The Journal of Animal & Plant Sciences, 25(5): 2015, Page: 1283-1289
ISSN: 1018-7081

A SHORT TERM FORECAST FOR MEXICAN IMPORTS OF UNITED STATES BEEF USING A UNIVARIATE TIME SERIES MODEL

E. Sánchez-López, C. Pérez-Linares, F. Figueroa-Saavedra and A. Barreras-Serrano

Instituto de Investigaciones en Ciencias Veterinarias, Universidad Autónoma de Baja California, Mexicali, BC, México. 21100
Corresponding Author E-mail: edsanmxl@hotmail.com

ABSTRACT

Using the monthly data for beef exports from the United States to Mexico between January 2000 to December 2012 and based on the Box- Jenkins methodology, an autorregressive moving average (ARMA) model was constructed to forecast the behavior of imported beef. Based on the correlogram and the Dickey-Fuller test on the time series, no evidence of non stationary behavior was found, the process was continued using ordinary least squares to estimate the parameters of a group of models with different autorregressive AR(p) and moving average MA(q) combinations until two were selected: a AR (1) and a ARMA (1, 2). To establish which model better represented the data generating process, the regression coefficients together with the Akaike and Schwarz criteria were used, to determine the presence of autocorrelation both the correlograms were inspected and the Ljung-Box test applied, the result of this evaluation lead to the selection of the AR (1) model, however after testing the forecasting ability of both models it was found that the ARMA (1, 2) model had a better fitting. Although the predicted values overestimated the real values it was concluded that this type of time series model may be considered as a useful tool to short term forecast Mexican imports of US beef.

Key words: Import, ARIMA, beef.

INTRODUCTION

Mexican imports of United States beef are seen as very important because of its value which according to GATS (2013) amounted in 2012 to 609 million dollars, however it must be considered that since 2008 this imports have exhibited a steady and important decline, so that in 2012 the volume of imported beef was 111,647 metric tons, 130, 446 metric tons less than in 2008, this is a 58% reduction in the last four years, nevertheless Peel *et al.* (2011) report that Mexico continues to be the number one importer of United States beef. From an economic standpoint this imports are relevant, the reason being that as reported by Márquez *et al.* (2004), when the supply of imported beef increases, Mexican beef production declines, this may be explained by the research of Benítez *et al.* (2010) which found that imported beef has a high elastic demand, so that a reduction in the price results in a more than proportionated increase in its demand. This behavior may clarify why Delgado *et al.* (2005) found that due to the product´s lower quality and price, Mexican producers see beef imports as a threat to their industry

The effect that imported beef has on the Mexican market support the use of tools that may enable producers and those responsible for establishing agricultural to better understand how beef imports behave in the present and in the future. According to Ayyub *et al.* (2011) when forecasting economic variables it is common to use one of three econometric approaches: multivariate models, univariate models or the combination of both, in the case of univariate models its use is mostly justified because they are easily constructed and as a result of this, cost is low, but also researchers use them when there is incomplete knowledge regarding the casual structure that the process has. Evans (2003) considers that another reason why univariate models are used is that, although multivariate models are widely employed to make predictions their results are not always very good and because of this Asteriou and Hall (2007) consider that researchers have to resort to univariate time series models which frequently provide better forecasting results, but with the disadvantage that the model is built without establishing contemporaneous relation between dependent and explanatory variables due to the fact that all the information about the variable is obtained the same variable itself, however in view that Koheler and Murphree (1988) suggest that the disadvantages of the univariated models be overlooked when the main objective of a model is forecasting, it was considered methodologically sound to use this type of models in this work.

To study the behavior of beef supply, researchers have successfully used autoregressive moving average methodology (ARMA) to forecast the behavior of the market’s variables. Yavuz *et al.* (2013) using a autoregressive integrated moving average model (ARIMA) in Turkey were able to determine the beef market tendency and use this information as an aid in the design of public policy, however the predictive capacity of this types of univariate models is not always optimal, Magagnin, (2008) in a comparative study of models to predict the demand of Brazilian chicken found that an

ARIMA model underperform, when compared to multivariate models.

Nelson (1998) suggest that to use an ARIMA model at least 50 observation are employed and it is recommended that the data is presented monthly or by trimesters, in the case of commercial agricultural variables like the one use in this study, this represents no difficulty because of how the imports data is reported.

Considering the effect that beef imports from the United States have on the Mexican beef industry and the good forecasting ability that ARMA models have, the object of this study is to describe and forecast the behavior of this type of imports, using an ARMA model.

MATERIALS AND METHODS

Using the metric tons of beef exported monthly to Mexico from the United States between January of 2000 to December of 2012, reported by the Foreign Agricultural System (GATS) (2013) of the United States Department of Agriculture (USDA) the Box-Jenkins time series methodology described by Gujarati and Porter, (2010) was applied to select a final model that was used to predict the behavior of the variable. The methodology was chosen because it achieves good results when determining the best forecasting model (Vogelvang, 2005).

The Box-Jenkins (1976) methodology uses three stages aimed at selecting an ARMA model or if the series is non-stationary an ARIMA model to forecast the series, the stages are: identification, estimation and diagnostic checking and is based on the principle of parsimony. As described by Asteriou and Hall (2007) ARMA model combines an autorregressive (AR(p)) and a moving average process (MA(q)) to give a new series of models. The general form of the of the model is the following ARMA (p,q)

$$Y_t= \Phi_1 Y_{t-1}+ \Phi_2 Y_{t-2}+\ldots+ \Phi_2 Y_{t-p}+u_t+\theta_1 u_{t-1}+ \theta_2 u_{t-2}+\ldots+ \theta_q u_{t-q}$$

Where:
Y_t= Dependent variable
Φ and θ= parameters in the model
u_t = error term
and
$|\Phi|< 1$

Harris and Sollis (2005) state that ARMA models can only be used when the series Y_t is stationary which means that the mean, variance and covariance of the series are constant over time. Kennedy (1998) recommends that if the case is that the series is non stationary, the condition may be remediated through a process of differencing. The first differences of a series Y_t are given by the following equation:

$$\Delta Y_t = Y_t-Y_{t-1}$$

Where:
Δ= change of Y_t

Asteriou and Hall (2007) propose that the identification stage start by determining stationarity by checking the series graph and through the examination of the autocorrelation functions plot which allows not only to determine if the series has a pronounced trend or shows no constant mean of variance or a tendency, but also to observe any extreme values or structural changes in de data (Enders, 2004). In this work the visual examination was complemented with the use of the augmented Dickey-Fuller unit root test to identify if the series was non stationary, as described by Ngurah (2009). This test considers three possible forms: a model that includes a constant, a model with a constant and linear trend an one with neither a constant or a trend . The p and q orders of the times series were identified through the evaluation of the autocorrelation (AC) and partial autocorrelation (PAC) functions graphs, so that a group of ARMA processes were selected as starting points, the proposed models were estimated using ordinary least squares (OLS), and following the recommendations from Stillman, (1985) their estimation together with the Akaike (AIC) and Schwarz (SC) information criterions values were used to compare the group and select the final two candidates.

Following the methodology applied by Asteriou and Hall, (2007) the final procedure entailed that the selected models correlograms were used to search for the presence of extreme values and periods when the model fails to fit, and also the Ljung- Box, Q statistic was applied to determine if an autocorrelation problem is present. The final step to select the best model was carried out considering the suggestions of Pyndick and Rubinfeld, (2001) so both models were submitted to a predictive efficacy evaluation using the Mean absolute error (MAE), the root mean squared error (RMSE), Theil´s inequality coefficient (TIC), bias proportion (BP), variance proportion (VP) and the covariance proportion (CP) statistics. All estimations, hypothesis testing and calculations were performed using the Eviews 7 econometric program (Quantitative Micro Software).

RESULTS

The visual inspection of the beef import graph (Fig. 1) shows an extremely variable behavior and a decreasing trend and no constant long run mean, all of this suggests the series may be non-stationary;

Following the Box Jenkins methodology the series correlogram was examined without finding clear evidence of non-stationary behavior. To formally identify the series as stationary an ADF test was preformed, the result of the test was the rejection of the null hypothesis, and because of this, the series was considered stationary and differentiation was unnecessary.

As a result of the identification procedure two models were selected a AR (1) and a ARMA (2,1) so it was established that the behavior of the imports for the following month was determine by how the same variable behave during the first and second preceding months. The models were estimated by OLS obtaining the results shown in Table 1 and Table 2 respectively:

Fig 1. Metric tons of United States beef imported by Mexico between 2000 and 2012.

The diagnostic checking of the two alternative models using the significance of the estimated coefficients and AIC and SC, although similar, suggested that the AR(1) model is the most appropriate one, this is also supported by the parsimony principle. The Q statistics of the correlograms of both models were checked and no autocorrelation of the residuals problem was found (Tables 2 and 3).

Although the differences between the statistics are small, the ARMA (2,1) model shows slightly better results, the MAE and RMSE values suggest that this model has a better forecasting ability, this is supported by the smaller values of the bias and variance proportion showed by the ARMA (2,1) model and that most of the variance is concentrated on the covariance proportions Pindyck and Rubinfeld, (2001).

To check the forecasting ability of the selected model a forecasted series was obtained using a dynamic method and plotted together with the actual series (Fig. 2) this allowed to visually examine the predictive capability of the model.

As Fig. 2 shows, the forecast series fits the actual series well. An ex-post forecast for January and February of 2013 was obtained and compared with the value observed for those months (Table 4).

Both month forecasts overestimate the behavior of the variable and although the difference for January is small, the bigger divergence for February may be explained by the large variability that the beef imports display, which makes them difficult to approximate with the selected model

Table 1. OLS results for the AR (1) model

Variable	Coefficient	Std. Error	t-Statistic	P>t
C	14433.81	965.9388	14.94278	0.0000
AR(1)	0.784929	0.051213	15.32666	0.0000
R-squared	0.605575	Mean dependent var		14565.92
Adjusted R-squared	0.602997	S.D. dependent var		4101.348
S.E. of regression	2584.184	Akaike info criterion		18.56503
Sum squared resid	1.02E+09	Schwarz criterion		18.60430
Log likelihood	-1436.790	F-statistic		234.9065
Durbin-Watson stat	2.044613	P>(F-statistic)		0.000000

Table 2. OLS results for the ARMA (2,1) model.

Variable	Coefficient	Std. Error	t-Statistic	P>t
C	14378.95	1006.186	14.29054	0.0000
AR(2)	0.620388	0.085478	7.257832	0.0000
MA(1)	0.830735	0.058809	14.12592	0.0000
R-squared	0.610109	Mean dependent var		14560.47
Adjusted R-squared	0.604945	S.D. dependent var		4114.166
S.E. of regression	2585.893	Akaike info criterion		18.57282
Sum squared resid	1.01E+09	Schwarz criterion		18.63198
Log likelihood	-1427.107	F-statistic		118.1440
Durbin-Watson stat	2.114696	P>(F-statistic)		0.000000

Table 3.Correlogram and Q statistics for model AR (1).

Autocorrelaction	Partial correlation		AC	PAC	Q-stat	Prob
.|. |	.|. |	1	-0.025	-0.025	0.1009	
.|. |	.|. |	2	-0.020	-0.021	0.1661	0.684
.|. |	.|. |	3	0.025	0.024	0.2660	0.875
*|. |	*|. |	4	-0.112	-0.111	2.2816	0.516
.|* |	.|* |	5	0.097	0.094	3.8164	0.431
.|* |	.|* |	6	0.074	0.074	4.7186	0.451
.|. |	.|. |	7	-0.036	-0.024	4.9276	0.553
*|. |	*|. |	8	-0.084	-0.102	6.0923	0.529
.|. |	.|. |	9	-0.056	-0.044	6.6153	0.579
.|. |	.|. |	10	-0.050	-0.048	7.0383	0.633
.|* |	.|* |	11	0.137	0.123	10.211	0.422
.|** |	.|** |	12	0.260	0.262	21.681	0.027
.|. |	.|. |	13	-0.010	0.028	21.698	0.041
.|. |	.|* |	14	0.054	0.066	22.201	0.052
*|. |	*|. |	15	-0.077	-0.064	23.224	0.057
*|. |	*|. |	16	-0.142	-0.149	26.737	0.031
.|* |	.|. |	17	0.078	-0.025	27.806	0.033
.|. |	.|. |	18	0.022	0.007	27.893	0.046
*|. |	.|. |	19	-0.069	-0.043	28.753	0.051
.|. |	.|* |	20	0.016	0.066	28.798	0.069
*|. |	.|. |	21	-0.071	0.023	29.710	0.075
*|. |	*|. |	22	-0.095	-0.086	31.369	0.068
.|** |	.|* |	23	0.227	0.137	40.899	0.008
*|. |	*|. |	24	-0.079	-0.170	42.062	0.009

AC: Autocorrelation, PAC: Partial Autocorrelation

Table 4.Correlogram and Q statistics for model AR (2, 1).

Autocorrelaction	Partial correlation		AC	PAC	Q-stat.	Prob
.|. |	.|. |	1	-0.025	-0.025	0.1009	
.|. |	.|. |	2	-0.020	-0.021	0.1661	0.684
.|. |	.|. |	3	0.025	0.024	0.2660	0.875
*|. |	*|. |	4	-0.112	-0.111	2.2816	0.516
.|* |	.|* |	5	0.097	0.094	3.8164	0.431
.|* |	.|* |	6	0.074	0.074	4.7186	0.451
.|. |	.|. |	7	-0.036	-0.024	4.9276	0.553
*|. |	*|. |	8	-0.084	-0.102	6.0923	0.529
.|. |	.|. |	9	-0.056	-0.044	6.6153	0.579
.|. |	.|. |	10	-0.050	-0.048	7.0383	0.633
.|* |	.|* |	11	0.137	0.123	10.211	0.422
.|** |	.|** |	12	0.260	0.262	21.681	0.027
.|. |	.|. |	13	-0.010	0.028	21.698	0.041
.|. |	.|* |	14	0.054	0.066	22.201	0.052
*|. |	*|. |	15	-0.077	-0.064	23.224	0.057
*|. |	*|. |	16	-0.142	-0.149	26.737	0.031
.|* |	.|. |	17	0.078	-0.025	27.806	0.033
.|. |	.|. |	18	0.022	0.007	27.893	0.046
*|. |	.|. |	19	-0.069	-0.043	28.753	0.051
.|. |	.|* |	20	0.016	0.066	28.798	0.069
*|. |	.|. |	21	-0.071	0.023	29.710	0.075
*|. |	*|. |	22	-0.095	-0.086	31.369	0.068
.|** |	.|* |	23	0.227	0.137	40.899	0.008
*|. |	*|. |	24	-0.079	-0.170	42.062	0.009

AC: Autocorrelation, PAC: Partial Autocorrelation

To select the final model a final evaluation of the two models was done by comparing the predictive efficacy using the MAE, RMSE, TIC, BP, VP, and CP statistics (Table 5).

Table 5. Forecast evaluation of AR(1) and ARMA(2,1) models.

Statistic	AR(1) model	ARMA (2,1) model
Mean absolute error	1881.04	1876.09
Root mean squared error	2567.45	2560.58
Theil´s inequality coefficient	0.0854	0.0852
Bias proportion	0.000	0.000
Variance proportion	0.1247	0.1158
Covariance proportion	0.8752	0.8884

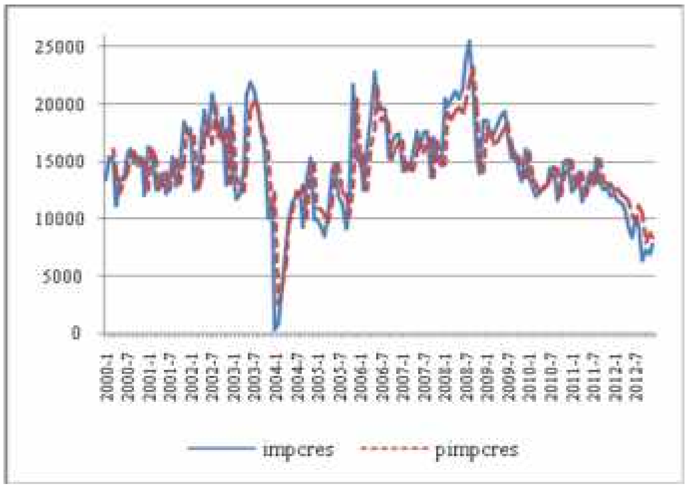

Fig. 2 Tons of actual (impcres) and forecasted (pimpcres) beef imports

Table 6. Comparation between real and forecasted monthly values of beef imports

Month	Actual value	Forecast	Difference
January 2013	9111.9	9298.55	186.65
February 2013	7892.70	10316.18	2423.48

DISCUSSION

The selected model forecasting graph exhibits a negative trend for United States exports of beef to Mexico in correspondence with the behavior of the original series, this may be explained by Henneberry and Mutondo, (2009) research results, which indicate that the additional purchases that Mexican beef consumer are willing to make will rather be on Mexican beef, this preference for Mexican meat can be seen as a relevant factor to encourage beef production in Mexico which is supported by the current increase in per capita consumption of beef which according to Peel *et al*, (2011) has risen 17.7 kilograms between 2000 and 2009.

Because of its economic impact it is relevant to take in to consideration the important increase in the demand for imported beef when its price falls reported by Benítez *et al*. (2010), but also the volatility that the exchange rate exhibits, this factor is relevant because according to Bonroy *et al.* (2007); it has been found that in pork this variability has been close linked to the quantity to be exported.

Liu *et al*. (1993) report that other factors that influence United States meat exports behavior are the domestic and foreign macroeconomic variables however of the two factor, the foreign variables exert more significant and persistent effect on this exports

Araujo and Cruz, (2010) found that in the case of beef trade between Mexico and the United States, Mexico is in chronic disadvantage because of its outdated production infrastructure and although according to Wise (2005) US industrial livestock operations are important beneficiaries of agricultural policies that depress the prices for feed which is the most important operating cost. The current trend that beef imports exhibit does not support that Mexico is in disadvantage, nevertheless it cannot be ignored that because of the high variability that this imports display and that before 2008 the variable presented a growing trend, no long run direction can be established for the behavior of Mexican imports of US beef and this is why it is important to apply forecasting models that may help to foresee the behavior of this variable so that more tools are available in the decision making process in the industry.

Box-Jenkins methodology determines that a series is non stationary by examining its plot and the behavior of the PACF and ACF, however for Dickey *et al.* (1986) this tools on occasions run to difficulties to support a conclusion that a series is stationary and because of this it is recommended to formally test for unit roots using at least one of the tests that are available for this purpose, because as stated by Harris and Sollis, (2003), regressions with non stationary series can lead to the problem of spurious regressions.

Due to the diversity of factors that influence the behavior of Mexican imports of U. S. beef it is difficult to establish a model to fully represent the data generating process so that better prediction values can be obtained, but also taking in consideration the research done by Myers *et al*. (2010) this type of imports may be one of the commodity market variables which ARIMA models do not fully capture the times series behavior, this may be the case, however the results of this study suggest that the ARMA model performed well as prediction tool, but as a result of what Pindyck and Rubinfeld, (1998) report, it must be taken into consideration that this type of models do not provide good long term forecasts and because of this when the predictions required are long term, a multivariate model should be preferred.

An interesting finding in this work was that both final candidate models had small orders for p and q, this indicates that the behavior of the beef imports is mostly influenced by how the variable performed in the immediate past and this situation limits the use of the models as government and industry tools for long term decision making and planning.

REFERENCES

Araujo-Andrade, L.A., and E. Cruz-Pacheco (2010) Estructura productiva y desequilibrio externo en carne de vacuno entre México y Estados Unidos. Rev. Mex. Agroneg., 27 Julio- diciembre: 419-433.

Asteriou, D.S. and G. Hall. (2007). Applied econometrics a modern approach. Palgrave MacMillan. New York. 397 p.

Ayyub, R.M., M. Bilal and M. Ahmed (2011). Meat price hikes and it`s forecasting in Pakistan. J. Anim. Plant Sci., 21(2): 256-259.

Benítez-Ramírez, J.G., R. García-Mata, J.S. Mora-Flores and J.A. García-Salazar (2010). Determinación de los factores que afectan el mercado de carne bovina en México. Agrociencia, 44 (1): 109-118

Bonroy, O., J.P Gervais and B. Larue (2007). Are exports a monotonic function of exchange rate volatility? Evidence from disaggregated pork exports. Can. J. of Econ., 40 (1): 127-154.

Box, G.P. and G.M. Jenkins (1976) Time series analysis, forecasting and control. Holdan Day. Oakland. California. 555 p.

Delgado, E.J., M.S. Rubio, F.A. Iturbe, R.D. Méndez, L. Cassís and R. Rosiles (2005). Composition and quality of Mexican and imported retail beef in Mexico. Meat Sci., 69: 465–471.

Dickey, D., A. Bell, R.W. and R.B. Miller (1986). Unit root in time series models: Test and implication. Am. Stat., 40(1): 12-26.

Enders, W. (2004) Stationary time-series models. In Applied econometrics Time Series. Wiley. Hoboken N J, (USA). 460 p.

Evans, M.K. (2003). Practical Business forecasting. Blackwell Publishers. Malden, (USA). 501 p.

GATS (2013). Foreign Agricultural Service. United States Department of Agriculture.

Gujarati, D.N. and D.C. Porter (2010). Econometría. 5ª ed. Mac Graw Hill. México D. F. 921 p.

Harris, R. and R. Sollis (2003). Applied time series modeling and forecasting. John Wiley & Sons. West Sussex. (UK) 302 p.

Henneberry, S.R. and J.E. Mutondo (2009). Agricultural Trade among NAFTA Countries: A Case Study of U.S. Meat Exports. Rev. Agric. Econ., 31(3): 424–445.

Kennedy, P.A. (1998) A guide to econometrics. 4th Ed. MIT press. Cambridge, (USA). 468 p.

Koheler, A.B. and E.S. Murphree (1988). A comparation of the Akaike and Schwarz criteria for selecting model order. Appl. Stat., 37, 187-195.

Liu, D. J.P.J.Chung., and W.H. Meyers (1993). The Impact of Domestic and Foreign Macroeconomic Variables on U.S. Meat Exports. Agric. Res. Econ. Rev., 22 (2): 210-221.

Ngurah, A.I.G. (2009) Time series data analysis using eviews. John Wiley & Sons. Singapore. 609 p.

Myers, R.J., R.J. Sexton, and W.G. Tomek (2010). A century of research on agricultural markets Amer. J. Agr. Econ., 92(2): 376–402

Nelson, B.K. (1998). Time series analysis using autoregressive integrated moving average (ARIMA) models. Acad. Emer. Med. 5: 739-744.

Márquez-Sánchez, I., R. García-Mata, G. García-Delgado, J.S. Mora-Flores and E. López-López (2004) El efecto de las importaciones de carne bovina en el mercado interno mexicano, 1991-2001. Agrociencia-Mexico., 38 (1):121-130.

Magagnin, G. (2008). Modelo para a previsão da demanda internacional de carne de frangoproduzida no Brasil. Dissertaçãoa presentada ao Programa de Pósgraduação em Engenharia de Produção, da Universidade Federal de Santa Catarina. Mestre em

Engenharia de Produção – Sistemas de Produção.

Peel, D.S., K.H. Mathews, R.J. Johnson (2011) Trade, the Expanding Mexican Beef Industry, and Feedlot and Stocker Cattle Production in Mexico. Economic Research Service. USDA.

Pindyck, R.S. and D.L. Rubinfeld (1998).Econometría modelos y pronósticos. 4th Ed. Mc Graw-Hill. México D.F. 661 p

Stillman, R.A. (1985). A quarterly model for livestock industry. USDA, Economic Research Service Technical Bulletin, 1711. On line: http://naldc.nal.usda.gov/download/CAT87201614/PDF.

Vogelvang, B. (2005). Econometrics. Theory and applications with Eviews. Pearson Education Limited. Essex, (UK). 363 p.

Wise, T.A. (2005). Identifying the Real Winners from U.S. Agricultural Policies. Global Development and Environment Institute Working Paper No. 05-07. Tufts University. 12 p.

Yavuz, F., A. Bilgic, M. Terin, I. O. Guler. (2013). Policy implications of trends in Turkey's meat sector with respect to 2023 vision. Meat Sci., 95: 798-804.