Dairy Supply Response under Stochastic Trend and Seasonality: A Structural Time Series Analysis

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A structural time series methodology was used to examine the role of stochastic trend and seasonality in dairy supply response model. In our analysis, the dairy supply model with stochastic seasonality and deterministic trend performs best in terms of diagnostic tests, goodness-of-fit measures, and forecasting accuracy.

Key words: Supply response, stochastic seasonality, stochastic trend, forecasting accuracy

Many researchers have analyzed the supply response function of US dairy and beef cattle industry. These studies differ in specific products, geographic areas, explanatory factors, modeling approaches, and method of analysis. The size and complexity of the market justify the different modeling approaches, research efforts, and diversity of analyses. The primary purposes of analyzing dairy and cattle supply response include: forecasting of future supplies, identifying the dynamic structure which best describes the observed aggregate data, and identifying the response to price levels (Foster, 1990).

For example, Maki (1963), Kulshreshthan and Wilson (1972), Tyfos (974), Freebairn and Rausser (1975), Martin and Haack (1977), Arzac and Wilkinson (1979), Rucker et al. (1984), Sun (1994), and Kaiser et al. (1994) have analyzed the dairy and cattle supply response behaviors of farmers. Traditionally dairy and cattle supply responses have been modeled as a function of feed cost, market price of animal, interest rate, institutional variables, and lagged dependent variables. Some of the above studies have also incorporated trend and seasonal dummy variables to capture of the impacts of technological progress and seasonal variations on dairy and cattle supply.

One of the severe limitations of above studies was to assume deterministic trend and seasonality components in the dairy and cattle supply model, implying that a model with a constant intercept, a time trend, and deterministic seasonal component is correctly specified. In this paper, we argue that assuming seasonality and trend as deterministic while it is actually stochastic might lead to a mis-specified model and false inferences. A deterministic seasonality and trend may or may not be correct, but it should not be assumed *a priori* while developing supply model for dairy and cattle industry. Therefore, the main objective our article is to develop a correctly specified dairy supply response model, especially incorporating seasonality and trend as stochastic components.

We begin our study by selecting a basic dairy cattle supply model as proposed by Sun, 1994, and by Kaiser et al, 1994. The selected model will be further improved by assuming different scenarios of fixed and stochastic seasonality and trend variables. In order to find a correctly specified model, four versions of dairy and cattle supply response were developed:

(i) Deterministic trend and deterministic seasonality (DTDS),

(ii) Deterministic trend and stochastic seasonality (DTSS),

(iii) Stochastic trend and deterministic seasonality (STDS), and

(iv) Stochastic trend and stochastic seasonality (STSS).

The structural time series model (STSM) proposed by Harvey, 1997, offers the theoretical justification needed to verify the methodological development.

Rationale

US dairy industry has undergone a dramatic restructuring in the last 50 years. During the period from 1940 to 1997, the numbers of dairy farms decreased by 69 percent. From 1950 to 1975, the average number of milk cows on dairy farms declined by over 49 percent from almost 22 million to just over 11.1 million. The average number of milk cow was further decreased by 18 percent from 1975 to 2000, making the dairy industry an increasingly concentrated livestock production system. In the meantime, the number of specialized dairy farms increased from 53 to 72 percent ((Blayney, 2002).

However, there exists an opposite trend in the case of milk production. Statistics show that almost 167.7 billion pounds of milk was produced in the United States in 2000, 45 percent more than in 1975. Milk per cow nearly doubled from 1950 to 1975 (95 percent greater) and grew an additional 76 percent from 1975 to 2000 (Blayney, 2002). Changes in production systems and innovational profits remain the major factors of structural change in the dairy industry. Innovational profits mostly arise from technological advances in the areas of nutrition, health, breeding, and genetics (Blayney, 2002).

While analyzing the dairy supply responses, the ideal condition would be to include all variables of technological progress. However, in reality it is not possible to measure the impacts of all these variables separately using different proxies. Therefore, most studies of dairy supply response capture the ongoing technological improvements by using a deterministic trend variable, which basically assumes an unchanged rate of technological improvement throughout the sample period. In our opinion, technological improvements evolve over time and assuming it to be a deterministic component misspecifies the dairy supply response model. Similarly, seasonal aspects of dairy farmers' decisions on culling and replacement of dairy cows might evolve over time. Therefore, we also suggest against assuming a deterministic seasonal component *a prior* while the developing dairy supply model.

Structural Time Series Model

First proposed by Harvey in 1989, the STSM allows the unobservable trend and seasonal components to change stochastically over time. The STSM is generally developed directly in terms of components of interest, such as trend, seasonal, cyclical, and residual or irregular components. The STSM relates to regression model in both technical formulation and model selection methodology. The Kalman filter, which is a simple statistical logarithm, and a state-space model play fundamental roles in analyzing structural time series models (Gonzalez and Moral, 1995). In STSM, the exogenous variables enter in to the model side by side with the unobserved components. Unlike the traditional ARIMA models, STSM explicitly consists of unobserved stochastic trend and seasonality components. STSM model reverts to a standard regression model in the absence of unobservable components (Harvey, 1989). Consider the following STSM quarterly dairy supply model:

$DS_t = \mu_t + \gamma_t + Z'_t \delta + \varepsilon_t$ ----------------------------------(1)

Where,

DS_t = quarterly dairy supply

μ_t = the trend component

γ_t = the seasonal component

Z'_t = Vector of explanatory variables (milk feed price ratio, price of slaughter cow, etc)

δ = k*1 Vector of unknown parameters

ε_t = Random white noise disturbance term

With deterministic trend and seasonality variables, the model coefficients of μ_t and γ_t in equation 1 are assumed to be constant. If these coefficients are statistically significant, the dairy supply response will be driven by deterministic trend and seasonality. However, this would be a highly restrictive assumption. Technical and genetic progress may lead to changes in the value of these coefficients over time. Changes in the values of μ_t and γ_t may take different forms, leading to either structural break or a smoothly changing stochastic trend. Therefore, there exist possibilities of mis-specification of the model and false inferences if we incorporate the seasonality and trend as strictly deterministic components. Proposed STSM allows specifying a possible alternative of the above problem by allowing a test for deterministic trend and seasonality against a stochastic trend and seasonality alternative. The stochastic trend, which represents the long term movement in the series can be represented by

$\mu_t = \mu_{t-1} + \beta_{t-1} + \eta_t$ --(2)

$\beta_t = \beta_{t-1} + \xi_t$ ---(3)

Where $\eta_t \sim NID\ (0, \sigma_\eta^2)$ and $\xi_t \sim NID\ (0, \sigma_\xi^2)$

Equations (2) and (3) represent the level and the slope of the trend, respectively. Here, μ_{t-1} is a random walk with a drift factor, β_t, which follows a first-order autoregressive process as represented by equation 3. A stochastic trend variable (μ_t) captures the technological progress and structural change in dairy industry in recent years. The exact form of the trend depends upon whether the variances, σ_η^2 and σ_ξ^2 (also known as the hyper parameters) are zero or not. If either σ_η^2 and σ_ξ^2 are non-zero, then the trend is said to be stochastic. If both are zero, then the trend is linear and the model reverts to a deterministic linear trend model as follows:

$DS_t = \alpha + \gamma_t + \beta_t + Z'_t\,\delta + \varepsilon_t$ -----------------------------------(4)

A trigonometric specification was used to model the stochastic seasonality. This seasonal component, γ_t, was modeled in terms of sine-cosine waves at the seasonal frequencies as suggested by Harvey, 1989:

$$\gamma_t = \sum_{j=1}^{s/2} \gamma_{jt}$$

$$\begin{bmatrix} \gamma_{jt} \\ \gamma^*_{jt} \end{bmatrix} = \begin{bmatrix} \cos\lambda_j & \sin\lambda_j \\ -\sin\lambda_j & \cos\lambda_j \end{bmatrix} \begin{bmatrix} \gamma_{jt-1} \\ \gamma^*_{jt-1} \end{bmatrix} + \begin{bmatrix} w_{jt} \\ w^*_{jt} \end{bmatrix}, \qquad j = 1,\ldots\ldots\ldots.(s/2)-1 \text{ ----(5)}$$

$\gamma_{jt} = \cos\lambda_j\, \gamma_{j,\,t-1} + w_{jt},$

$j=s/2;$

where $\lambda_j = 2\pi j/s$. j= 1, 2,….., s/2 are the seasonal frequencies, w_{jt} *and* w^*_{jt} are normal errors with zero means and equal variance, $\sigma^2_{w,}$ and s is the number of seasons of the year. Seasonality changes slowly by means of a mechanism that guarantees that the sum of the seasonal factors over any consecutive s time periods has an expected value of zero and a variance that remains constant over time. The smaller the variance, the more stable the component (Gonzalez and Moral, 1995).

Economic Model Specification

Following Foster (1990), Rucker et al. (1984), Sun (1994), and Kaiser et al. (1994), the structural dairy supply response structural time series model is specified as:

$$DS_t = \mu_t + \gamma_t + \beta_1 DS_{t-1} + \beta_2 DS_{t-2} + \beta_3 DS_{t-3} + \beta_4 MFPR_t + \beta_5 DPSC_t + \varepsilon_t \quad \text{---(6)}$$

where,

DS_t = the dairy cattle inventory in current quarter in thousands in Georgia

μ_t = the trend component

γ_t = the seasonal components

DS_{t-1} = the dairy cattle inventory in previous quarter in thousands in Georgia

DS_{t-2} = the dairy cattle inventory in two lagged quarters in thousands in Georgia

DS_{t-3} = the dairy cattle inventory in three lagged quarters in thousands in Georgia

$MFPR_t$ = Milk Feed Price Ratio

$DPSC_t$ = Price of slaughter cow deflated by CPI (1982-84= 100) in cents per pound

ε_t = Random white noise disturbance term

If $\sigma_\eta^2 = \sigma_\xi^2 = \sigma_w^2 = 0$, equation 6 collapses to a standard regression model having a linear deterministic time trend and seasonal component and explanatory variables. Therefore, the STSM with explanatory variables in equation 6 is a generalization of the classical linear regression model.

Data

In order to carry out the objectives of the study, inventory data (1985-2002) of dairy cow in Georgia were collected from National Agricultural Statistics Services (NASS) of United States Department of Agriculture (USDA) and Georgia Agricultural Facts. Information about the milk feed price ratio, consumer price index, and price of cow slaughter were collected from the Economic Research Service (ERS) of United State Department of Agriculture (USDA)'s publications. The price of cow slaughter was deflated by using consumer price index (all urban consumer, US city) average (1982-84=100). In order to analyze the impacts of seasonality in dairy supply response, we consider a quarterly observation. In our model, dummy variables for first, second and third quarters capture the effects of seasonality and a trend variable is used to model the impacts of technological progress in dairy industry in recent years.

Results and Discussions

First, the variance-covariance matrices of each time series component, Ω_η for the levels of the trends, Ω_s for the slopes of trend, Ω_d for seasonal dummies, and Ω_ε for the random components, were estimated. The assumptions of DTDS, DTSS, STDS, and STSS were obtained by imposing restriction of variance-covariance matrices as such that:

DTDS iff ($\Omega_\eta = 0$, $\Omega_s =0$, $\Omega_d = 0$),

STDS iff ($\Omega_\eta \neq 0$, $\Omega_s \neq 0$, $\Omega_d = 0$),

DTSS iff ($\Omega_\eta = 0$, $\Omega_s = 0$, $\Omega_d \neq 0$),

STSS iff ($\Omega_\eta \neq 0$, $\Omega_s \neq 0$, $\Omega_d \neq 0$)

Structural Time Series Analyzer, Modeller, and Predictor (STAMP) 6.0 version was used for the analysis purposes. STAMP allows options to run different versions (DTDS, DTSS, STDS, and STSS) of the dairy supply model. Table 1 reports estimates of trend, season, and explanatory variables for four different models of dairy supply. Also included in Table 1 are measures of diagnostic and goodness-of-fit of the model such as Durbin-Watson (DW) test, Ljung-Box Q statistic, Jarque and Bera normality statistic, standard error of the estimated equation (σ’), Aikake information criterian (AIC), and Bayes information criterian (BIC). The conventional R^2 is not very useful to measure the goodness of fit in our model due to the use of quarterly time series model. Therefore, we report R^2_S, a coefficient of determination, as suggested by Harvey (1989)

The time-varying parameter estimates of table 1 are related to the final state vector when the information in the full sample has been utilized. The trend variable (μ_t) and the slope of the trend (β_t) in table 1 are equivalent to the constant and coefficient of trend variable, respectively, in the standard regression equation. In the meantime, variables $\gamma_1, \gamma_2,$ and γ_3 represent the first, second, and third quarter seasonal dummy of the classical regression model, respectively.

Except DTDS, remaining dairy supply models (DTSS, STDS, and STSS) show a strong convergence, reflecting successful maximum likelihood estimation by the numerical optimization procedure of STAMP. N value in Table 1 is the Jarque and Bera normality test, which follows asymptotically a χ^2 distribution with two degree of freedom under the null hypothesis (Gaujrati, 1995). At 5% critical level, $\chi^2_{(2)}$ yields a value of 5.99. Except DTDS (N= 9.46), the other dairy supply models, DTSS (N= 4.66), STDS (N=0.82), and STSS (N= 5.60), fail to reject the null hypothesis of the presence of non-normality. Therefore, the diagnosis shows that except DTDS model, there is no indication of non-normality in the residual. The residuals and QQ plot (Figure 2) also confirm the results.

The Box-Ljung Q statistic, Q (p,q), is a test for serial correlation, which is based on the first 'p' residual autocorrelations and should be tested against a chi-square distribution with 'q' degree of freedom (Table 1). In our analysis DTDS, DTSS, STDS, and STSS dairy supply models' p values of 0.1406, 0.77, 0.83, and 0.63, respectively, fail to reject the null hypothesis of no serial correlation in the model. Darbin-Watson d statistic examines the presence of serial correlation in the model. In our analysis, the DTDS, DTSS, STDS, and STSS dairy supply models yield DW d values of 2.08, 1.83, 1.84, and 1.92 respectively. With the sample size of 68 and 5 explanatory variables, the critical d_L and d_U values range from 1.446 to 2.232. All of the DW d values of our dairy supply models fall between these critical d_L and d_U values, and therefore, fail to reject the null hypothesis of no positive autocorrelation. The results suggest that there is no autocorrelation in the disturbances.

H(g) is a test for heteroscedasticity and the 1% critical values of F(g,g), for DTDS, DTSS, STDS, and STSS dairy supply models are 2.05, 2.23, 2.19, and 2.03 respectively. These values fail to reject the null hypothesis of presence of heteroscedasticity in the residuals. In our analysis, the estimation procedures converge and the results of diagnostic tests appear satisfactory for the different models of dairy supply response suggesting that DTDS, DTSS, STDS, and STSS dairy supply model is appropriately specified.

Structural Time Series Analysis with Explanatory Variables

After confirming the validity of the models using different diagnostic tests, we further analyze the four dairy supply models by using explanatory variables as proposed by Harvey 1989. The parameter estimates of dairy supply models and hyper parameters are given in Table 1. The study results show a positive and statistically significant role of one quarter lagged dairy cow inventory in all dairy supply models. However, in DTDS, and DTSS model, two quarter lagged cow inventory also show significant but negative results, a result consistent with the finding of Kaiser et al 1994.

As expected, all dairy supply models show a statistically significant and inverse relationship between milk feed price ration ($MFPR_t$) and dairy cow supply. The finding is consistent with the findings of Chin, 1994, and Kaiser et al., 1994. Analysis shows that an increase of milk feed price ratio by 1 percent decreases the supply of dairy cow by 0.0421, 0.0433, 0.0341, and 0.0416 percent respectively in DTDS, DTSS, STDS, and STSS dairy supply models. Except DTSS, remaining dairy supply models show a significant and positive impact of slaughter cow price on supply of dairy cows. This finding demonstrates that an increase in price of slaughter cow by 1 percent increases the supply of dairy cows by 0.025, 0.0667, and 0.064 percent, respectively, in DTDS, STDS, and STSS dairy supply models.

The Best model and Supply Forecasts

The main goal of our analysis was to specify a correct dairy supply model. The values of AIC, BIC and R^2_S values were considered as the main criteria of the best model specifications. In our analysis, DTSS dairy supply model yields the smallest AIC and BIC values of 0.784 and 1.098 respectively (Table 1). The DTSS model also yields highest R^2_S value of 0. 452 (Table 1). These statistics are significantly different from remaining dairy supply models, especially the STDS and STSS, making DTSS a superior and correctly specified model of dairy supply. The study results clearly reject the classical idea of incorporating deterministic seasonal variables in the dairy supply model as *a priori*.

We further analyze the forecasting performance of DTDS, DTSS, STDS, and STSS dairy supply model using out-of-sample predictions (Table 2). Forecasts are made for all dairy supply models for the period from the first quarter of 2004 to the fourth quarter of 2005. The forecasting performance of the model is evaluated by comparing these forecasts with the true values of corresponding variables for the 2000-2003 periods. A root mean square error (RMSE) criterion is used to evaluate the forecasting ability of the model. The forecasts, together with their estimated root mean square errors and actual dairy supplies are reported in table 2. With small RMSE values, DTDS and DTSS dairy supply models lead to more accurate forecasts in comparison to the STDS and STSS dairy supply model. However, the smallest RMSE value clearly show that DTSS model is superior in forecasting performance. Forecast and actual values of the dairy cow supply in figure 3 shows that a directional change was also correctly forecast in the 2004-2005 period by the DTSS model.

To further assess the robustness, structural integrity, and forecasting accuracy and thereby to confirm the superior dairy supply model, we also use the measures of root mean square percentage error (RMSPE) and mean absolute percentage error (MAPE). RMSE is the squared root of the average of the set of squared differences between real and forecasted or predicted values. while mean absolute percentage error (MAPE) represents the average value of the absolute values of errors express in percentage terms. These were calculated as:

RMSPE = $\{1/T \sum_{t=1}^{T} [(Y_t^P - Y_t^a)/ Y_t^a]^2\}^{1/2}$ and

MAPE = $\{1/T \sum_{t=1}^{T} [(Y_t^P - Y_t^a)/ Y_t^a]$

Where T = the number of forecasts

Y_t^P = the predicted value of Y

Y_t^a = the corresponding actual value

Both RMSPE and MAPE measure the absolute mean prediction error of an endogenous variable. The use of percentage measures facilitates comparison different dairy supply models. Table 3 reports RMSPE and MAPE values of real in-sample data and structural time series forecasts for all dairy supply models. As expected, in both cases RMSPE and MAPE in-sample values of DTSS dairy supply model were smaller than corresponding values obtained from the remaining DTDS, STDS, and STSS dairy supply models. The RMSPE value of 0.0957 (in-sample forecast) and 0.16991 (out-of-sample forecast) are clearly smaller than RMCPE values of remaining dairy supply models. The small MAPE values of 0.0059 (in-sample forecast) and 0.0028 (out-of-sample forecast) also confirm the robustness of DTSS models in comparison to the other models of dairy supply response.

Conclusions

Contrary to the classical idea of using a deterministic seasonal variable in the dairy supply model, our results demonstrate that a dairy supply model incorporating stochastic seasonality (DTSS) yields the best and correctly specified model. The results also demonstrate that the out-of-sample forecasting power of the correctly specified model is superior. However, our analysis suggests against incorporating stochastic trend variable in the dairy supply model. In our opinion, technological advancements are a slowly evolving phenomenon and have been on going in the dairy sector over the past 50 years. The quarterly time series data, or 3 months time period might be not be enough to capture the evolving technological progresses in the dairy industry. Based on our analysis, we do not rule out the possibilities of different empirical results for different statistical and econometric applications, but our study does show the importance of incorporating stochastic trend variable in applied supply studies.

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Table 1: Estimation Results of Dairy Supply Response Model under Different Assumptions of Trend and Seasonality Variable

Parameter	DTDS	DTSS	STDS	STSS
μ_t	15.630**	13.888**	42.817**	42.817**
β_t	-0.0231	-0.041**	-0.027	-0.275
γ_1	0.831**	0.6176**	1.103**	0.993**
γ_2	0.0741	-0.0404	-0.047	0.061
γ_3	0.101	-0.463	-0.884**	0.109
DS_{t-1}	1.324**	1.383**	0.591**	0.591**
DS_{t-2}	-0.652**	-0.676**	-0.193	-0.193
DS_{t-3}	0.171	0.147	0.067	0.067
$MFPR_t$	-1.357**	-0.952**	-1.712**	-1.712**
	(-0.0421)	(-0.0433)	(-0.0341)	(-0.0416)
$DPSC_t$	9.213**	4.678	25.031**	25.031**
	(0.0253)	(0.0251)	(0.0667)	(0.06404)
σ’	1.327	1.290	1.440	1.761
DW	2.085	1.836	1.844	1.927
Q	9.640	4.029	2.777	4.288
R^2_S	0.420	0.452	0.419	0.132
AIC	0952	0.784	1.123	1.558
BIC	1.332	1.098	1.539	2.008
N	9.46	4.66	0.82	5.60
H(g)	2.05	2.23	2.19	2.03

Note: ** shows variables statistically significant at 10 percent level. The number in the parenthesis shows corresponding elasticity

Table 2: Dairy Supply Forecasts (In Thousands) and Root Mean Square Error (RMSE) Under Different Models

		DTDS		DTSS		STDS		STSS	
Period	Real	Forecast	RMSE.	Forecast	RMSE.	Forecast	RMSE.	Forecast	RMSE
2002. 1	85.31	86.36	1.54	86.36	1.51	82.53	3.66	82.53	3.67
2002. 2	85.56	84.77	1.54	84.77	1.51	81.47	4.04	81.47	4.06
2002. 3	85.59	86.60	1.54	85.60	1.51	83.14	4.39	83.14	4.41
2002. 4	85.44	86.84	1.55	85.84	1.51	82.53	4.73	82.53	4.73
2003. 1	85.81	86.43	1.55	86.43	1.52	82.45	5.06	82.45	5.07
2003. 2	85.73	86.15	1.55	86.15	1.52	82.30	5.37	82.30	5.38
2003. 3	85.43	85.56	1.55	85.56	1.52	80.96	5.67	80.96	5.68
2003. 4	84.22	87.11	1.56	85.11	1.53	83.56	5.96	83.56	5.96
2004. 1		86.21	1.57	86.21	1.53	82.37	6.25	82.37	6.26
2004. 2		85.57	1.57	85.57	1.53	81.49	6.53	81.49	6.54
2004. 3		86.19	1.57	85.19	1.54	82.17	6.81	82.17	6.82
2004. 4		87.36	1.57	84.36	1.54	83.40	7.08	83.40	7.08
2005. 1		86.47	1.58	84.47	1.54	82.22	7.34	82.22	7.35
2005. 2		85.83	1.58	85.83	1.55	81.34	7.60	81.34	7.62
2005. 3		86.45	1.58	84.45	1.55	82.02	7.86	82.02	7.87
2005. 4		87.62	1.58	84.62	1.55	83.25	8.12	83.25	8.12

Table 3: Mean Absolute Percentage Error (MAPE) and Root Mean Square Percentage Error (RMSPE) for the In-Sample and Forecast Periods

	RMSPE		MAPE	
Models	Sample	Forecast	Sample	Forecast
DTDS	0.1446	0.3137	0.00201	0.0981
DTSS	0.09579	0.16991	0.00059	0.0028
STDS	0.38706	0.25875	0.01498	0.0067
STSS	0.38706	0.25875	0.01498	0.0149

Figure 1. Time Series Plotting of Dairy Cow Inventory in Georgia (1985-2003)

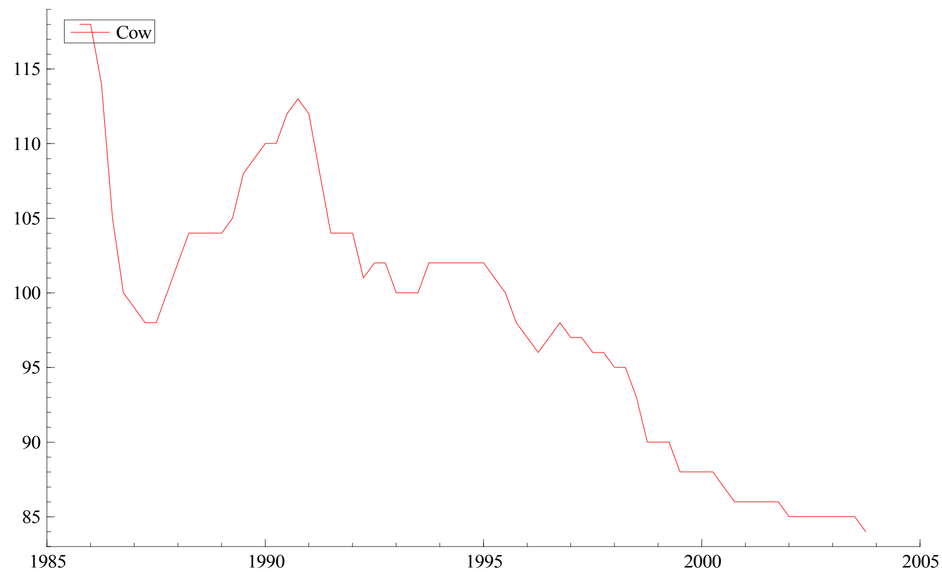
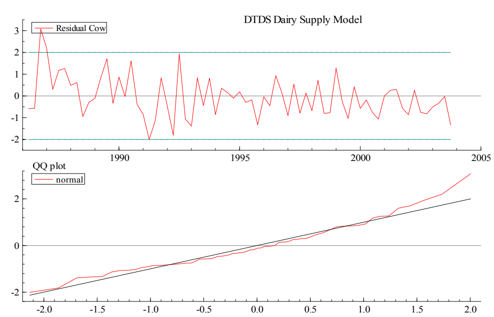
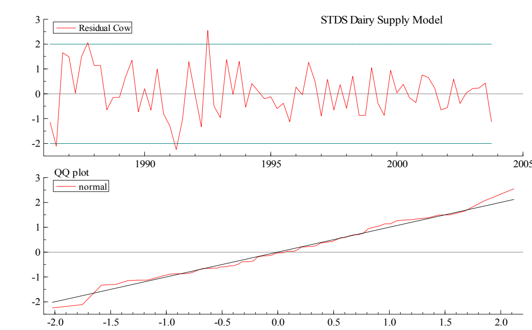


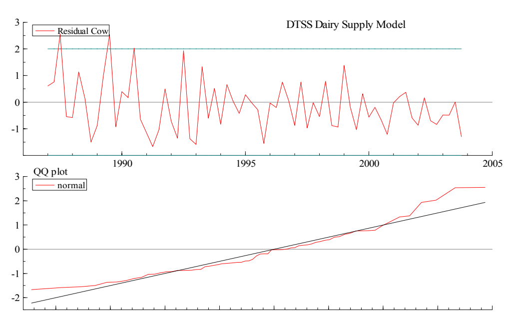
Figure 2. Residual and QQ Plotting of Different Dairy Supply Models



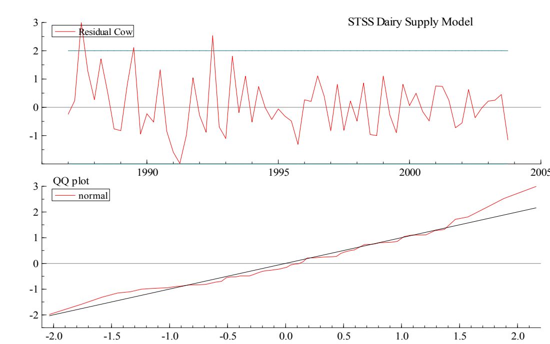
DTDS)



DTSS



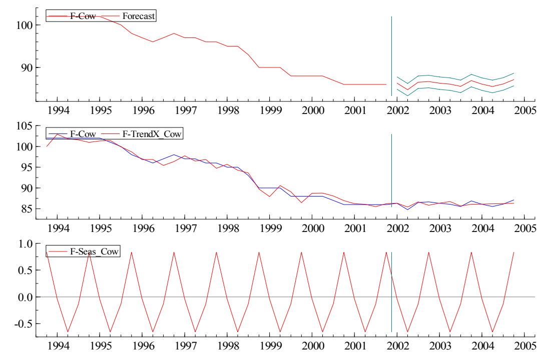
STDS



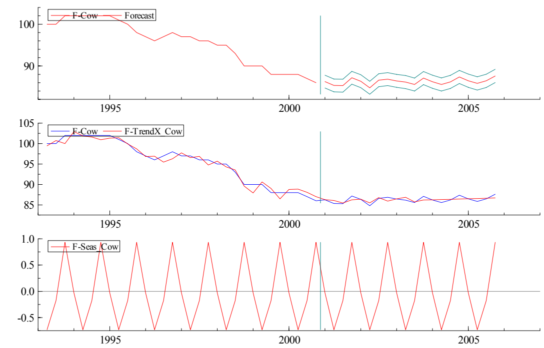
STSS

Figure 3. Forecasting Accuracy and Component Graphic of Different Dairy Supply Model

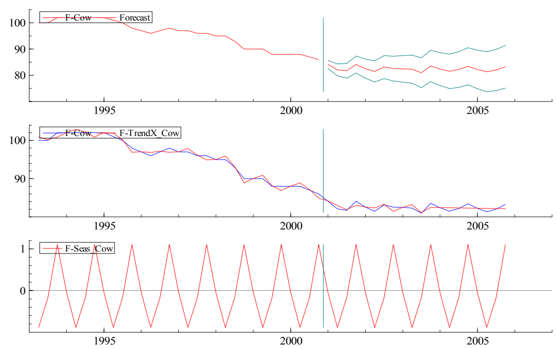
DTDS



DTSS



STDS



STSS