Measuring the Impact of a New Policy on Industry in Gaza

قياس أثر سياسة جديدة على الصناعة في غزة

Abdalla El-Habil

عبد الله الهبيل

Department of Applied Statistics, Faculty of Economics and Administrative Sciences; Al-Azhar University, Gaza, Palestine

E-mail: abdalla20022002@yahoo.com

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Abstract

This paper demonstrates an application on intervention modeling focusing on measuring the impact of Yazegi company's decision to intervene (delivering new kinds of soft drink) and the intervention impact of the Israeli constraints on sales delivery. It is found that there is a significant impact on the company sales due to the company intervention (positive impact), and the Israeli intervention (negative impact). A comparison between the non-intervention model and the intervention model has been made. It is concluded that the forecasts of the intervention model are better than forecasts of the non-intervention model, because it is closer to the actual data and has smaller standard error. This empirical study sheds light on the impact evaluation of the huge number of policies, legislations, and other intervention events.

Key words: ARIMA model, dynamic effects, forecasting, intervention modeling, time series outliers.

ملخص

تم في هذا البحث عرض تطبيق على نموذج التدخل من خلال التركيز على قياس أثر قرار تدخل شركة اليازجي للمشروبات الخفيفة في غزة بتسويق وتوزيع أنواع جديدة من تلك المشروبات وكذلك أثر القرار الإسرائيلي في الحد من توزيع تلك المشروبات داخل الوطن وخارجه. تبين من خلال هذه الدراسة أنه نتيجة تدخل الشركة يوجد تأثير إيجابي معنوي

(ملموس) على مبيعاتها، وكذلك تأثير سلبي معنوي (ملموس) على المبيعات نتيجة التدخل الإسرائيلي. بإجراء مقارنة بين نموذج عدم التدخل ونموذج التدخل، تم الاستنتاج من خلال هذه الدراسة أن التنبؤ بقيم مبيعات الشركة باستخدام نموذج التدخل أقرب للقيم الأصلية (الحقيقية) للمبيعات لنفس الفترات الزمنية من التنبؤ بقيم المبيعات بواسطة نموذج عدم التدخل بالإضافة إلى أنها تتميز بخطأ معياري أقل. توضح هذه الدراسة التطبيقية أهمية نموذج التدخل في تقييم أثر عدد كبير من السياسات والتشريعات والأحداث الجديدة المتدخلة الأخرى التي يمكن أن تحدث في الحياة العملية.

Introduction

Outlier detection and adjustment is indispensable part of time series analysis. The detection of outliers may highlight the occurrences of those external events affecting a series, and in what manner. Unknown external events can alter the structures of statistics typically used for model identification. Moreover, even if we employ the proper model for a series, the presence of unaccounted external events may seriously affects the parameter estimates of the model. As a result, we can employ an intervention model.

In this case, we need to be certain that the intervention effects are not contaminated by any outlier effect. In this manner, we are also more confident that test statistics for parameter estimates will not be biased due to an inflated variance. In addition, should a detected event re-occur, we may be able to better forecast how a series will respond to it.

Since the outlier detection and adjustment are essential to the estimation of an intervention model, we have to detect and adjust any existing outlier. It may lead to change in the parameters estimates and the significance levels of intervention effects. (Causing a once not significant test statistic to become significant) or a change in the parameter estimate due to the adjustment of outlier effects.

The dynamic model of intervention analysis introduced by Box and Tiao (1975) was found to be useful when dealing with effect of known events on a time series. Moreover, the methodology of Box and Jenkins introduced by Box and Jenkins (1970) has been used in order to deal with the ARIMA part which is an essential part of the intervention model.

Harvey (1986) defined the intervention analysis as it is concerned with making inferences about the effect of known events that occurred in the past. These effects are measured by including intervention, or dummy variables as explanatory variables and the other explanatory variables may or may not be present or included in the model.

The research problem is: how to measure the impact of a new policy by employing a proper model for a series and be certain that the intervention effects are not contaminated by an outlier effect.

I will illustrate the time series intervention analysis approach by which many problems can be handled, and provide details on the application of this analysis to the data set. So, in this paper, I will use the same methodology of box and Jenkins introduced by box and Jenkins and box and Tiao.

The importance of this study stems from the huge number of policies, legislations and other intervention events and their impacts on corresponding fields. For example, if the impact of such events could be statistically modeled, it would be easy to forecast and predict the future circumstances behind these events more accurately. Moreover, omitting such events during the statistical analysis phase will lead to underestimating the parameters, see Pankratz (1991).

The paper is organized as follows. Section 2 recalls the technical background of Intervention model. Section 3 presents the data. Section 4 intervention modeling. Section 5 concludes.

The Intervention model

Time series are often affected by various external events such as political or economic policy changes, technological changes, sales promotions, advertising, and so forth. These external events are commonly known as interventions.

If a time series was subjected to an intervention at a particular time period, say T, its effect in changing the mean level of the series as determined by using a two-sample t-test. The mean level in the preintervention period was contrasted with that after the intervention occurred. Box and Tiao (1965) showed that the t-test is not appropriate in the case of serially correlated data. (Available procedures such as a Student's t test for estimating and testing for a change in mean have played an important role in statistics for a very long time. However, the ordinary t test would be valid only if the observations before and after the event of interest varied about means $\mu 1$ and $\mu 2$ not only normally and with constant variance but independently). Moreover, an intervention may not be a step change, which is the basic assumption of the two-sample t-test.

Box and Tiao (1975) provided a procedure for analyzing a time series in the presence of known external events. In their approach, a time series is represented by two distinct components: an underlying disturbance term, and the set of interventions of the series. In the case of a single intervention, the form of the intervention model is

$$Yt = C + [\omega (B)/\delta(B)] It + Nt$$

It is a binary indicator vector (that is, a vector assuming the values 0 or 1) that defines the period of the intervention. The term $\omega (B)/\delta(B)$ is a characterization of the effect(s) of the intervention. The term Nt is called the disturbance, which can expressed as

$$Nt = Yt - C - [\omega (B)/\delta(B)] It$$

Nt may be modeled as an ARIMA process. In the case that there are no exogenous events, then the model for Yt reduces to the ARIMA models.

An indicator variable representing an intervention that takes place for one time period only is called a pulse function. It is usually represented as Pt**T, where T is the time that the intervention occurs (i.e., has the value 1). An indicator variable representing an intervention that remains in effect beginning from a particular time period is called a step function. The variable is usually represented as St**T, where T is the time that the intervention begins. The response to an intervention is characterized by the rational polynomial $\omega (B)/\delta(B)$.

The operator in the numerator, $\omega(B)$, represents the impact(s) of the intervention and the length of time (delay) it takes the impact(s) to be reflected in the time series. For example, the effect of a strike may only be in the time period in which it occurred, while the effect of an advertising campaign may affect the current time period and have a residual effect on the next period. Hence we may use the characterization $\omega(B)= \omega0$ to indicate a contemporaneous effect; $\omega(B)= \omega1(B)$ to describe an effect not felt until the next time period; or $\omega(B)= \omega0+ \omega1(B)$ to describe an event that affects the measured response in both the current and next time period.

The operator in the denominator, $\delta(B)$, represents the way in which an impact dissipates. In most cases, the $\delta(B)$ of an intervention model is a low order polynomial, for example, $\delta(B) =1 - \delta1(B)$.

If an intervention has a relatively long term residual effect (or growth pattern), then the value of $\delta1$ will be moderate to large. However, if the effect is short term, then the value of $\delta1$ will be small. In an extreme case, the intervention may not have any residual effect. In such a case, we have $\delta1=0$.

To summarize, the rational polynomial $\omega(B)/\delta(B)$ consists of the operators:

$\omega(B)= \omega0+ \omega1(B)+ \omega2(B)**2+\ldots\ldots\ldots+ \omega[s-1](B)**[s-1]$

and $\delta(B) =1 - \delta1(B)- \delta2(B)**2-\ldots\ldots..- \delta r(B)**r$.

However, in practice $\omega(B)$ usually consists of only a few terms (often no more than 1 or 2 terms) while $\delta(B)$ usually can be represented as either $\delta(B) =1$ or $\delta(B) =1 - \delta1(B)$.

Finally, an intervention can be described equally well be either a pulse or a step function because there is an exact relationship between a step and a pulse function. That is, (1-B) St**T = Pt**T.

This intervention model can be directly extended to include more than one interventions.

Data

Here, I will conduct an application on intervention model using industrial data of a Palestinian soft drink company (Pepsi Yazegi group for soft drink L.T.D.), which is located in Gaza, and it is considered as a committable middle size company.

Soft drink industry has been receiving an increasing interest in Palestine, because of its increasing role in the economic process. However, this sector may be exposed to many obstacles, such as intervention influences and constraints.

Here, I consider the positive effect of the company's decision to produce new kinds of soft drink and the negative effect of the Israeli constraints on the company sales caused by preventing this company from delivering its production to some regions in Palestine and outside.

Only one variable is available to be analyzed by using the SCA (the Scientific Computing Associate Corporation) statistical system, namely, the monthly sales of soft drink cartoons (in thousands), [one cartoon equal 24 units]. The of data is the yazegi company records.

So, a time series of the monthly sales of soft drink cartoons over the period from January 1990 to September 2000, is used in the application. This period is considered as a stable period before the Intifada that started at the beginning of October 2000.

The data analyzed here are the time series of the log-transformed monthly sales of soft drink cartoons. Since manufacturing firms often use retail months (a retail month equal 28 days) to avoid trading day variation and to facilitate production planning, so I used in the analysis 13 retail months in a year.

Intervention Dates

It is obviously seen from the data that the abnormal behavior of sales in January 1997, which is considered as a positive effect of the company's decision. The number of sales of soft drink cartoons is 77.5 thousand, while it is 49 thousand in January 1996. Also, one can see the negative effect of the Israeli decision, the number is 75 thousand in January 1999, while it is 96 thousand in January 1998.

The non-Intervention Model

Upon examining the corresponding Sample Auto-Correlation Function (SACF) and the Sample Partial Auto-Correlation Function (SPACF) of the logarithm of the original time series (logarithmic transformation is used to stabilize the increase variability over time), one can see a strong seasonal pattern in the time series plots. I modeled various models with different differencing operators. The Extended Auto-Correlation Function (EACF) is considered. Based on EACF, we may observe a triangular region of '0' values (insignificant autocorrelations) appears to emanate from the vertex where $p \geq 0$, $q \geq 0$.

Typically, we judge that an autocorrelation is significant if it is greater (in absolute value) than twice of its standard error.

It has been found that ARIMA (0,1,0) $(1,1,1)_{12}$ model fits the data and it was found to be adequate, according to the Auto-Correlation Function (ACF) of the residuals. (The t-value of the mean of residuals is insignificant -0.87>-2.0).

So, we retain the univariate ARIMA (0,1,0) $(1,1,1)_{12}$ model

$(1- \phi_{12}B^{**}12)$ (1-B) $(1-B^{**}12)y_t = [(1 - \theta_{12}B^{**}12)]a_t$ where

y_t: the logarithm of monthly sales

B: backshift operator such that $B^{**}k\ y_t = y_{t-k}$

(1-B) (1-B**12): differencing operators

θ_{12}: the seasonal moving average parameter

ϕ_{12}: the seasonal autoregressive parameter

a_t: stochastic error which follows a normal distribution with mean equal zero and variance equal to $\sigma_a^{\ 2}$, see Liu, L.-M., Hudak, G. B. (1992 - 2000).

It was fitted to the data and the estimates are listed below (numbers in parentheses are the t-values of the estimates): the estimate of ϕ = 0.2128 (1.96), θ_{12} = 0.8759 (11.86) and the estimate of σ_a = 0.05476 whereas these estimates are: ϕ = - 0.5266(-27.50), θ_{12} = -1.00(-27.63) and the estimate of σ_a = 0.01051 with outlier detection and adjustment. Based on those estimates mentioned above, the importance of outlier detection and adjustment can be realized. The standard deviation of our logarithm sales series is 0.476. Consequently, [0.547/0.476]**2 = 0.013=1.3 % of the variation of the logarithm sales series is still unexplained. This is reflected in the R-square value of 0.987 (i.e., 1-0.013).

The most basic assumption made in ARIMA models is that the errors a_t's are independently and normally distributed. Such a serially independent series is also referred to as a white noise series. If the assumption is correct then the residuals of our model should approximate a serially independent sample and follow a normal distribution with zero mean and constant variance. By using the ACF for residuals, we found that the mean of the residuals is not distinguishable from zero. Also, we are provided in the ACF table (the 'Q Row' with a crude global check on the residuals, a portmanteau test, the Ljung-Box Q statistic, represents a scaled sum of squares of the computed ACF values). It is scaled so that we can use a χ^2 distribution, with (l-p-q degrees of freedom, to determine its significance. From ACF table, we see that the all values are insignificant at the 5 % level for a χ^2 distribution with 10 degrees of freedom. So, we conclude that our model fits the data.

However, beside the abnormal observations caused by the effects of the company's decision and the Israeli constraints, the analysis revealed two outliers at January 1998 and January 2000 [both of them are Innovational Outliers (IO)-type]. See the summary of outlier detection and adjustment from the SCA output files.

Intervention Modeling

Based on the significances of the outliers, I started with the outlier at 85 position. A univariate time series model (0,1,0) $(1,1,1)_{12}$ is retained for the span from 1 to 84 and it was found fits the data. The outliers effects of lnsales data are assumed to be pulse variables and the period of each of them is assumed to be one month.

The following intervention time series model was found to be appropriate to describe the intervention events under consideration and the above situation:

$(1-\phi_{12}B^{**}12)\,(1\text{-}B)\,(1\text{-}B^{**}12)\ \text{lnsales} = \omega_{1,1}\, p_{1t}^{(T)} + \omega_{1,2}\, p_{2t}^{(T)} + \omega_{1,3}\, p_{3t}^{(T)} + \omega_{1,4}\, p_{4t}^{(T)} + [(1-\theta_{12}B^{**}12)]a_t$

where

$p_{1t}^{(T)} =$

1	t = January 1997
0	otherwise

$p_{2t}^{(T)} =$

1	t = January 1998
0	otherwise

$p_{3t}^{(T)} =$

1	t = January 1999
0	otherwise

$p_{4t}^{(T)} =$

1	t = January 2000
0	otherwise

$\omega_{1,1}$, $\omega_{1,2}$, $\omega_{1,3}$, $\omega_{1,4}$ are intervention parameters to be estimated.

According to the ACF of residuals, the model fits the data.

Using the exact maximum likelihood method, the following estimates of the model are obtained:

Table (1): Parameter estimates, the standard error, and t-value of the intervention time series model for logarithm of monthly soft drink sales

Parameter	Estimate	Standard Error	T-Value
ω_1	0.1442	0.0315	4.57
ω_2	0.1120	0.0657	1.71
ω_3	-0.1729	0.0841	-2.05
ω_4	-0.1924	0.0999	-1.92
ϕ_{12}	-0.6189	0.0686	-14.57
θ_{12}	-0.999	0.0681	-9.09

Since the estimates of ω_2 and ω_4 are insignificant, and the estimate of θ_{12} is equal approximately one, we can apply the model

$(1- \phi_{12}B^{**}12)(1 - B)(1-B^{**}12)$ lnsales $= \omega_{1,1}\, p_{1t}^{(T)} + \omega_{1,3}\, p_{3t}^{(T)} +[(1 - \theta_{12}B^{**}12)]a_t$

The following estimates of the new model are obtained (number in parentheses are t-values of the estimates):

The estimate of ω_1=0.1601(5.44), ω_3 =-0.1729(-5.67), ϕ_{12} = 0.1969 (2.26), and θ_{12}= 0.7279 (8.32).

So, our model is

$(1- 0.1969B^{**}12)\ (1 - B)(1-B^{**}12)$ lnsales $= 0.1601p_{1t}^{(T)} + (-0.1729)p_{3t}^{(T)} +[(1 - 0.7279B^{**}12)]a_t$

It is found that the model fits the data.

Based on the new estimates of ω_1, ω_3, one can see that there is a significant impact on the company sales due to the company intervention (positive impact), and the Israeli intervention (negative impact).

Table (2): Forecasts of the logarithm of soft drink sales according to the non-intervention and intervention

Data	**Actual Data**	**Forecasts (Non-Intervention)**	**Forecasts (Intervention)**
December 1999	4.3529	4.3573	4.3340
January 2000	4.3188	3.8698	4.3540
February 2000	4.3438	4.5617	4.3243
March 2000	4.3707	4.4591	4.3698
April 2000	4.3845	4.4873	4.3924
May 2000	4.4164	4.5011	4.4138
June 2000	4.4344	4.4820	4.4491
July 2000	4.4625	4.4865	4.4552
August 2000	4.4830	4.5246	4.4858
September 2000	4.4438	4.4630	4.4557

From table (2), we conclude that the forecasts of the intervention model are better than forecasts of the non-intervention model, because it is closer to the actual data and has small standard error (standard error for forecasts of the non-intervention model is 0.0438, and of intervention model is 0.0105.

Conclusion

Time series intervention analysis approach introduced by Box and Tiao (1975) was found to be useful when dealing with effect of known events on a time series. In this application, the different steps govern this approach were introduced by using the SCA system, these steps include identification, estimation, diagnostic checking, and forecasting. Moreover, the methodology of Box and Jenkins introduced by Box and Jenkins (1970) has been used in order to deal with the ARIMA part which is an essential part of the intervention model.

In this application, we focused on measuring the impact of Yazegi company's decision to intervene (delivering new kinds of soft drink) and the intervention impact of the Israeli constraints on sales delivery. A comparison between the non-intervention model and the intervention model has been made. The intervention model was found to be the better model in describing the behavior of the sales and in calculating the future behavior of the time series. We demonstrated how to accommodate the outliers effects by using the intervention modeling. We assessed the impacts of the economic and political decisions.

The conclusion, which we come up with, is that the intervention model better track the time series data as compared to the ARIMA models. Also, the intervention model is flexible time series model that can be used for a variety applications for handling many problems in real life.

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