An analysis of tomato prices at wholesale level in Turkey: an application of SARIMA model.

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Abstract

Price forecasting is more acute with vegetable crops particularly tomato due to its highly perishable nature and seasonality. Forecasting tomato prices can provide critical and useful information to tomato growers making production and marketing decisions. The objectives of this paper were to analyse the seasonal price variation of tomato crop and to develop a Seasonal ARIMA (SARIMA) model to forecast the monthly tomato prices at wholesale level in Antalya, a city located in the Mediterranean Region, Turkey, on the basis of reported prices from 2000 to 2010. In addition, some suggestions were made for the existing and potential tomato producers based on the predicted prices of tomato. The highest tomato prices adjusted seasonaly appear on October. SARIMA $(1, 0, 0) (1, 1, 1)_{12}$ model was selected as the most suitable model to forecast of tomato prices. It is clear that tomato prices will not considerably flactuate by 2014 on the real base. It is important to produce tomato with GAP techniques against the price risks.

Keywords: Tomato Prices, SARIMA model, Turkey

1. Introduction

Most people are employed in jobs where their salary or hourly wage is fixed. This gives them security and allows them to plan their expenditures well in advance. The income from other professions is not so certain. Entrepreneurs must take economic uncertainty as a fact of life, especially those in the agricultural sector. The price farmers receive is rarely fixed and is difficult to predict. This also makes life difficult for those who purchase farm products.

In order to develop a viable strategy for dealing with volalite farm prices, one must understand how and why agricultural prices change (Norwood, F.B. and Lusk, J.L, 2008).

The last few years there has been an increase in the volatility of many agricultural commodity prices. This has increased the risk faced by agricultural producers. Therefore, the importance of accurate price forecasting for producers has become even more acute. The main purpose of agricultural commodity price forecasting is to allow producers to make better-informed decisions and to manage price risk (Ticlavilca et al., 2010).

Price forecasting is more acute with vegetable crops particularly tomato due to its highly perishable nature and seasonality. The tomato is grown in practically every country of the world and is one of the most important agricultural products among fresh vegetables in most countries in the world. Turkey is among the countries producing various kind of vegetable at high production level due to suitable ecological conditions.

According to 2011 data, 27.5 million tons of vegetables are produced in Turkey. Tomato production accounts for 40% of the total vegetable production, appoximately 11 million tons. On the other hand, tomatoes have a significant place in total fresh fruit and vegetables exports with a share of 24.6%, which corresponds to 433 million USD in 2011 (Anonymous, 2012a).

Next to open field production, vegetable production in Turkey takes place under glass and/or plastic. Vegetables account for 96% of the total cultivation under glass/plastic. Among the main vegetables produced in greenhouses are tomato, cucumber, pepper, melon, watermelon and pumpkin. Tomato is produced in half of all greenhouses (Keskin et al., 2009).

Wholesalers have an important role in the marketing of tomato. According to the results of a survey conducted in the Antalya province of Turkey, most of the tomato growers (89,3%) are selling their products in the Antalya wholesale market hall by commissioners to the other buyers such as to the retailers. It must be underlined that there is no collective marketing organism in the area. (Yercan et al., 2012). So, there exists a need to forecast the tomato prices in the wholesale market hall to evaluate the marketing opportunities in time of all the tomato growers. Forecasting tomato prices can provide critical and useful information to tomato growers making production and marketing decisions.

The objectives of this paper were to analyse the seasonal price variation of tomato crop and to develop a Seasonal ARIMA (SARIMA) model to forecast the monthly tomato prices at wholesale level in Antalya, a city located in the Mediterranean Region, Turkey, on the basis of reported prices from 2000 to 2010. In addition, some suggestions were made for the existing and potential tomato producers based on the predicted prices of tomato.

2. Data and Methodology

2.1. Data

The price data is gathered from the fresh fruit and vegetables wholesale market in Antalya/Turkey with the eleven year period from 2000 to 2010 (Anonymous, 2012b). The city hall prices reflects the wholesale prices of the classic variety of tomato.

2.2. Methodology

All analysis are done with the real prices. Current prices must be converted to "real" prices to compare prices across time meaningfully (Norwood, F.B. and Lusk, J.L, 2008). Current prices are converted to the real prices by using the 2003 base year producer price indexes (TurkStat, 2012). The formula is given as follows;

Real Price = (Current Price/PPI Base Year =2003) * (100) (1)

The index numbers before January 2003 are derived using the monthly rate of change in 2003=100 producer price index.

Seasonal indexes were used to detect the fluctuations and seasonalities on tomato prices. Seasonal index measures how much the average for a particular period tends to be above or below the expected value. Seasonal variation is a component of a time series which is defined as the repetitive and predictable movement around the trend line in one year or less. It is calculated a seasonal index for each month in our time series (2000-2010) using the 12-month centered moving average approach:

SItm = Ptm/CMAtm (2),

where SItm is the Seasonal Index for month m during year t, Ptm is the price during month m of year t, and CMAtm is the 12 month centered moving average of Ptm. Because the CMA term "uses up" the first and last six months of a time series, this procedure generates an index for all but the first and last six months. As can be seen in equation (2), SItm (i.e., the seasonal index for a specific month during a specific year) shows by what percentage the price for that month was above or below the prices of the surrounding 12 months. (Mathenge and Tschirley, 2006). A typical set of monthly indexes consists of 12 indexes that are representative of the data for a 12-month period Each index is a percent, with the average for the year equal to 100.0; that is, each monthly index indicates the level of sales, production, or another variable in relation to the annual average of 100.0 (Lind et al., 2009). For example, if the estimated index for June is 1.3, this means that June's values are typically about 30% larger than the average for all months (Albright, S.C. et al., 2011).

Once the seasonal indexes are obtained, each observation is divided by its seasonal index to deseasonalize the data. The reason for deseasonalizing the price series is to remove the seasonal fluctuations so that the trend and cycle can be studied (Lind et al., 2009). For example, if you see a time series of sales that has not been deseasonalized, and it shows a large increase from November to December, you might not be sure whether this represents a real increase in sales or a seasonal phenomenon. However, if this increase is really just a seasonal effect, the deseasonalized version of the series will show no such increase in sales (Albright, S.C. et al., 2011).

In this study, we used SARIMA (seasonal ARIMA or seasonal autoregressive integrated moving average) model to forecast four-period ahead of the monthly tomato price series by applying Box-Jenkins approach. SARIMA model is useful in situations when the time series data exhibit seasonality-peridic fluctuations that recur with about the same intensity each year (Martinez, et al., 2011).

The seasonal ARIMA model incorporates both non-seasonal and seasonal factors in a multiplicative model. One shorthand notation for the model is (Anonymous, 2012c):

ARIMA $(p, d, q) \times (P, D, Q)S$,

with p = non-seasonal AR order, d = non-seasonal differencing, q = non-seasonal MA order, P = seasonal AR order, D = seasonal differencing, Q = seasonal MA order, and S = time span of repeating seasonal pattern (in a monthly data s = 12).

Without differencing operations, the model could be written more formally as

$$(\Phi(B^S)\varphi(B)(x_t - \mu) = \Theta(B^S)\theta(B)w_t \quad (3)$$

The non-seasonal components are:

AR: $\varphi(B) = 1 - \varphi_1 B - ... - \varphi_p B^p$

MA: $\theta(B) = 1 + \theta_1 B + ... + \theta_q B^q$

The seasonal components are:

Seasonal AR: $\Phi(B^S) = 1 - \Phi_1 B^S - ... - \Phi_P B^{PS}$

Seasonal MA: $\Theta(B^S) = 1 + \Theta_1 B^S + ... + \Theta_Q B^{QS}$

Note that on the left side of equation (3) the seasonal and non-seasonal AR components multiply each other, and on the right side of equation (3) the seasonal and non-seasonal MA components multiply each other.

Example; suppose we specify ARIMA (0, 0, 1) × (0, 0, 1)12 for examined series

The model includes a non-seasonal MA(1) term, a seasonal MA(1) term, no differencing, no AR terms and the seasonal period is $S = 12$.

The non-seasonal MA(1) polynomial is $\theta(B) = 1 + \theta_1 B$.

The seasonal MA(1) polynomial is $\Theta(B^{12}) = 1 + \Theta_1 B^{12}$.

The model is $(x_t - \mu) = (1 + \Theta_1(B^{12}))(1 + \theta_1(B))w_t$.

When we multiply the two polynomials on the right side, we get

$$(x_t - \mu) = (1 + \theta_1(B) + \Theta_1(B^{12}) + \theta_1\Theta_1 B^{13})w_t$$

$$= w_t + \theta_1 w_{t-1} + \Theta_1 w_{t-12} + \theta_1\Theta_1 w_{t-13}.$$

Thus the model has MA terms at lags 1, 12, and 13. This leads many to think that the identifying ACF for the model will have non-zero autocorrelations only at lags 1, 12, and 13.

The Box-Jenkins approach is widely used to examining the SARIMA model because of it's capability to capture the appropriate trend by examining historical patterns. The BJ methodology has several advantages, including being able to extract a great deal of information from the time series using a minimum number of parameters and the capacity in handling stationery and nonstationary time series in non-seasonal and seasonal elements (Permanasari et al., 2009).

The Box-Jenkins (BJ) methodology consists of four iterative steps:

1) Step 1: Identification

The foremost step in the process of modelling is to check for the stationary of the series, as the estimation procedures are available only for stationary series (Bhar and Sharma, 2007). Stationarity is a very important concept in the analysis of time series data. Broadly speaking, a time series is said to be stationary if there is no systematic change in mean (no trend), if there is no systematic change in variance, and if strictly periodic variations have been removed (Tebbs, 2011). To test whether the monthly data are stationary or non-stationary, autocorrelation function (ACF) and Augmented Dickey-Fuller test (ADF) have been used in some studies (Dobre and Alexandru, 2008). The most common method for checking stationarity in data series is examining the graph or time plot of the data and ACF and PACF (Singh et.al., 2011). In this study, Augmented Dickey-Fuller test (ADF) and the graph or time plot of the data and ACF and PACF were used to test whether the monthly tomato price data are stationary or non-stationary.

An Augmented Dickey-Fuller (ADF) test was performed to determine whether a data differencing is needed. The null hypothesis of the Augmented Dickey-Fuller t-test is:

- $H_0 : \theta = 0$, meaning that the data needs to be differenced to make it stationary, versus the alternative hypothesis of

- $H_1 : \theta < 0$, meaning that the data is stationary and doesn't need to be differenced.

Thus, if 'X_t' denotes the original series, the non-seasonal diffrence of first order is:

$Yt = X_t - X_{t-1}$

followed by the seasonal differencing (if needed):

$Zt = Y_t - Y_{t-s} = (X_t - X_{t-1}) - (X_{t-s} - X_{t-s-1})$ (4)

Seasonality usually causes the series to be non-stationary because the average values at some particular times within the seasonal span (months, for example) may be different than the average values at other times. Seasonal differencing is defined as a difference between a value and a value with lag that is a multiple of *S*. Seasonal differencing removes seasonal trend and can also get rid of a seasonal random walk type of non-stationarity (Anonymous, 2012c).

With $S = 12$, which may occur with monthly data, a seasonal difference is $(1-B^{12})x_t = x_t - x_{t-12}$.

The next step in the identification process is to find the initial values for the orders of seasonal and non-seasonal parameters, p, q, and P, Q. They could be obtained by looking for significant autocorrelation and partial autocorrelation coefficients.

2) Step 2: Estimation

At the identification stage, one or more models are tentatively chosen that seem to provide statistically adequate representations of the available data. Then precise estimates of parameters of the model are obtained by least squares as advocated by Box and Jenkins.

3) Step 3: Diagnostic checking

The diagnostic check is a procedure that used to check the residuals (Halim and Bisono, 2008). Various diagnostic tests are used to check the adequacy of the tentatively model. The best model is obtained with following diagnostics (Bhar and Sharma, 2007) :

- Low Akaike Information Criteria (AIC)/Schwarz-Bayesian Information Criteria (SBC)

AIC is given by AIC = (-2 log L+2m) where m=p+q+P+Q and L is the likelihood function. As an alternative to AIC, sometimes SBC is also used which is given by SBC = log σ^2 + (m log n)/n

In this study, the most appropriate SARIMA model was determined according to the smallest AIC and SBC values.

- Non-significance of auto correlations of residuals via Box-Pierce or Ljung-Box tests After tentative model has been fitted to the data, it is important to perform diagnostic checks to test the adequacy of the model. One way to accomplish this is through the analysis of residuals. It has been found that it is effective to measure the overall adequacy of the chosen model by examining a quantity Q known as Box-Pierce or Ljung-Box statistic.

The model is diagnosed using the Ljung-Box Q statistic to check the overall adequacy of the model. The test statistic, Q, is (Shukla and Jharkharia, 2011):

$$Q_n = nr\,(nr+2)\sum_{l=1}^{n}\frac{r_1{}^2 e}{nr-1} \quad (5)$$

Where r (e) l = the residual autocorrelation at lag l

nr = the number of residuals

n= the number of time lags includes in the test

For model to be adequate, p-value associated with Q statistics should be large (p-value>α).

4) Step 4: Forecasting

After the identification of the model and its adequacy check, it is used to forecast the values in the next periods. In this study, firstly, the selected SARIMA model was used to forecast the mean monthly real tomato prices for the January-2011 to December-2011 by using the observed data of the period January-2000 to December-2010 in order to validate the model. After obtaining satisfactory forecasting results over a short period, the selected SARIMA model was employed to forecast stream flow over a longer period, from 2012 to 2014.

Forecasting performance of the the selected SARIMA model is measured by using mean absolute percentage error (MAPE) criteria. The MAPE is based on the one ahead forecast errors, which are the difference between the data value at time *t* and the forecast of that value at time t − 1 and time t + 1 (Makukule et al., 2012). For example, MAPE is 3.86%, meaning that the forecasts are off by about 4% on average (Albright, S.C. et al., 2011).

3.Results and Discussion

3.1.Variability and seasonality of tomato prices

The prices of classic tomato vary along the year with the time period from 2000 to 2010 (Table 1, Figure 1). The prices show a declining tendency during the first quarter of the year. They are picked in April and prices decline in June because of open field growing and the excess supply of tomatoes. Moreover, supply to the wholesale market is on the increase and picked in the May and June. (Figure 2). Classical types of tomatoes has an increasing trend after the period of June and continue in the last quarter of the year. Open field tomato harvest ends in the last quarter and then greenhouse tomatoes complete the cycle. The average real tomato prices is 0.48TL/kg in time period between 2000 and 2010. And the lowest tomato price was 0.26 TL/kg in June and the highest price was 0.80 TL/kg in April (Table 1).

Monthly seasonal index was calculated to evaluate the fluctuations of tomato prices between 2000 and 2010 (Table 2). According to the monthly seasonal indexes calculated for tomatoes; the prices for January (9.89%), February (21.98%), March (46.39%), April (69.76%), May (0.65%), November (6.44%) and December (16.59%) were above the average for all months prices. The price for June (45.18%), July (40.38%), August (42.09%), September (40.41%) and October (3.62%) were below the average price for all months . According to these findings, the highest monthly seasonal index occurred in April, whereas the lowest was in June. While the prices in April were approximately 70% more than the average for all months, in June it was 45% less.

Deseasonalized prices were calculated as well for the purpose of better interpretation of monthly changes in prices for tomatoes (Table 2). Considering deseasonalized prices or seasonally adjusted prices for tomatoes, a different structure of price is encountered. Thus, in accordance with the average of seasonally adjusted prices of an 11 year period between 2000-2011, the highest price for tomatoes was in September and October respectively, while the lowest was in January (Table 2, Figure 3). In September and October, the termination of production for tomatoes in the field, and the lag of production for greenhouse tomatoes are important factors driving prices higher. The supply of tomatoes in this period is provided by the production produced in the highlands of the region. Not being sufficiency of production of highland tomatoes causes for increasing in the prices. It is possible to state that the farmers producing highland tomatoes obtain important advantages until the production of greenhouse tomatoes starts, which is produced mainly on the plains.

On the other hand, while the seasonal adjustment is not made it was noted that the highest prices occured in April, the lowest prices were in June. However, according to the prices obtained by the seasonal adjustment, we think that this case is due to a seasonal effect. But, the seasonally adjusted prices obtained by months are quite close to each other. A horizontal trend in the time series graph for these prices' proves this situation. (Figure 3). According to this trend line, tomato prices do not show any trend towards increase or decrease in the years between 2000-2010. In other words tomato prices display a stationary structure.

3.2.Empirical Results

3.2.1.Model identification and Estimation

The first step in developing a SARIMA model is to determine if the monthly tomato price series are stationary. For this, we used the Augmented Dickey-Fuller test (ADF) and the graph or time plot of the data and ACF and PACF.

As observed from Figure 4, tomato prices do not indicate a significant trend. This indicates that the series is in a stationary structure. In fact, null hypothesis was rejected in Augmented Dickey-Fuller (ADF) test, which was performed to determine if the series is stationary or not. This shows that the series does not have a root unit which means it is stationary (Table 2).

It is indicated that all ACF and PACF values should extend within the cofidence limits in stationary series (Singh et.al, 2011). ACF and PACF values were found to be high at specific lags for this series. These values were determined as making sudden peak and not disappearing especially at periodic lags of 12 months (12, 24, 36, etc) (Figure 5). This demonstrates that the series has a seasonal structure. To provide the stationary at average, seasonal differences should be taken.

ACF and PACF values of the series from which the seasonal differences are taken are presented in Figure 6. The seasonal spikes at ACF and PACF after 1 lag (12, 24, …) are observed as being cut off after taking the seasonal difference of the series. This also indicates the seasonal model of AR (1) and MA (1). Therefore, to include the model of (1,1,1) to the part (P,D,Q) of the model will be formed can be considered as one of the best possibilities among the alternative choices. At the non-seasonal part of the model (p,d,q); the discontinuation of PACF value after 1 lag indicates that the addition of the AR (1) term may be appropriate (see Figure 3). On the other hand, even the discontinuations occurs after 1 lag at ACF values, these values are observed to be increased after a certain lag. Therefore, there is no clarity for the MA term at the non-seasonal part of the model. In this case, two alternatives to be taken into account occur for the non-seasonal part of the model. One of these alternatives is the model which MA term is not added to (1,0,0), and the other one which MA term is added (1,0,1).

3.2.2.Model Selection

Four possible alternative models were analyzed based on the seasonal part of the model in order to select the SARIMA model which will be used to forecast the prices of tomatoes. Two of them are the models of $(1, 0, 0)\ (1, 1, 1)_{12}$ and $(1, 0, 1)\ (1, 1, 1)_{12}$ which are mentioned above. The analyzed models are compared according to the Akaike Information Criterion (AIC) and the Schwarz Bayesian Criterion (SBC). The model selected should have the smallest AIC and SBC values (Wang and Lim, 2005). $(1, 0, 0)\ (1, 1, 1)_{12}$ model has comparatively lower AIC and SBC values (Table 4). Therefore, this model was selected as the most suitable model or the best fit model from amongst the four models.

Considering this model, the autoregressive and seasonal parameters were estimated respectively (Table 5). Although the constant term in the estimated SARIMA model is not significant at the different levels, the autoregressive and seasonal parameters are significant at the 1% level.

After estimating the parameters of this model, further analysis was done with the selected SARIMA $(1, 0, 0)\ (1, 1, 1)_{12}$ model to check whether the residuals of the model are independent. The autocorrelation and partial autocorrelation up to 36 lags were computed and their significance was tested using Box-Ljung test. It is evident from Figure 7 that the values of the SARIMA (1, 0, 0) $(1, 1, 1)_{12}$ residuals lie within the upper and lower confidence limits. Panel (b) shows p-values for the Ljung-Box statistics. Given the high p-values associated with the statistics, we cannot reject the null hypthesis of independence in this residual series. The results indicate that none of these correlations are significantly different from zero at a 95% confidence level. This shows that the selected SARIMA (1, 0, 0) $(1, 1, 1)_{12}$ model is appropriate model for the monthly tomato price forecasting.

3.2.3. Model Forecasting

The selected SARIMA (1,0,0) $(1,1,1)_{12}$ model was used to forecast the mean monthly real tomato prices from January-2011 to December-2011 by using the observed data of the period January-2000 to December-2010. The predicted prices were compared with the observed prices (Table 6). The predicted real tomato prices are close to the observed prices, except for the months of March and April. This result indicates that the model provides an acceptable fit to predict the tomato prices.

The higher price estimates for March and April compared to the observed values are because of a special case that occurred in 2011. The European Union applied an entry price system for the tomatoes imported from Turkey since 2011. The EU protects EU growers of 15 kinds of fresh fruits and vegetables against international competition not only by using ad valorem tariffs of up to 20%, but also by the EU entry-price system (EPS), which is designed to restrict imports below the product-specific, politically designated entry price level. This system was established in 1995, replacing the former reference price system (RPS) (Goetz and Grethe, 2008).

Keeping the entry price high especially in April which is being applied by EU has decreased of tomato exports of Turkey. Thus, tomato exporters had to pay taxes because of the price of exported tomatoes to EU remaining below the entry price of EU. (Anonymous, 2011b). The tomato export value in April of 2011 (88.1 million \$) was decreased by 15% compared to the of 2010 (103.5 million \$) (Anonymous, 2011c). A decrease in tomato exports caused the prices remain below the seasonal averages that tended to increase along with tomato exports every year in April.

After obtaining satisfactory forecasting results over a short period, the selected SARIMA (1,0,0) $(1,1,1)_{12}$ model was employed to forecast stream flow over a longer period. Table 7 displays a forecast of the monthly real tomato prices in Turkey from 2012 to 2014. The forecasted tomato prices were compared with the observed prices in Figure 8. As evident from Figure 8, SARIMA (1,0,0) $(1,1,1)_{12}$ model is able to capture the flow trend. The forecast series tracks the actual series quite well during the period. The accuracy of this model is calculated based on the MAPE. The outcome shows that the proposed model can forecast the real tomato prices with an accuracy of MAPE value 24.35. MAPE is 24.35%, meaning that the forecasts are off by about 24% on average. The error at the estimation is at an acceptable level considering the extraordinary factors. For instance, the pest "Tuta Absoluta" has decreased the production of tomato in recent years, therefore, the prices has increased at the unpredicted level (see Figure 8). In addition, tomatos, which occupy first place in Turkey's export for fresh vegetables, is quite affected by the developments export policy, at least in terms of price. Changes of conditions in the market entry of exporting countries immediately impact the tomato export and the prices (entry price, request for active ingredient, etc.).

As shown in Figure 8; the structure of fluctuation of the prices predicted for the following three years is similar to previous years, but it exhibits a more stationary structure. This result indicates that important changes will not occur in tomato prices until the end of 2014 under normal conditions.

4. Conclusions

The results obtained from this study shows that the prices of tomatoes in Turkey have not showed any trend towards an increase or a decrease, in other words the prices exhibit a stationary structure. The forecasts predicted from the SARIMA (1,0,0) $(1,1,1)_{12}$ model which has chosen in order to determine the course of the prices of next 3 years show that any significant changes will not occur in Real Tomato Prices by the end of 2014.

The stationary structure of Real prices can be considered as negative regarding the sustainability of tomato production while the increase (Lundell et al., 2004) in real prices of input is taken into account. In fact, the decrease of income of tomato growers may bring out the farmer group who is unwilling to continue to produce tomato. It can already be stated that the tomato producers work away from the profitability. According to a survey conducted in the Antalya province of Turkey, the gross margin per decare of tomato produced in 1 decar glass greenhouse is 506.02 € since 2010 (Yercan et al., 2012). Considering the fixed costs, it is clearly observed that the net profit obtained by the growers will be very low.

The price forecasts put forward that the tomato growers face with a price risk caused by the uncertainty of the market. Many growers who want to take advantage from increases in

April focus form of their production according to this month. However, the entry price applied by European Union in 2011 for the tomatoes originated in Turkey influenced the exportation negatively, this caused the actual prices remained much lower that the expected,

In terms of the sustainability of tomato production, to provide a reasonable price which would be accepted by the growers and to measure against risk factors of the price to be taken are required. For this purpose, considering consumers requests under good agricultural practices, the production which is qualified and proper to the food safety carries importance. So, increase in consumption in the country and also expansion towards new international markets will be possible. Lately, arriving to the awareness of this situation of the tomato growers is thought. Thus, the survey in the Antalya province of Turkey in 2011 conducted by Yercan and et al. has showed that the tomato producers produce proper to the good agricultural practices.

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6. Acknowledgements

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Table 1. The Real Tomato Prices of Classical Type of Tomato by months (TL[a]/kg) (2000-2010)

Months	Mean	Minimum	Maximum	Range	Std. Deviation
January	0,50	0,31	1,00	0,70	0,1872
February	0,59	0,33	0,89	0,56	0,1931
March	0,70	0,47	1,37	0,89	0,2704
April	0,80	0,53	1,15	0,62	0,1737
May	0,47	0,25	0,81	0,56	0,1541
June	0,26	0,15	0,43	0,28	0,0964
July	0,28	0,14	0,41	0,27	0,0858
August	0,28	0,20	0,33	0,13	0,0465
September	0,31	0,22	0,61	0,39	0,1109
October	0,50	0,23	1,13	0,89	0,2569
November	0,51	0,30	0,77	0,47	0,1377
December	0,55	0,26	0,91	0,64	0,1801
Total	0,48	0,14	1,37	1,23	0,2337

[a]Turkish Lira (TL), the monthly average exchange rate for Turkish Lira (TL) vs Euro (€) in 2003; Jan: 1.75, Feb : 1.75, Mar.: 1.79, Apr. :1.76, May:1.71, June:1.66, July:1.59, Aug.:1,56, Sep.:1.54, Oct.:1.67, Nov.:1.72, Dec.:1.75, annual rate : 1.69

Table 2. Seasonal Index, Actual and Deseasonalized Prices for Tomato

Year		Jan	Feb	Mar	Apr	May	June	July	Aug	Sep	Oct	Nov	Dec
	SI[*]	1,0989	1,2198	1,4639	1,6976	1,0065	0,5482	0,5962	0,5791	0,5959	0,9638	1,0644	1,1659
2000	a	0,43	0,89	0,88	0,90	0,62	0,22	0,26	0,33	0,30	0,40	0,50	0,48
	b	0,39	0,73	0,60	0,53	0,61	0,41	0,44	0,57	0,50	0,42	0,47	0,41
2001	a	0,31	0,44	0,47	0,89	0,50	0,43	0,37	0,28	0,39	0,67	0,65	0,68
	b	0,28	0,36	0,32	0,52	0,50	0,78	0,62	0,48	0,65	0,70	0,61	0,58
2002	a	0,48	0,78	1,37	1,15	0,34	0,19	0,14	0,20	0,22	0,30	0,49	0,51
	b	0,44	0,64	0,93	0,68	0,34	0,35	0,24	0,34	0,36	0,31	0,46	0,44
2003	a	0,50	0,76	0,71	0,98	0,81	0,42	0,34	0,29	0,27	0,25	0,30	0,33
	b	0,45	0,62	0,48	0,58	0,80	0,77	0,57	0,51	0,45	0,26	0,28	0,29
2004	a	0,40	0,44	0,59	0,63	0,45	0,15	0,22	0,29	0,27	0,49	0,53	0,91
	b	0,37	0,36	0,40	0,37	0,44	0,27	0,37	0,49	0,45	0,51	0,50	0,78
2005	a	0,57	0,68	0,60	0,68	0,42	0,16	0,21	0,22	0,26	0,66	0,58	0,26
	b	0,52	0,56	0,41	0,40	0,42	0,29	0,35	0,38	0,44	0,68	0,54	0,23
2006	a	0,31	0,33	0,50	0,71	0,54	0,26	0,37	0,27	0,25	0,35	0,52	0,67
	b	0,28	0,27	0,34	0,42	0,54	0,47	0,62	0,47	0,41	0,36	0,49	0,57
2007	a	1,00	0,81	0,92	0,80	0,31	0,31	0,28	0,32	0,32	0,58	0,56	0,61
	b	0,91	0,66	0,63	0,47	0,31	0,56	0,47	0,54	0,53	0,60	0,53	0,52
2008	a	0,49	0,44	0,48	0,73	0,49	0,17	0,19	0,22	0,22	0,48	0,43	0,48
	b	0,45	0,36	0,33	0,43	0,49	0,32	0,31	0,37	0,37	0,50	0,40	0,41
2009	a	0,56	0,45	0,74	0,80	0,48	0,27	0,41	0,30	0,28	0,23	0,30	0,46
	b	0,51	0,37	0,50	0,47	0,47	0,48	0,68	0,51	0,47	0,24	0,29	0,40
2010	a	0,45	0,52	0,49	0,53	0,25	0,24	0,32	0,33	0,61	1,13	0,77	0,66
	b	0,41	0,43	0,34	0,31	0,24	0,45	0,53	0,57	1,02	1,17	0,73	0,57
Mean	b	0,45	0,49	0,48	0,47	0,47	0,47	0,47	0,48	0,51	0,52	0,48	0,47

[*]SI : Seasonal Index; a: actual real tomato price (TL/kg); b: deseasonalized real tomato price (TL/kg)

Table 3. The Augmented Dickey-Fuller test results

Null Hypothesis: PRICE has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Fixed)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.452642	0.0001
Test critical values:	1% level	-4.029595	
	5% level	-3.444487	
	10% level	-3.147063	

*MacKinnon (1996) one-sided p-values.
Augmented Dickey-Fuller Test Equation
Dependent Variable: D(PRICE)
Method: Least Squares
Date: 03/15/12 Time: 14:47
Sample (adjusted): 2000M02 2010M12
Included observations: 131 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
PRICE(-1)	-0.379751	0.069645	-5.452642	0.0000
C	0.194347	0.048421	4.013726	0.0001
@TREND(2000M01)	-0.000164	0.000429	-0.382678	0.7026

R-squared	0.188552	Mean dependent var	0.001772
Adjusted R-squared	0.175873	S.D. dependent var	0.203867
S.E. of regression	0.185074	Akaike info criterion	-0.513492
Sum squared resid	4.384286	Schwarz criterion	-0.447648
Log likelihood	36.63372	Hannan-Quinn criter.	-0.486736
F-statistic	14.87133	Durbin-Watson stat	1.578448
Prob(F-statistic)	0.000002		

Table 4 . Akaike Information Criteria (AIC), Schwarz Bayesian Criterion (SBC), and RSquare Adj values considering different SARIMA (p,0,q) (1,1,1)12 models

Model	DF	Variance	AIC	SBC	RSquare Adj
$(1, 0, 0)(1, 1, 1)_{12}$	116	0,0204345	-462,9319	-451,7819	0,561
$(1, 0, 1)(1, 1, 1)_{12}$	115	0,0205425	-461,3382	-447,4007	0,558
$(0, 0, 1)(1, 1, 1)_{12}$	116	0,0217725	-455,3209	-444,1709	0,532
$(0, 0, 0)(1, 1, 1)_{12}$	117	0,0293681	-420,3795	-412,0170	0,364

Table 5. Parameters estimators of SARIMA $(1, 0, 0)(1, 1, 1)_{12}$

term	coefficient	std. error	t ratio	p-value
const	-0.0037	0.0089	-0,42	0,6752
phi_1 (AR1,1)	0.5668	0.0750	7,55	<.0001[a]
Phi_1 (AR2,12)	-0.3576	0.1026	-3,49	0,0007[a]
Theta_1 (MA2,12)	0.7071	0.0943	7,50	<.0001[a]

[a]it is significant at the 1% level.

Table 6. Real Tomato prices observed in 2011 and out of sample predicted prices obtained from the SARIMA (1,0,0) $(1,1,1)_{12}$, (TL/kg)

Date	Observed	Prediction	lower CL[a]	upper CL[b]
2011-01	0,49	0,62	0,34	0,90
2011-02	0,44	0,56	0,24	0,88
2011-03	0,39	0,70	0,37	1,03
2011-04	0,37	0,79	0,45	1,13
2011-05	0,34	0,48	0,14	0,82
2011-06	0,21	0,23	-0,11	0,57
2011-07	0,27	0,28	-0,06	0,62
2011-08	0,34	0,25	-0,09	0,59
2011-09	0,28	0,23	-0,11	0,57
2011-10	0,42	0,35	0,01	0,69
2011-11	0,53	0,40	0,06	0,74
2011-12	0,56	0,49	0,15	0,83

[a]lowerCL: lower confidence limits of forecasts, [b]upperCL: upper confidence limits of forecasts.

Table 7. Out-sample forecasts for the SARIMA (1,0,0) $(1,1,1)_{12}$, (TRY/kg)

Date	Prediction	lower CL	upper CL	Date	Prediction	lower CL	upper CL	Date	Prediction	lower CL	upper CL
2012-01	0,50	0,16	0,85	2013-01	0,54	0,19	0,89	2014-01	0,52	0,16	0,88
2012-02	0,51	0,17	0,85	2013-02	0,52	0,17	0,88	2014-02	0,52	0,15	0,88
2012-03	0,60	0,26	0,95	2013-03	0,63	0,28	0,99	2014-03	0,62	0,26	0,98
2012-04	0,69	0,34	1,03	2013-04	0,72	0,36	1,08	2014-04	0,70	0,34	1,06
2012-05	0,38	0,04	0,72	2013-05	0,41	0,05	0,77	2014-05	0,40	0,03	0,76
2012-06	0,23	-0,11	0,57	2013-06	0,22	-0,13	0,58	2014-06	0,22	-0,14	0,58
2012-07	0,29	-0,05	0,63	2013-07	0,28	-0,08	0,64	2014-07	0,28	-0,08	0,64
2012-08	0,27	-0,07	0,61	2013-08	0,26	-0,10	0,62	2014-08	0,26	-0,10	0,62
2012-09	0,36	0,02	0,70	2013-09	0,31	-0,05	0,67	2014-09	0,32	-0,04	0,68
2012-10	0,62	0,28	0,96	2013-10	0,52	0,16	0,88	2014-10	0,55	0,19	0,91
2012-11	0,53	0,19	0,87	2013-11	0,48	0,12	0,84	2014-11	0,49	0,13	0,86
2012-12	0,55	0,21	0,89	2013-12	0,52	0,17	0,88	2014-12	0,53	0,17	0,89

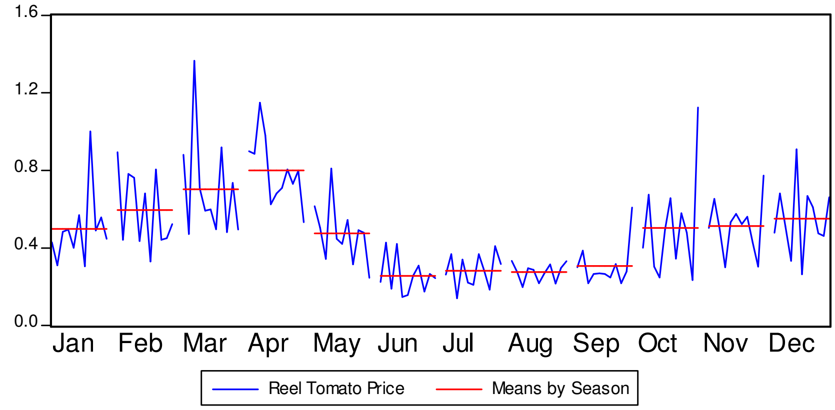


Figure 1. Average Wholesale Prices of Tomato by Seasons (2000-2010), TRY/kg

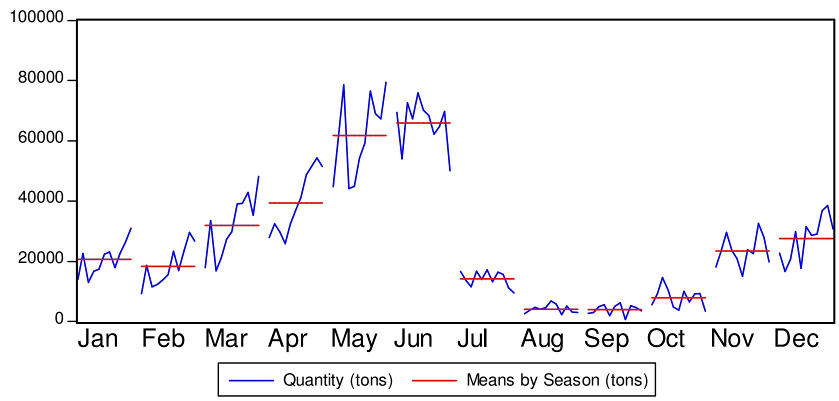


Figure 2. Average Wholesale Sales of Tomato by Months (2000-2010), tons

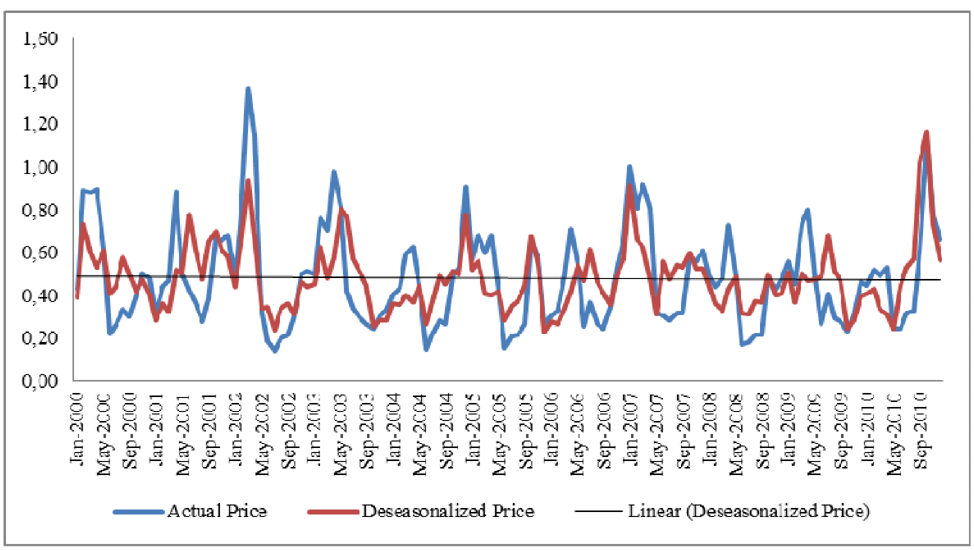


Figure 3. Actual and Deseasonalized Prices for Tomato (TL/kg)

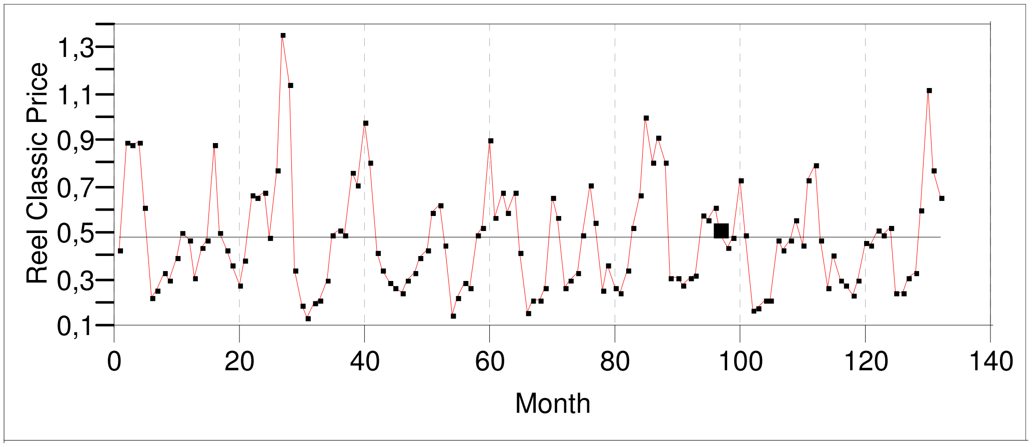


Figure 4. Monthly real tomato prices in period of 2000-2011.

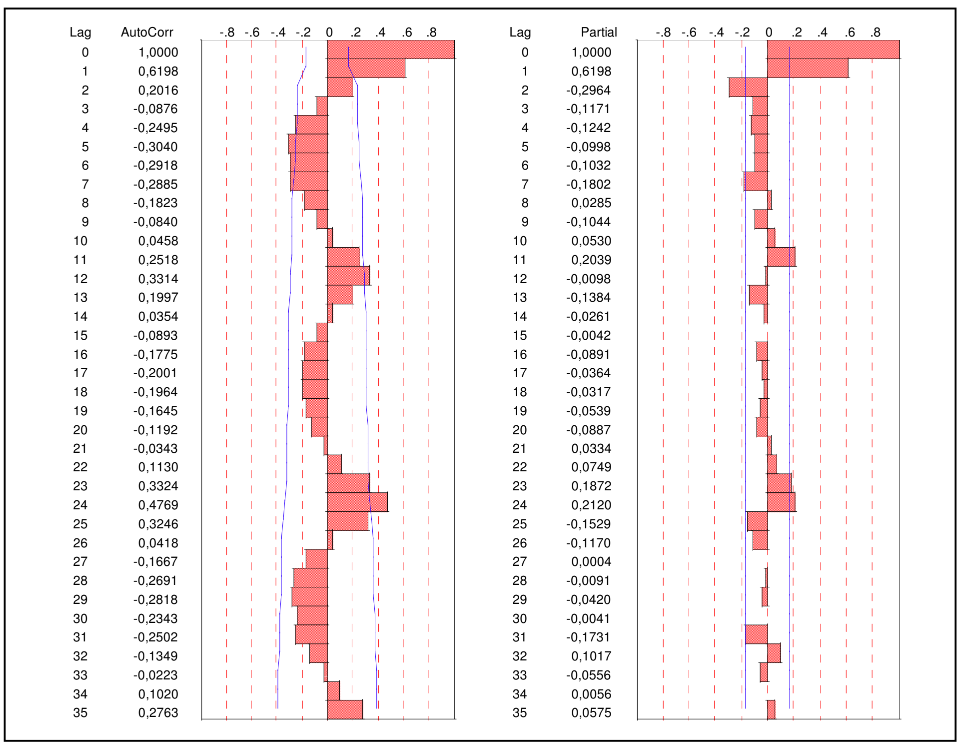


Figure 5. ACF&PACF of the monthly data without differencing.

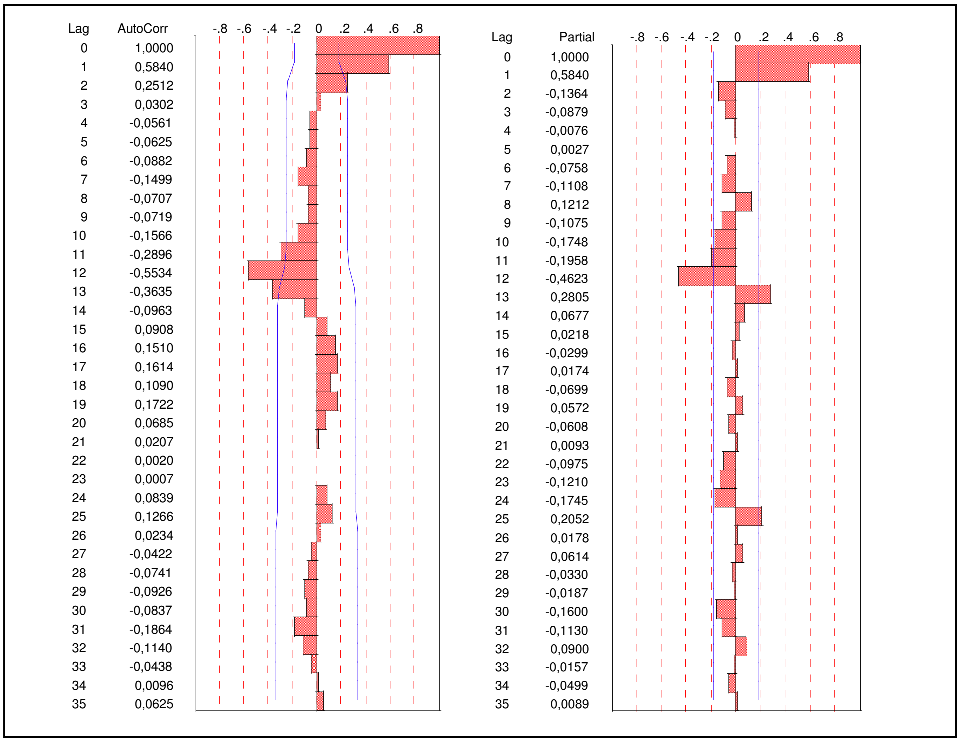
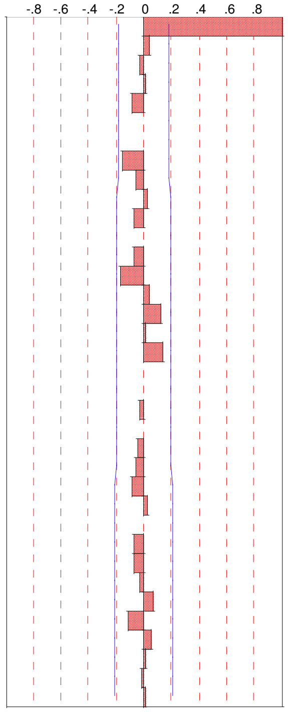
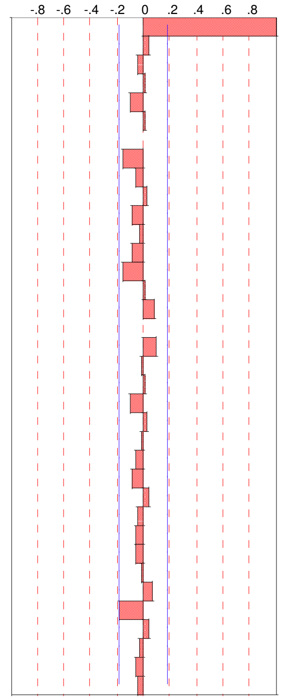


Figure 6. ACF&PACF of the monthly differenced data.

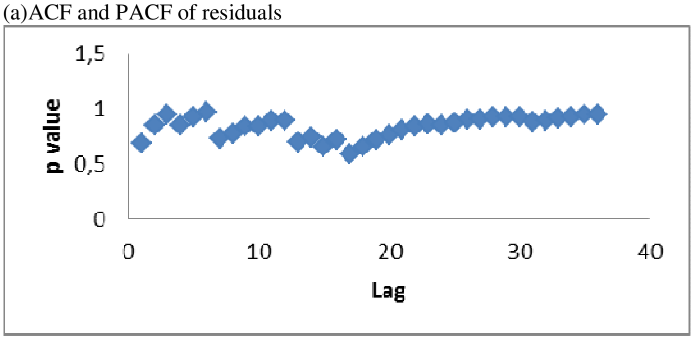
Lag	AutoCorr
0	1,0000
1	0,0363
2	-0,0345
3	0,0140
4	-0,0901
5	0,0012
6	0,0040
7	-0,1529
8	-0,0596
9	0,0285
10	-0,0722
11	-0,0025
12	-0,0716
13	-0,1621
14	0,0464
15	0,1214
16	0,0196
17	0,1379
18	0,0010
19	0,0056
20	-0,0317
21	0,0032
22	-0,0395
23	-0,0528
24	-0,0846
25	0,0342
26	0,0044
27	-0,0701
28	-0,0677
29	-0,0235
30	0,0758
31	-0,1157
32	0,0608
33	0,0158
34	-0,0121
35	0,0128



Lag	Partial
0	1,0000
1	0,0363
2	-0,0359
3	0,0167
4	-0,0928
5	0,0095
6	-0,0035
7	-0,1511
8	-0,0579
9	0,0227
10	-0,0775
11	-0,0235
12	-0,0905
13	-0,1608
14	0,0109
15	0,0909
16	0,0029
17	0,1033
18	-0,0141
19	0,0106
20	-0,0958
21	0,0240
22	-0,0168
23	-0,0598
24	-0,0772
25	0,0425
26	-0,0350
27	-0,0556
28	-0,0552
29	-0,0096
30	0,0696
31	-0,1867
32	0,0370
33	-0,0305
34	-0,0510
35	-0,0430



(a)ACF and PACF of residuals



(b)P values for the Ljung-Box statistic

Figure 7. Graphical diagnostics for assessing the SARIMA (1,0,0) $(1,1,1)_{12}$ model fit

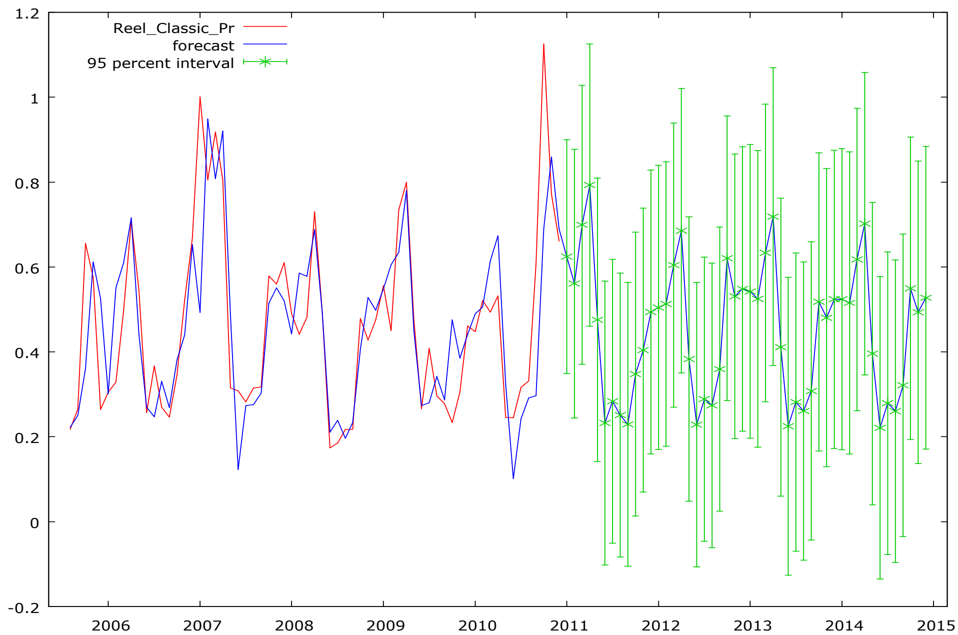


Figure 8. Forecast and Original Observations for the Real Tomato Prices