative, which suggests a general decline in beef demand over time, while the positive intercepts for the poultry meats suggests increases in poultry demand over the time period

The B_i coefficients show an interesting pattern None of the mean estimates is significant at conventional levels When the B_i are zero for the CBS system, the implied expenditure elasticities are exactly 1 With the exception of turkey, the expenditure elasticities of demand implied by the mean coefficient values in table 4 are all close to one

While the mean values of the B_i are relatively close to zero, the standard deviations of these random coefficients are among the largest of any of the random coefficients The B_i for beef and pork have the two largest estimated standard deviations These large standard deviations imply that the expenditure elasticities are particularly unstable over time

The uncompensated demand elasticities are functions of the B_i and C_{ij} The instability of the B_i also affects all the regular price elasticities The instability of the B_i could be a sign that taste variations has a great impact on expenditure elasticities and, consequently, on the expenditure effects of price changes

On the other hand, values of B_i other than zero imply non-linear Engle curves As Deaton and Muellbauer noted in their article on the AIDS system (which has the same type of expenditure effects as the CBS system), consumer demand systems with this type of nonlinear Engle curve require nonlinear aggregation to market level demands Some of the instability of the B_i could be the result of aggregation problems in estimating changes in meat expenditures over time

I made no effort to constrain the estimated mean C_{ij} coefficients to meet the inequality restrictions of demand theory As it turned out, the mean estimates meet the restrictions without constraints The coefficient of the cross price effects between chicken and turkey is negative, though small in absolute value and not significant The sign implies that chicken and turkey are on average complements This coefficient also has a large standard deviation relative to the mean value of the coefficient, suggesting that the chicken/turkey cross price effect is not stable and these two could be substitutes for much of the time period Other goods are on average substitutes with one another Beef and pork have the largest cross price coefficient This coefficient and the elasticity estimates in table 4 suggest that beef and pork are (on average) better substitutes with one another than any other pair of meats

Summary and Conclusions

Previous work (Chalfant and Alston, 1988, Alston and Chalfant, 1991a) has shown that it is possible to test for the stability of consumer tastes However, econometric models of demand are implicitly based on the assumption that consumer tastes fluctuate randomly Consequently, evidence that tastes are not stable does not rule out the possibility that econometric models are appropriate

I have estimated a random coefficient model for this paper, using U S meat demand data for the 1980's and early 1990's The one disadvantage of the random coefficient approach is that it is quite computer-intensive Rather than specify the model as a "classic" random coefficient model, I ended up specifying it as a problem in generalized least squares This approach limits the choices of stochastic specification for the model In theory, one can specify random coefficient models with rather complex autocorrelation processes generating the coefficients However, even with the use of high quality hardware and software, I was unable to get a "classic" random coefficient model without autocorrelation to converge Future improvements in computational technology may solve some of these problems

Technical problems aside, there are real advantages to using the random coefficient model in this instance Hypothesis tests demonstrate that a general, random coefficient specification is superior to the more typical specification for modeling U S meat demand The random coefficient specification implies that meat demand elasticities have fluctuated over the sample period because of fluctuations in consumer tastes

The results also show that the general trend in consumer tastes had tended to favor poultry demand over beef demand Pork demand appears to be relatively stable The estimates support the views of those that believe that shifts in consumer tastes have hurt the demand for beef relative to the demand for poultry

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Appendix: Proving the Equivalence of the Swamy-Tinsley and GLS Estimates of the RCCBS

The first step in this proof is setting up (16) as a Lagrangian

$$\textit{Minimize} \quad \sum_n (T_n - T)' \, s_\theta^{-1} \, (T_n - T) + 2(Y_n - Z_n T_n)' \, \lambda_n \tag{22}$$

In (23), the term Y_n is three by 1 vector consisting of three of the four $y_{i,n}$ terms (the fourth is irrelevant because of adding up) and Z_n a stacked matrix of the $z_{i,n}$ vectors Taking the first derivative with respect to T_n gives

$$2s_\theta^{-1} (T_n - T) - 2Z_n' \, \lambda_n = 0 \tag{23}$$

which gives the following solution for T_n

$$T_n = T + s_\theta \, Z_n' \lambda_n \tag{24}$$

Now, take the derivative with respect to the multiplier, substituting (25) for T_n

$$2(Y_n - Z_n \, (T + s_\theta \, Z_n' \lambda_n)) = 0, \rightarrow$$

$$\lambda_n = (Z_n s_\theta Z_n')^{-1} \, (Y_n - Z_n \, T) \tag{25}$$

Note that the term $(Z_n s_\theta Z_n)$ in (26) is the convariance matrix for the heteroskedastic error terms Equation (26) can be substituted into (25) to give the following solution for T_n

$$T_n = T + Z_n \, (Z_n s_\theta Z_n')^{-1} \, (Y_n - Z_n \, T) \tag{26}$$

Now, take the derivative of (23) with respect to T

$$-2 \sum_n s_\theta^{-1} \, (T_n - T) = 0, \tag{27}$$

and substitute (27) for T_n and solving for T gives

$$T = \left(\sum_n Z_n' (Z_n s_\theta Z_n')^{-1} Z_n\right)^{-1}$$

$$\left(\sum_n Z_n' (Z_n s_\theta Z_n')^{-1} Y_n\right) , \qquad (28)$$

which is the GLS estimator of T