Demand Estimation in the Presence of Stochastic Trend and Seasonality: The Case of Meat Demand in the United Kingdom

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If budget shares have stochastic trend or seasonality or both, then demand equations based on the assumption of deterministic trend and deterministic seasonality will be mis-specified. We test this proposition by estimating a Linearized Almost Ideal (LAI) demand system for meat demand in the United Kingdom using Harvey's structural time series methodology. We demonstrate that the model specification allowing for stochastic trend and deterministic seasonality performs best in terms of diagnostic tests and goodness of fit measures. It is also shown that the model with stochastic trend is better at out-of-sample forecasting.

Key words: demand estimation, forecasting performance, stochastic seasonality, stochastic trend.

When estimating demand systems for food, it is common practice to assume that budget shares have deterministic trends and seasonality, implying that a model with a constant intercept, a time trend and deterministic seasonal dummies is correctly specified. For example, Piggott et al., Burton and Young, Kinnucan et al., Arnade and Pick, and Alston et al. all employ deterministic trends and seasonal dummies in demand estimation. However, assuming seasonality is deterministic when it is actually stochastic will yield a mis-specified model. Similarly, a deterministic trend may or may not be true, but it should not be assumed *a priori*. A preferable approach would be to test for deterministic trend and seasonality against stochastic trend and seasonality alternatives.[1]

The objective of this article is to show that if deterministic trend or seasonality or both are assumed *a priori*, then the resulting model may be mis-specified, and any inference based on the estimated values of the coefficients would have problems. We also demonstrate that the out-of-sample forecasting power of the correctly specified model is superior. For this purpose, three versions of a linearized almost ideal demand (LAI) demand system for meat are estimated based on the assumptions of (i) deterministic trend and deterministic seasonality (DTDS), (ii) stochastic trend and deterministic seasonality (DTSS), and (iii) stochastic trend and stochastic seasonality (STSS).

The stochastic trend and seasonality are incorporated into the LAI model following the structural time series methodology of Harvey (1989)—seemingly unrelated time series equations (SUTSE). This is the time series equivalent of seemingly unrelated regressions (SUR). Harvey and Marshall used this methodology to model the demand for energy in the UK. Several modifications and extensions to SUTSE have been introduced, which we also employ in this article.

We begin by specifying the basic LAI model and illustrate how stochastic seasonality and stochastic trend are incorporated into this specification. We also describe the structural time series methodology that is used to estimate the system of demand equations. Next, we detail the data used in the study and the results obtained from the estimation. Conclusions are provided at the end of the article.

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[1] There are also examples of demand estimation in which only deterministic trends are used (e.g., Lariviere et al.) and only seasonal dummies are used (e.g., Cashin, and Xu and Veeman).

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Model Specification

The LAI model with a time trend and deterministic seasonal dummies included for the budget share of commodity i, w_i, is specified as

$$w_{it} = \mu_i + \phi_i \psi_t + \sum_k \theta_{ik} D_{kt} + \sum_j \delta_{ij} \log P_{jt} + \lambda_i \log\left(\frac{Y_t}{P_t}\right) + \varepsilon_{it} \tag{1}$$

where t is the time period ($t = 1, \ldots, T$), P_{jt} is the price of commodity j, Y_t is total expenditure on all commodities, P_t is a Laspeyres price index,[2] ψ_t is a time trend, D_{kt} are zero–one seasonal dummies and ε_{it} is the stochastic error term. To yield economically meaningful results, we impose homogeneity, adding-up and Slutsky symmetry: $\sum_i \mu_i = 1$, $\sum_i \delta_{ij} = \sum_j \delta_{ij} = 0$, $\sum_i \lambda_i = 0$, and $\delta_{ij} = \delta_{ji}$.

With deterministic trend and seasonality, the LAI model coefficients μ_i, ϕ_i, and θ_{ik} in equation (1) are assumed to be constant. If these coefficients are statistically significant, then the budget shares are driven by deterministic trend and seasonality. This assumption is highly restrictive because factors such as taste and habits may very well lead to changes in the values of these coefficients over time. Changes in the values of μ_i, ϕ_i, and θ_{ik} may be abrupt, leading to a structural break, or gradual, leading to a smoothly changing stochastic trend. Hence, it is likely that the equations incorporating deterministic trend and seasonality are mis-specified and unlikely to pass structural stability tests.

An alternative approach used in this study is to specify a general model that encompasses deterministic trend and seasonality and allows a test for deterministic trend and seasonality against a stochastic trend and seasonality alternative. In this case, equation (1) is modified to

$$w_{it} = \mu_{it} + \gamma_{it} + \sum_j \delta_{ij} \log P_{jt} + \lambda_i \log\left(\frac{Y_t}{P_t}\right) + \varepsilon_{it} \tag{2}$$

where μ_{it} is a stochastic trend, γ_{it} is a stochastic seasonal component, and ε_{it} is now redefined as the random component (or irregular component) such that $\varepsilon_{it} \sim \text{NID}(0, \sigma^2_{\varepsilon_i})$.

The stochastic trend, which represents the long-term movement in a series, can be represented by

$$\mu_{it} = \mu_{i,t-1} + \beta_{i,t-1} + \eta_{it} \tag{3}$$

$$\beta_{it} = \beta_{i,t-1} + \zeta_{it} \tag{4}$$

where $\eta_{it} \sim \text{NID}(0, \sigma^2_{\eta_i})$, and $\zeta_{it} \sim \text{NID}(0, \sigma^2_{\zeta_i})$. Here μ_{it} is a random walk with a drift factor, β_{it}, which follows a first-order autoregressive process as represented by equation (4). This is a general representation of the trend that encompasses many other possibilities. For example, this process collapses to a simple random walk with drift if $\sigma^2_{\zeta_i} = 0$, and to a deterministic linear trend if $\sigma^2_{\eta_i} = 0$ as well. If, on the other hand, $\sigma^2_{\eta_i} = 0$ whereas $\sigma^2_{\zeta_i} \neq 0$, then the process will have a trend that changes relatively smoothly.

To model stochastic seasonality, we use a trigonometric specification which, for some even s, is written as

$$\gamma_{it} = \sum_{k=i}^{s/2} \gamma_{i,k,t} \tag{5}$$

where $\gamma_{i,k,t}$ is given by

$$\gamma_{i,k,t} = \gamma_{i,k,t-1} \cos\lambda_k + \gamma^*_{i,k,t-1} \sin\lambda_k + \kappa_{i,k,t} \tag{6}$$

$$\gamma^*_{i,k,t} = -\gamma_{i,k,t-1} \sin\lambda_k + \gamma^*_{i,k,t-1} \cos\lambda_k + \kappa^*_{i,k,t} \tag{7}$$

for $k = 1, \ldots, s/2 - 1$, where $\lambda_k = 2\pi k/s$ and

$$\gamma_{i,k,t} = -\gamma_{i,k,t-1} + \kappa_{i,k,t}, \tag{8}$$

for $k = s/2$, where $\kappa_{i,k,t} \sim \text{NID}(0, \sigma^2_{\kappa_i})$ and $\kappa^*_{i,k,t} \sim \text{NID}(0, \sigma^2_{\kappa*_i})$. Following Harvey and Scott, we assume that $\sigma^2_{\kappa_i} = \sigma^2_{\kappa^*_i}$ to make numerical optimization easier. Intuitively, stochastic seasonality means that the seasonal factor corresponding to each season is not fixed, but varies over time. However, if $\sigma^2_{\kappa_i} = \sigma^2_{\kappa*_i} = 0$ we will have deterministic rather than stochastic seasonality, implying constant seasonal factors. When the seasonal factors are graphed over the time span of the sample period they will look like horizontal lines under deterministic seasonality and smooth curves with changing slopes under stochastic seasonality. The trigonometric representation of seasonality allows for a smoother change in the seasonals.

The extent to which the trend and seasonal components evolve over time depends on the

[2] Moschini and Buse both show that the LAI model is not invariant to changes in the unit of measurement when the Stone index is used and recommend the Laspeyres price index instead.

values of the variances $\sigma^2_{\eta_i}$, $\sigma^2_{\zeta_i}$, and $\sigma^2_{\kappa_i}$, which are called hyperparameters. What is important is the size of $\sigma^2_{\eta_i}$, $\sigma^2_{\zeta_i}$, and $\sigma^2_{\kappa_i}$ relative to $\sigma^2_{\varepsilon_i}$. For example, the bigger the value of $\sigma^2_{\kappa_i}$ relative to $\sigma^2_{\varepsilon_i}$, the more past observations are discounted in constructing a seasonal pattern for the forecast function.

Before applying our model and presenting results, we need to detail several limitations of the generalized stochastic trend and seasonality model. First, it is arguable, that budget shares are bounded variables and so they cannot have stochastic trends. As Shea (p. 351) noted in his study of the term structure of interest rates, some variables (such as interest rates) cannot, in an unqualified sense, be nonstationary if nonstationarity is taken to mean that the variable is unbounded (presumably the same applies to budget shares). However, Shea argues that such considerations should not strictly prevent us from modeling such a variable with a stochastic trend. He justifies this position on the grounds that there are no models without some limitations in accurately depicting the behavior of the underlying variable—there is a trade-off between theoretical desirability and empirical convenience and accuracy.[3]

Second, we may well be better served in attempting to identify and measure variables that cause the stochastic trend and seasonality effects instead of allowing the effect of these variables to be represented by the behavior of the stochastic components. There have been attempts to build explicit variables that model the effects that we attempt to proxy via a trend and seasonal dummies (for example, McGuirk et al.). Although it may be preferable to use explicit variables (Davis) as opposed to the proxies employed in this article, many datasets still rely on the use of such proxy measures. This can be the result of data limitations, nonquantifiable variables and measurement errors. Furthermore, even when researchers have introduced such variables, Moschini and Moro noted, "Whereas, in principle, this approach is attractive, it still involves rather arbitrary choices, or may turn out to be econometrically equivalent to a trend." (p. 248).

Although these are legitimate concerns about our generalized approach, they also apply to deterministic trend and seasonal dummy variables. That is, if budget shares are bounded they cannot have a deterministic trend either, and clearly the deterministic trend and seasonal dummies are accounting for (presumably unobservable) underlying influences just like the stochastic specification. Hence, the generalization represents an improvement over the conventional approach of including only a deterministic trend and seasonal dummies.

Data and Empirical Results

The results presented in this article are based on a sample of quarterly, seasonally unadjusted per capita data covering the period 1960:1–1994:4. The data series were obtained from the National Food Surveys of household food expenditure (excludes food purchased and consumed outside the home) in Great Britain, undertaken by the Ministry of Agriculture, Fisheries and Food. The data are average price and per capita quantity consumed for beef, lamb, pork and chicken. The beef and lamb classifications are based on carcass meat only and include veal and mutton. For pork, bacon and ham (uncooked and cooked) are included. Chicken includes all poultry. The analysis is restricted to the budget shares of beef, lamb and chicken because only three equations can be estimated independently.

We estimate the system of equations represented by (2) using SUTSE. Because we have three equations (commodities) we estimate the (3×3) variance-covariance matrices of each time series component: Ω_η for the levels of the trends, Ω_ς for the slopes, Ω_κ for the seasonal components and Ω_ε for the random components. SUTSE is more efficient than single equation estimation because it utilizes the information contained in the cross-correlations of the residuals. By estimating the covariance matrices of the time series components of the budget shares, we take into account the fact that the components

[3] There is a difference between testing for a unit root and testing for a stochastic trend with the methodology employed here. In the unit root literature, the null hypothesis is that a variable has a unit root (stochastic trend in that sense) against the alternative of stationarity. In this article, the null hypothesis of a deterministic trend is represented by is $\sigma^2_{\eta_i} = 0$. Whereas the alternative of a stochastic trend is represented by $\sigma^2_{\eta_i} = 0$. Unit root testing is criticised on the grounds that it ignores the alternative of deterministic trend (Harvey and Scott). Harvey (1997) provides further insightful criticism of traditional time series analysis and the benefits of the methodology employed in this article.

Table 1. Estimation Results for the Seemingly Unrelated Time Series Models

	DTDS			STDS			STSS		
Parameter	Beef	Lamb	Chicken	Beef	Lamb	Chicken	Beef	Lamb	Chicken
μ_t	−0.273	0.134	0.607	0.040	0.087	0.437	0.021	0.101	0.042
	(−4.98)	(3.56)	(16.79)	(0.48)	(1.41)	(7.13)	(0.25)	(1.64)	(6.63)
β_t	−0.0002	−0.001	0.001	−0.001	−0.001	0.002	−0.001	−0.001	0.002
	(−2.67)	(−15.6)	(35.2)	(−1.22)	(−4.26)	(7.25)	(−1.02)	(−4.22)	(5.87)
γ_{1t}	0.016	−0.008	−0.004	0.018	−0.008	−0.004	−0.013	0.007	0.003
	(7.2)	(−5.14)	(−2.21)	(10.3)	(−5.83)	(−3.09)	(−4.04)	(3.10)	(1.30)
γ_{2t}	−0.012	0.0007	0.006	−0.013	0.001	0.007	0.014	−0.002	−0.008
	(−4.34)	(0.42)	(3.42)	(−6.86)	(0.69)	(4.95)	(4.18)	(−0.68)	(−3.14)
γ_{3t}	−0.015	0.012	0.0003	−0.017	0.013	0.001	−0.002	0.002	−0.001
	(−6.85)	(7.71)	(0.19)	(−9.89)	(8.53)	(0.77)	(−0.67)	(0.87)	(−0.27)
δ_b	−0.065			−0.074			−0.079		
	(−2.69)			(−2.47)			(−2.63)		
δ_l	0.055	−0.025		0.041	−0.018		0.055	−0.02	
	(2.01)	(−1.54)		(1.64)	(−1.04)		(2.12)	(−1.11)	
δ_c	−0.02	0.021	0.028	0.018	0.0001	0.013	0.012	−0.001	0.013
	(−1.95)	(2.36)	(3.22)	(0.68)	(0.001)	(0.76)	(0.48)	(0.02)	(0.70)
λ	0.187	−0.011	−0.107	0.082	0.002	−0.048	0.088	−0.002	−0.042
	(9.91)	(−0.84)	(−8.73)	(3.00)	(0.12)	(−2.36)	(3.24)	(−0.11)	(−2.02)
R_s^2	0.14	0.34	0.24	0.32	0.34	0.33	0.30	0.32	0.30
$\tilde{\sigma}$	0.015	0.010	0.011	0.013	0.010	0.01	0.013	0.011	0.011
AIC	−8.32	−8.01	−8.87	−8.53	−8.97	−9.01	−8.50	−8.93	−8.95
SBC	−8.14	−8.85	−8.63	−8.31	−8.77	−8.83	−8.25	−8.70	−8.74
DW	1.23	1.54	1.35	1.86	1.82	1.80	1.87	1.86	1.84
Q	55.47	20.27	30.12	11.93	10.23	10.75	11.83	10.60	9.24

Note: The Q-statistic is distributed as χ^2 (10) for the DTDS model, χ^2 (8) for the STDS model, and χ^2 (7) for the STSS model. The t-statistics are given in parentheses.

must be related given that the shares sum to one.[4]

The assumption of DTDS is obtained by imposing the restriction $\Omega_\eta = \Omega_\varsigma = \Omega_\kappa = 0$. Then we relax the assumption $\Omega_\eta = \Omega_\varsigma = 0$ to allow for a stochastic trend, whereas maintaining the deterministic seasonality assumption $\Omega_\kappa = 0$ (STDS). Finally, we also relax the assumption $\Omega_\kappa = 0$ to allow for STSS. All estimation is carried out using STAMP 5.0 (Structural Time Series Analyser, Modeller and Predictor) of Koopman et al.

Parameter estimates, along with various diagnostic and goodness of fit measures are presented in table 1.

The time-varying parameter estimates reported in table 1 pertain to the final state vector when the information in the full sample has been utilized. We could have presented time-varying parameter estimates for the entire time period covered by the data, but for the analysis this was not. In table 1, μ_t is the level of the trend, which is equivalent to the constant term in a conventional regression; β_t is the slope of the trend, which is equivalent to the coefficient on a time trend in a conventional regression equation; γ_{1t} is the seasonal component corresponding to the last quarter in the sample, and γ_{2t} and γ_{3t} are the seasonal components corresponding to observations T-1 and T-2 where T is the sample size. The time-varying estimates exhibit a pattern in terms of sign, statistical significance and magnitude that relates to model specification. For example, the seasonal components differ depending on whether a deterministic or stochastic specification is employed.

Goodness of fit measures that are reported include the modified coefficients of determination R_s^2, the standard error of the estimated equation ($\tilde{\sigma}$) as well as information criteria: Akaike's information criterion (AIC) and the Schwarz Bayesian criterion (SBC). Two serial correlation diagnostics are reported: the Durbin–Watson (DW) statistic and the Ljung–Box Q statistic.

The DTDS model has a positive R_s^2, implying that it is better than a simple random walk with drift model. However, there seems

[4] Estimates of the variance-covariance matrices are available from the authors on request.

to be some residual serial correlation as indicated by the DW and the Q statistics. The existence of serial correlation is a likely consequence of model mis-specification.

The STDS model is certainly better than the DTDS model in terms of the diagnostic tests. Serial correlation disappears, whereas the goodness of fit measures improve as indicated by a higher R_s^2, a lower $\tilde{\sigma}$, and lower AIC and SBC. Although the STSS model does not show any sign of serial correlation, it does not show any improvement in the goodness of fit over the STDS model. In fact, the AIC and SBC rise, whereas the R_s^2 declines. Hence, from our initial inspection of the results STDS is the preferred model.

As the three models estimated are nested, we employed a likelihood ratio test to see if the apparent differences between the models are statistically significant (Harvey and Marshall). The STSS model is the unrestricted specification. The STDS model has one restriction, $\sigma^2_{\kappa_i} = 0$. The DTDS model has three restrictions, $\sigma^2_{\eta_i}$, $\sigma^2_{\zeta_i}$ and $\sigma^2_{\kappa_i}$ all equal to zero. To undertake the likelihood ratio test, we estimated the log likelihood for each of the equations in each of the models, which in turn yielded the nine test statistics reported in table 2.

The results in table 2 confirm the differences between the models previously identified. We are able to reject the null hypothesis at the five percent level of significance when we compare DTDS versus STDS and DTDS versus STSS. However, we are unable to reject the null when we compare STDS versus STSS. Thus, STDS is the most parsimonious preferred model.

Another more informal means of evaluating the models is to assess the economic reasonableness of the various elasticity estimates. Uncompensated and compensated price elasticity estimates and expenditure elasticity estimates are reported in table 3.

All elasticity estimates are for the end values of the data period given that the parameter estimates are for the final state vector. The results in table 3 show that the uncompensated and compensated own price elastic-

Table 2. Likelihood Ratio Test Statistic Results

Share Equation	Likelihood Ratio Statistics	p-values
	DTDS vs STDS	
Beef	44.80	0.0000
Lamb	10.20	0.0060
Chicken	10.42	0.0054
	DTDS vs STSS	
Beef	47.08	0.0000
Lamb	9.60	0.0222
Chicken	26.49	0.0000
	STDS vs STSS	
Beef	2.29	0.1302
Lamb	0.60	0.4385
Chicken	0.42	0.5169

Note: The likelihood ratio test is distributed χ^2, where the degrees of freedom are number of restrictions. DTDS vs STDS has 2 restrictions, DTDS vs STSS has 3 restrictions, and STDS vs STSS has 1 restriction.

Table 3. Uncompensated, Compensated and Expenditure Elasticity Estimates

Model and Equation	Beef	Lamb	Chicken	Pork
Uncompensated Elasticities				
DTDS				
Beef	−1.32	0.37	0.032	0.132
Lamb	0.06	−1.15	0.26	−0.11
Chicken	−0.20	0.16	−0.65	−0.03
Pork	−0.10	−0.31	0.03	−0.79
STDS				
Beef	−1.27	0.26	0.19	0.07
Lamb	0.08	−1.12	0.03	−0.05
Chicken	−0.001	−0.0003	−0.83	−0.06
Pork	−0.03	−0.15	−0.09	−0.85
STSS				
Beef	−1.30	0.36	0.14	0.06
Lamb	0.12	−1.13	0.04	−0.07
Chicken	−0.03	−0.003	−0.85	−0.04
Pork	−0.05	−0.22	−0.07	−0.82
Compensated Elasticities				
DTDS				
Beef	−0.96	0.59	0.11	0.32
Lamb	0.35	−0.98	0.32	0.04
Chicken	0.42	0.40	−0.57	0.18
Pork	0.48	−0.01	0.14	−0.54
STDS				
Beef	−0.99	0.50	0.37	0.28
Lamb	0.31	−0.93	0.11	0.12
Chicken	0.31	0.26	−0.63	0.17
Pork	0.37	0.17	0.11	−0.57
STSS				
Beef	−1.00	0.59	0.31	0.27
Lamb	0.35	−0.94	0.18	0.09
Chicken	0.29	0.25	−0.66	0.20
Pork	0.36	0.10	0.11	−0.55
Expenditure Elasticities				
DTDS	1.56	0.93	0.33	0.80
STDS	1.24	1.01	0.70	0.89
STSS	1.26	0.99	0.74	0.87

ity estimates for all three models have the correct sign according to theory.[5] There are some differences of magnitude between the elasticity estimates that are more pronounced for the uncompensated estimates. For example, the uncompensated own price elasticity for chicken increases from −0.718 in the DTDS model to −0.871 and −0.877 in the STDS model and the STSS model, respectively. There is also a smaller increase for pork. The uncompensated cross-price elasticity estimates are sensible, although not all meat types are found to be gross substitutes. Compensated cross-price elasticity estimates show that all meat types are net substitutes with some marked differences between specifications. There are also differences between the expenditure elasticity estimates that are particularly pronounced for beef and chicken. For beef, the expenditure elasticity estimates fall when moving to the stochastic trend and seasonality models but for all other meats they increase. Although, all the models yield sensible elasticity estimates, the different specifications do impact the magnitude of the elasticity estimates. Hence, it is important to use the correct specification, which in this case was found to be STDS.

Out-of-Sample Forecasting

We now examine the out-of-sample forecasting power of the STDS model against the DTDS model. The models are estimated over the period 1960:1–1989:4 and subsequently used to forecast the budget shares over the period 1990:1–1994:4. Table 4 reports two measures of forecasting power: the mean absolute error and the root mean square error. The results indicate that the STDS model has better out-of-sample performance.

A question that may legitimately arise here is whether the difference between the forecasting powers (as measured by the RMSE) of the two models is statistically significant. For this purpose we use the Ashley, Granger and Schmalensee test employed by Kastens and Brester for the difference of the RMSE's of two models. The Ashley, Granger and Schmalensee test requires that we estimate the linear regression

$$D_t = \beta_0 + \beta_1(S_t - \overline{S}) + w_t \quad (9)$$

Table 4. Forecasting Performance of Models

Meat/Model	Mean Absolute Error	Root Mean Square Error
Beef		
STDS	0.0138	0.0232
DTDS	0.0379	0.0437
Lamb		
STDS	0.0137	0.0158
DTDS	0.0196	0.0236
Chicken		
STDS	0.0121	0.0197
DTDS	0.0154	0.0278

Ashley, Granger and Schmalensee Test

Meat	$t(\beta_0)$	p-values	$t(\beta_1)$	p-values
Beef	12.34	0.0000	−1.23	0.1172
Chicken	2.18	0.0213	−1.27	0.1101
Lamb	9.67	0.0000	−0.08	0.4685

where $D_t = e_{1t} - e_{2t}$, $S_t = e_{1t} + e_{2t}$, $\overline{S}$ is the mean of S, e_{1t} is the out-of-sample error at time t of the model with the higher RMSE (DTDS), e_{2t} is the out-of-sample error at time t of the model with the lower RMSE (STDS) and $t = 1, 2, \ldots, n$. If the sample mean of the forecast errors from either model is negative, the forecast error series must be multiplied by −1 before running the regression.

The estimates of the intercept term (β_0) and the slope (β_1) are used to test the statistical difference between the RMSE of the two models. If the estimates of β_0 and β_1 are both positive, then an F-test of the joint hypothesis $\beta_0 = \beta_1 = 0$ is appropriate. However, if one of the estimates is negative and statistically significant, then the test is inconclusive. Further, if the estimate is negative and statistically insignificant, then the test remains conclusive, and significance is determined using the upper-tail of the t-test on the positive coefficient estimate.

The results of the Ashley, Granger and Schmalensee test for the beef, lamb and chicken equations are presented in the lower part of table 4. In all cases, at least one coefficient is negative, in which case we resort to the t-test. The coefficient β_0 is positive and significant at the one percent level for beef and lamb, and at the five percent level for chicken. This result shows us that the RMSE for the STDS model is statistically sig-

[5] The compensated own price elasticities indicated that a necessary condition for concavity is satisfied. This condition held for all data points in the sample.

nificantly smaller, so this model is superior in out-of-sample forecasting. The results presented here support the use of a stochastic trend even though we are only dealing with a short forecasting period.

Conclusion

For the UK meat demand data examined in this study, the results demonstrate that a model incorporating STDS using Harvey's SUTSE methodology is statistically preferred to a model incorporating a DTDS. Differences in the magnitude of the elasticity estimates derived using the alternative model specifications have also been identified. The statistically preferred model (STDS) was also shown to be superior in out-of-sample forecasting performance. Of course, different applications may find different empirical results, but this article does demonstrate the importance of allowing and testing for stochastic trend and seasonality in applied demand studies.

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