KU LEUVEN

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Analysis of Coffee Export Volume and Production in Colombia

Advanced Time Series Analysis

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Contents

1 Introduction

Colombia's average annual coffee production is the third highest in the world, after Brazil and Vietnam. The data has been retrieved from the Colombian Coffee Growers Federation (FNC in Spanish), which is an institution that represents both nationally and internationally the coffee growing community in the country (see FNC, 2018).

The first series is the monthly *export volume* of green coffee measured in thousands of 60 kilogram bags. The second series is the monthly *production* of green coffee, also measured in thousands of 60 kilogram bags. Both series contain data from January 1990 until September 2018.

In the following, a univariate analysis is conducted on *exports* series to investigate the stochastic process that generates the data and to make reliable predictions in a window of 12 month period. Then, a bivariate analysis is performed using *exports* and *production* to complement the results obtained. This analysis is conducted in the statistical software R.

2 Univariate Analysis

As it is mentioned above, *export* volume is a monthly series measured in thousand of bags. The left plot in Figure 1 shows the behavior of this series, which suggests no clear trend and the possible existence of stationary, because the expected value and the variance seem to be the same for all time window.

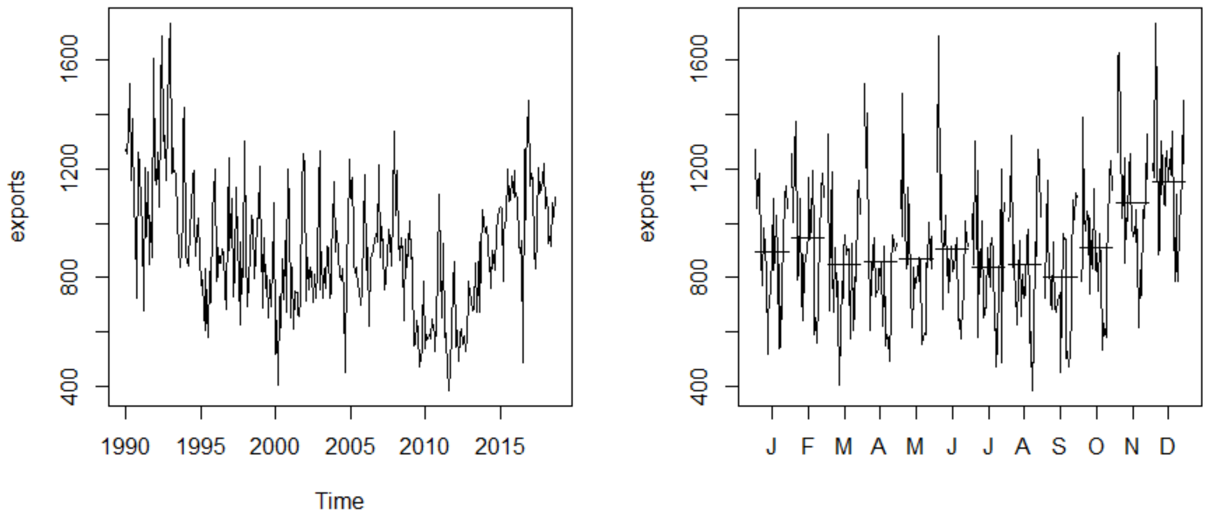

Figure 1: Coffee export volume in thousands of bags (left) and seasonal plot (right).

However, given that the analysis of univariate time series depends on whether the series is indeed stationary or not, and to be completely certain about the stationarity characteristic of the *exports* series, a unit root test is conducted. The p-value associated with this test is $0.161 > 0.05$, thus the null hypothesis that the series is a random walk is not rejected and therefore it can be concluded that is not stationary. To be able to work with a stationary series, the *exports* series is analyzed in seasonal differences (see right plot in Figure 1). The p-value associated to the unit root test is $0.0001 < 0.05$, suggesting that this series is indeed stationary.

The next step is to assess the structure of the series in terms of autocorrelations and partial autocorrelations, see Figure 2. The left hand plot suggests that the series is persistent, i.e., the value of exports at a certain date is closely related to previous values. In fact, there are still significant correlations at lag 15. The right hand plot suggests that an autoregressive model may work, because it seems to have fewer significant values at the beginning than in the previous plot. Note, however, that in this case there are also significant partial correlations from lag 12 to 15 and even at lag 24.

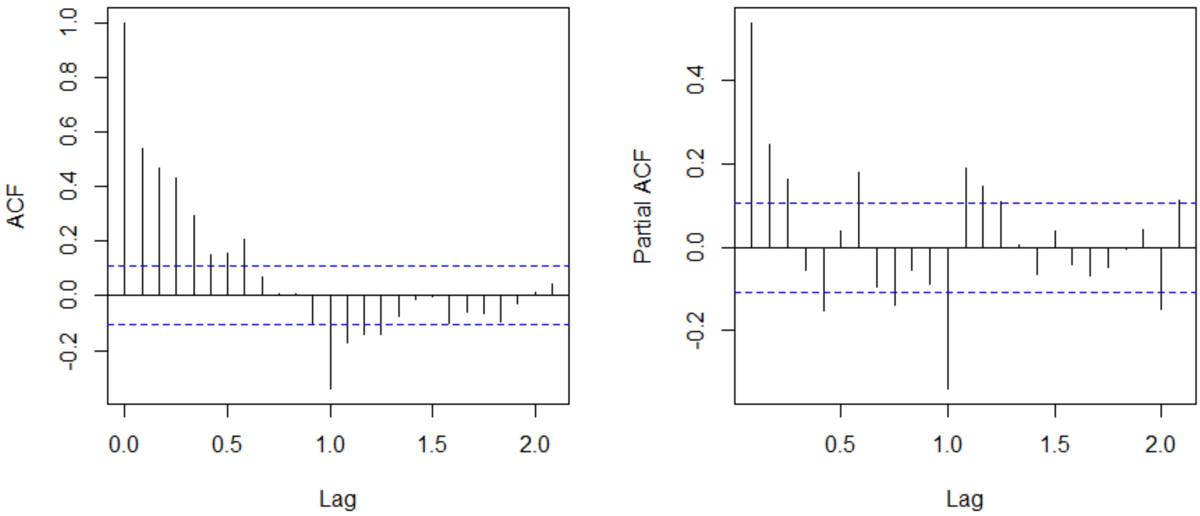

Figure 2: Correlogram (left) and partial correlogram (right) of *exports* series in seasonal differences.

Several models are fitted and their residuals are checked to see whether they are valid models or not, i.e., they follow a white noise process. As always, this process starts with ”simple” models such as an MA(7), AR(3) and ARMA(1,1), but none of them are valid. The residuals' correlograms of these models show significant values at lag 12 and 24 (not shown here), suggesting that seasonal ARMA models, or SARMA, may improve the fit. Then, different seasonal MA models are considered, like SARIMA(0,0,7)(0,1,1) and SARIMA(0,0,8)(0,1,1), but still none of them are valid. On the other hand, some seasonal autoregressive models as well as SARMA models are valid. Table 1 lists all **valid** models considered.

Now, to decide which model is better in terms of complexity as well as in prediction, a comparison is made under different criteria. In-sample criteria such as AIC and BIC to penalize the complexity of the model and out-of-sample criteria like Mean Absolute Error (MAE) and Mean Squared Error (MSE) to measure prediction performance, see Table 1. It is important to mention that out-of-sample criteria depend on the estimation window and the horizon of prediction. The estimation window considered here is 3/4 of the data set and the horizon of prediction is 12 months ahead.

Model	AIC	BIC	MAE	MSE
SARIMA(3,0,0)(1,1,0)	4285.19	4304.41	139.65	30894.17
SARIMA(4,0,0)(1,1,0)	4286.96	4310.02	144.51	31688.00
SARIMA(3,0,0)(2,1,0)	4264.49	4287.55	144.50	31686.78
SARIMA(1,0,1)(1,1,1)	4243.30	4262.52	157.92	36211.42
SARIMA(1,0,1)(0,1,1)	4241.58	4256.95	140.79	31018.18
SARIMA(1,0,1)(1,1,0)	4289.92	4305.29	159.89	37136.23

Table 1: Comparison of models

These results suggest that the most parsimonious model is the SARIMA(1,0,1)(0,1,1) since it only has three parameters to estimate, and the model with better forecast performance is the SARIMA(3,0,0)(1,1,0). These results complement each other because it is telling that the best prediction is given by a model with four parameters to estimate, but a model with just three parameters predicts with almost the same quality. For this reason, the Diebold-Mariano test is used to check if there are significant differences between the MAE and MSE measures of both models. As a result the p-value for the difference in MAE is $0.584 > 0.05$ and $0.807 > 0.05$ for MSE, suggesting that both models perform equally in terms of prediction. For this reason, the model considered to continue the analysis is the parsimonious one, the SARIMA(1,0,1)(0,1,1).

Now, it is important to check whether the conditional variance remains constant over all time window because in case that this assumption is violated, a GARCH model would be necessary. This can be checked by looking the correlogram of the squared residuals of the model, see the right plot in Figure 3. This plot shows that there is only one significant autocorrelation at lag 1 suggesting that a GARCH model could be fitted. However, given that it is out of scope of this course to fit SARIMA-GARCH models and that there is only one significant value, the analysis is continued with this model.

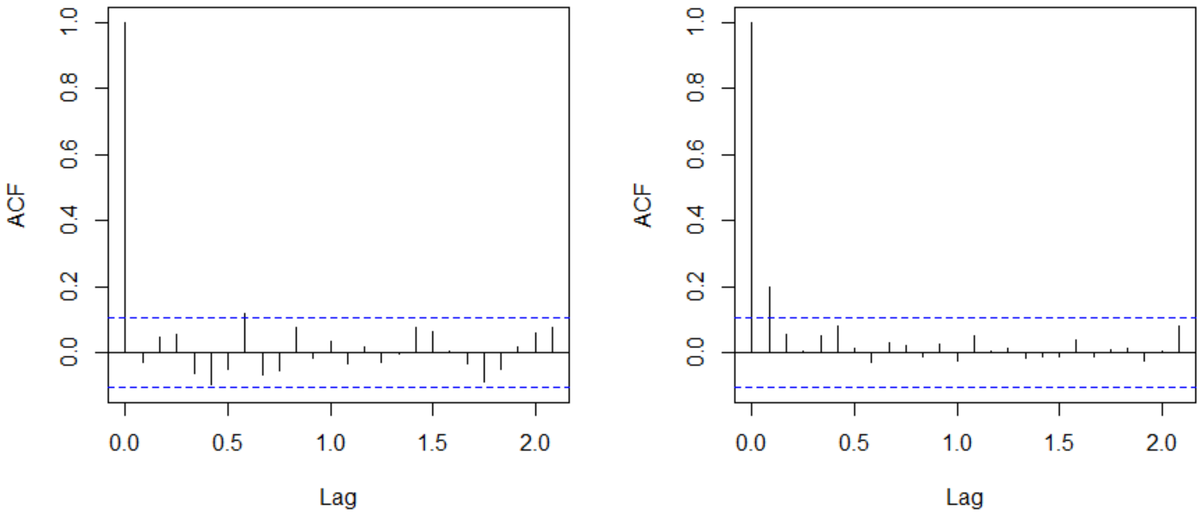

Figure 3: Correlogram of residuals (left) and squared residuals (right) of model SARIMA(1,0,1)(0,1,1)

Having defined the final model, it is right to present a prediction of *exports* coffee bags. Figure 4 shows these predictions until September 2019. In this plot can be seen how the export volume increases in December, decreases in January, then remain somewhat constant until June and increases again in July. This behavior is quite similar to the one showed in the seasonal plot (Figure 1, right hand plot), so the prediction is consistent with the data obtained in past years.

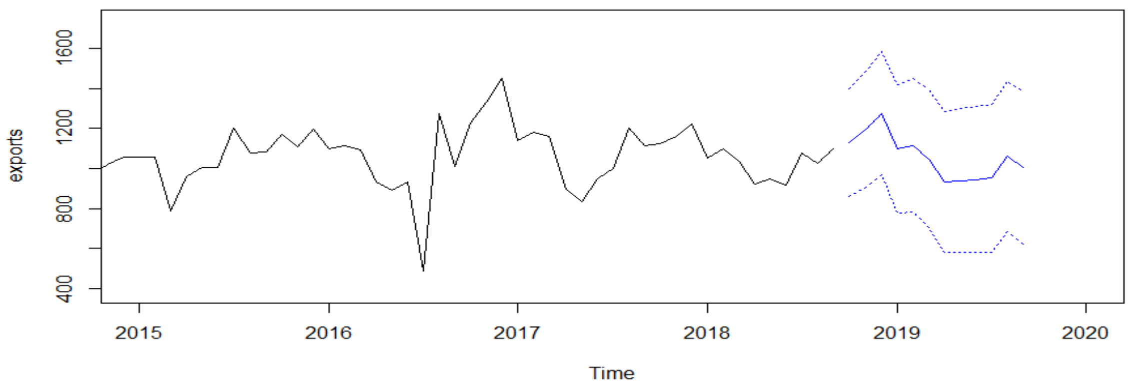

Figure 4: Prediction of coffee export volume in thousands of bags.

3 Bivariate Analysis

Production series, which is also measured in thousands of sacks, is used to complement the univariate analysis of *exports* (see Figure 5). The first step is to determine whether both series are integrated of order 1, $I(1)$. The unit root test is conducted in both series in levels and in differences to test whether they are stationary or not. As a result, both series in levels are not stationary and both series in differences are stationary, suggesting that *exports* and *production* are I(1).

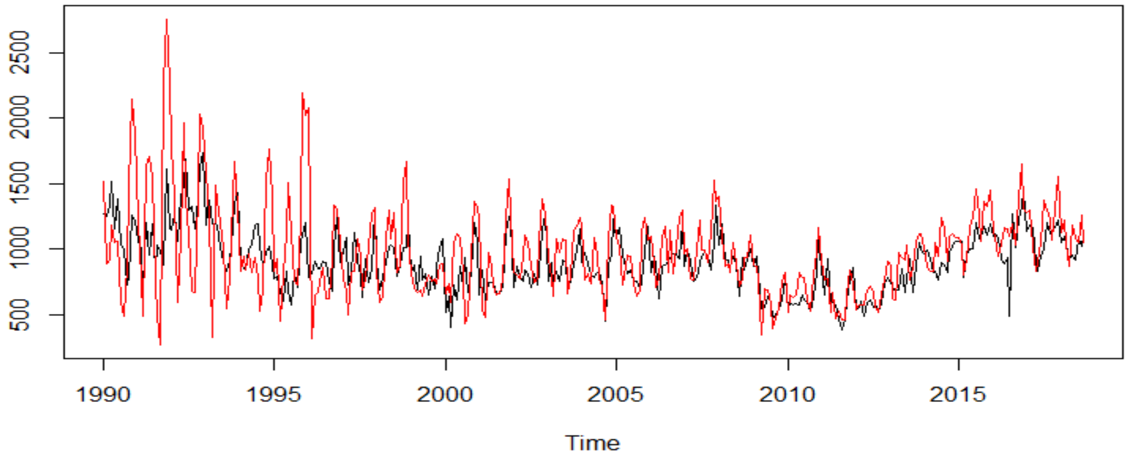

Figure 5: *Exports* in black and *production* in red.

The next step is to check whether both series are cointegrated[1]. To do so, the Engle-Granger approach is used by fitting an OLS model with *exports* as response and *production* as a covariate; and then testing whether its residuals are stationary with the unit root test. As a result, the test statistic obtained is -7.48, which in contrast with the critical value -3.41 (given in the computer sessions) leads to conclude that they are stationary and therefore both series are cointegrated.

Given this result, an Error Correcting Model is conducted by fitting an OLS model as before but with the series in differences and adding an extra term, called error correcting term, that comes from the residuals of the previous OLS model. Having done this, the validity of the model is tested by looking whether the residuals are white noise (see correlogram in Figure 8). The result of the Ljung-Box test for these residuals suggest that they are not white noise and therefore the model is not valid.

Another approach is to fit a VAR model, ignoring the possible existence of cointegrated equations. The lag length is chosen automatically using the BIC, resulting in a VAR(11). This model, though, is not valid because there are significant autocorrelations, again at lag 12 and 24, and cross-correlations (see Figure 9). Nevertheless, in the sake of getting an insight of the model, an impulse response function is estimated with a 95% confidence interval using a bootstrap procedure. In Figure 6 it can be seen that a unitary impulse in *exports* in differences at time t, leads to a significant negative response of *exports* in differences at time $t+1$ and no significant changes in *production*. Moreover, a unitary impulse in *production* in differences leads to a significant positive response in *exports* at time $t+1$ and a significant negative response at time $t+3$.

[1]It is important to mention that several Distributed Lag models, up to order 9 ($DL(9)$), and Autoregressive Distributed Lag models (up to $ADL(9)$) are fitted to check whether *production* Granger causes *exports*, only $ADL(9)$ model is valid. Then, a F-test is performed to compare this model with a model with just lagged values of *exports* as covariates, resulting in a significant difference. Thus, it can be said that *production* Granger causes *exports*.

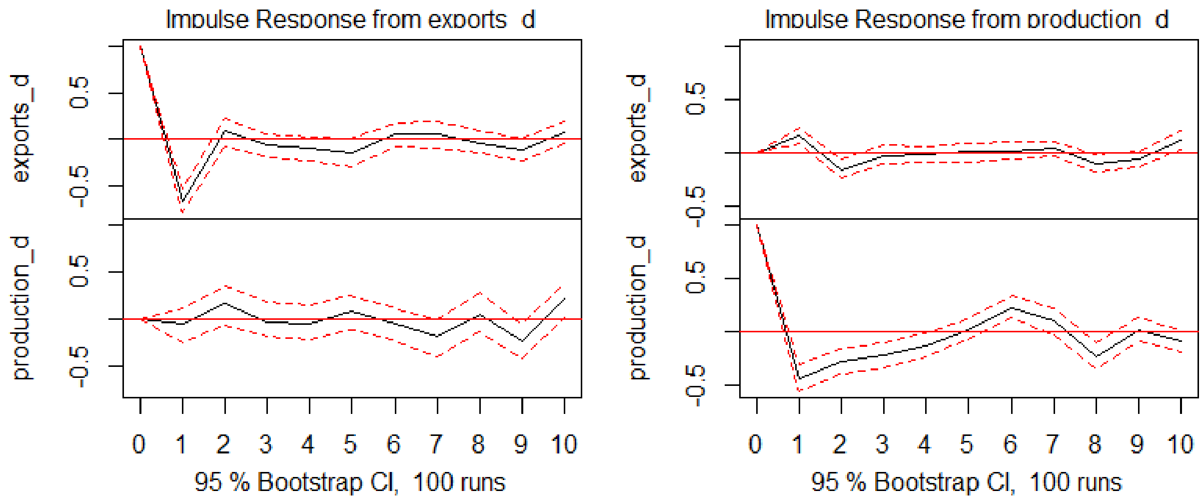

Figure 6: Impulse response function from shocks in *Exports* (left) and *Production* (right) in differences.

As a final approach, the existence of cointegrated equations is at hand, so a Vector Error Correcting Model is fitted. The automated BIC selects the order 5 for the VAR model on the time series in levels; thus, the Johansen trace test is conducted. As a result, for $r = 0$ and $r = 1$, the test statistics are larger than the critical value, suggesting that there are more than one cointegrated equation. The conclusion is that both series are cointegrated even though there is a contradiction in the result, because only 1 possible cointegrated equation can exist[2]. Then, a $VECM(4)$ is fitted which results in the following cointegrated equation:

$$-64.44 + exports_t - 0.85\, production_t = \delta_t$$

Where δ_t is a stationary time series.

In addition, Figure 7 plots the 12 step-ahead forecast for *exports* and *production* based on the VECM(4). The forecast of *exports* fluctuates around 1 million bags and the forecast of *production* is around 1.1 million bags.

4 Conclusion

Exports series is analyzed in a univariate context where different models are fitted and validated. The selection of the final model is based on in-sample and out-of-sample criteria, resulting in a SARIMA(1,0,1)(0,1,1). The forecast is consistent with the data at hand because it is similar to the monthly behavior found.

In the bivariate part different models are fitted, but almost none of them are valid. The main reason is because of the seasonality found at lag 12 and 24 in most cases, suggesting the use of seasonal models. However, seasonal multivariate models are out of the scope and so the models are kept and analyzed.

It is important to mention that the significance at lag 12 and lag 24 could be explained by weather patters, such as ”El niño” and ”La niña” (NOS, 2018, see). The first one is characterized by a decrease of rainfall and increase of temperature, and the second one is characterized by an increase in rainfall and decrease of temperature. Each phase usually takes two years, impacting not only coffee production but the whole agricultural sector in the country.

[2]Similar results are obtained using Max eigenvalue test

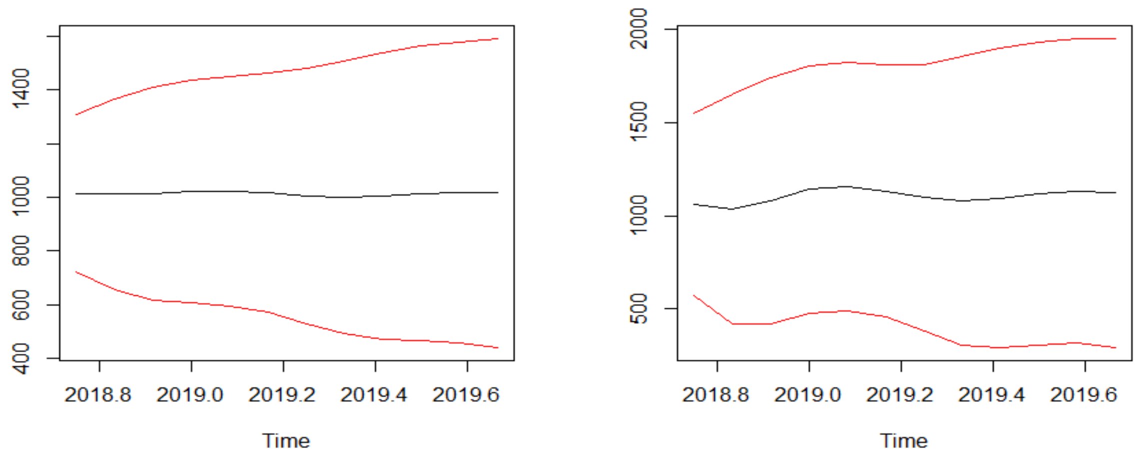

Figure 7: 12 step-ahead forecast of *Exports* (left) and *Production* (right) based on $VECM(4)$.

References

FNC (2018). Federación nacional de cafeteros. https://www.federaciondecafeteros.org/particulares/en/. [Online; accessed 12-December-2018].

NOS (2018). What are el niño and la niña? https://oceanservice.noaa.gov/facts/ninonina.html. [Online; accessed 13-December-2018].

5 Appendix

- Correlograms of residuals from Error Correcting Model

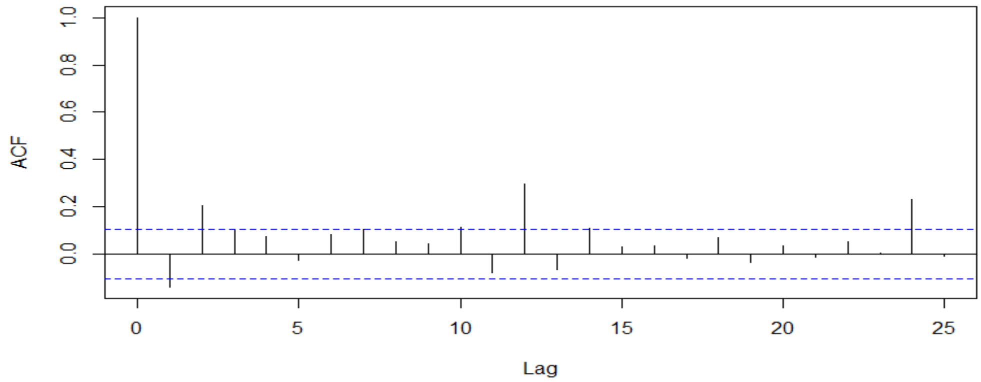

Figure 8: Correlogram of residuals from ECM

- Correlograms and cross-correlogram of residuals from VAR(11) model

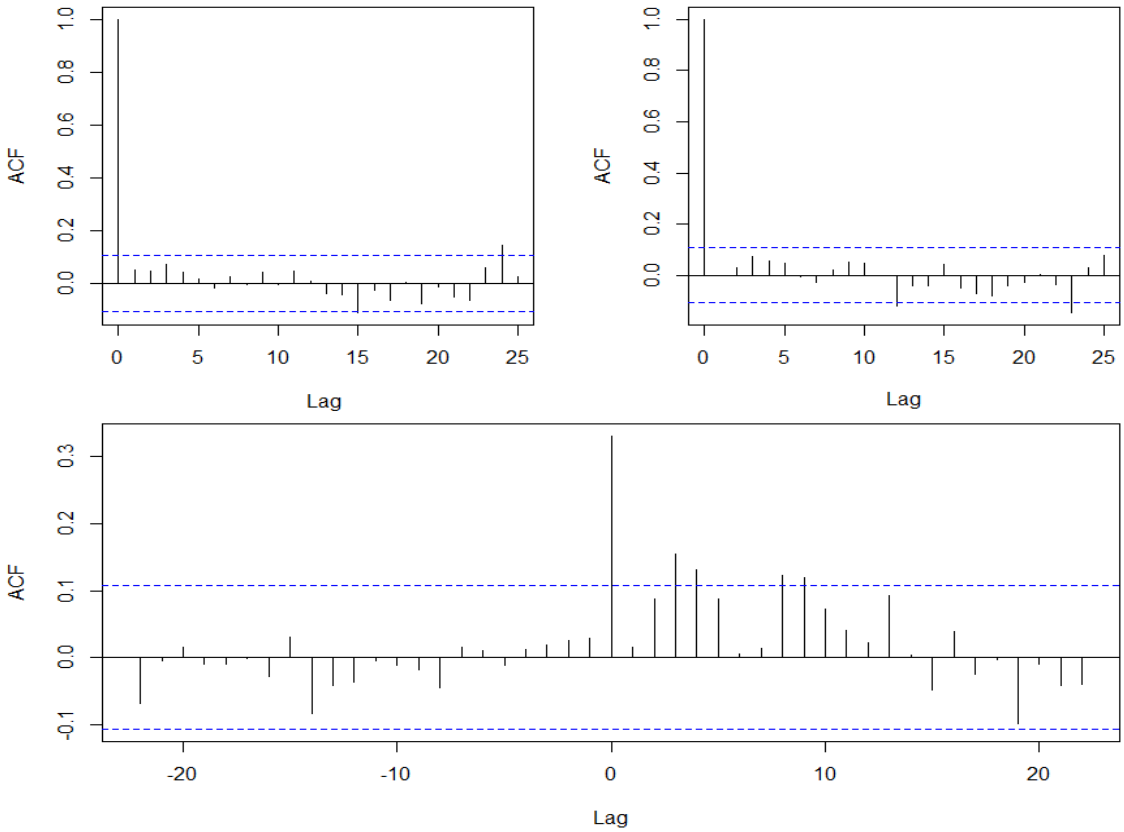

Figure 9: Correlograms (top) and crosscorrelogram (bottom) of resisuals from VAR(11) model.