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An Intervention Analysis of Share Index Data for Banks and Other Financial Institutions in Bangladesh

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Abstract

This study deals with construction of intervention models for the share index data of Banks and Other Financial Institutions in Bangladesh. Intervention model is constructed for time series data and its comparison is done with ARIMA model. In our study we established superiority of intervention model over the ARIMA model. Using the share index data, we have shown that due to existence of external events, intervention model has lower residual variance and fits the data better.

Keywords and Phrases: Intervention; External events; Outliers; Dynamic regression; Transfer function.

AMS Classification: 62M10

1 Introduction

Stock market is a way to raise new corporate cash and makes the firms not fail in a high cashing problem. By selling some of their stocks in a public offering, the founders can diversify their holdings and thereby reduce somewhat the risks of their personal portfolios.

The share index measure changes in the cost of earnings income at a certain level from investment to shares of joint stock companies and it changes very frequently with the fluctuation of the reputation of the companies. This change may be very high due to some external events such as policies taken by companies, war, political unrest, natural calamities etc. A simple time series model may not be adequate to predict share index considering the effect of external events. One may use ARIMA model for this purpose but fluctuation in the data may often affect the underlying ARIMA structure and the true ARIMA pattern will not be properly determined. In such a case, intervention analysis is a way to describe dynamic pattern of distributed lag responses of the output series to the input series and the autocorrelation of the disturbances (Debny and Martin, 1979; Chang et al., 1988).

Intervention model has been discussed by many authors (Tsay, 1986 and 1988; Chang et al., 1988). They proposed that deterministic inputs could be used in dynamic regression models to represent identified event, called interventions. Same idea may be used to account for unexplained outliers in a time series. This type of models has a broad variety of applications. For examples, Box and Tiao (1975) considered environmental and economic policy issues; Wichern and Jones (1977) consider marketing and management issues; and Zimring (1975) considered effects of gun control legislation. Application of intervention analysis on share index data in Bangladesh is rare. Thus, the purpose of the present study is to apply intervention analysis to share index data for Banks and Other Financial Institutions and compare it with ARIMA model.

2 Materials and Method

The data, used in this empirical work, has been taken from the journal "Index Numbers of Dhaka Stock Exchange Share Prices", published by Statistics Department, Bangladesh Bank (Bangladesh Bank, 1998, 1999, 2000). The framework we use to evaluate an intervention effect represented by a single intervention variable is the rational form of the Dynamic Regression (DR) model (Liu, 1984). The model is:

$$P_t = C + \frac{w(B)B^b}{\delta(B)} I_t + E_t, \tag{1}$$

where P_t is the output variable,
I_t is the input variable,
$W(B) = w_0 + w_1B + \cdots\cdots + w_hB^h$,
$\delta(B) = 1 - \delta_1B - \cdots\cdots \delta_rB^r$,
B is the backshift operator i.e., $B^i(I_t) = I_{t-i}$,
C is an additive constant,
E_t is the disturbance term may be described by an ARIMA process (Box and Jenkins, 1976).

$f(I_t) = \frac{w(B)B^b}{\delta(B)} I_t$ is known as transfer function.

In intervention model, the input variable, I_t is a deterministic variable used to represent the possible intervention.

Several approaches have been proposed to identify the transfer function. This empirical work has been prepared on the basis of the following method.

Transfer function Identification by Outlier Detection (Chang et al., 1988; Tsay, 1986 and 1988): Intervention models can be constructed according to the nature of outliers or level shift (LS) present in the data series. According as the nature of external events, outliers can be additive or innovational.

Additive outliers (AO) is similar as the one-period pulse intervention and innovational outliers (IO) are additions to the random shock series e_t: an IO affects the output series P_t through the ARIMA structure of the disturbance series in the model for P_t. Permanent level shift (LS) is similar as step intervention.

When a time series is affected by an outlier or by an external event, we observed a contaminated series rather than a stationary ARIMA series. Therefore, an observed time series variable P_t may be composed of a stationary ARIMA series plus a contamination term such as,

$$P_t = \begin{cases} w_AI_t + \frac{\theta(B^s)\theta(B)}{\varphi(B^s)\varphi(B)\nabla_s^D\nabla^d}e_t & for\ AO \\ \frac{w_s}{\nabla}I_t + \frac{\theta(B^s)\theta(B)}{\varphi(B^s)\varphi(B)\nabla_s^D\nabla^d}e_t & for\ LS, \\ \frac{\theta(B^s)\theta(B)}{\varphi(B^s)\varphi(B)\nabla_s^D\nabla^d}w_II_t + \frac{\theta(B^s)\theta(B)}{\varphi(B^s)\varphi(B)\nabla_s^D\nabla^d}e_t & for\ IO \end{cases} \tag{2}$$

where the first term of the right hand side is known as contamination term, represents the effect of intervention: w_A and w_s are the coefficients of AO and LS, respectively and the second term represents the ARIMA structure (Box and Jenkins, 1976) of the disturbance: e_t is a white noise disturbance term; $\theta(B) = 1 - \theta_1B - \theta_2B^2 - \cdots - \theta_qB^q$

is the time-lag series of moving average (MA) coefficients; $\varphi(B) = 1 - \varphi_1 B - \varphi_2 B^2 - \cdots - \varphi_q B^q$ is the time-lag series of autoregressive (AR) coefficients; $\theta(B^s)$ and $\varphi(B^s)$ represents the seasonal MA and AR coefficients with length s; $\nabla^d = 1 - B^d$ represents order of integration; ∇_s^d represents the order of integration seasonally. To detect the presence and type of outliers in a particular point, we first simply obtain the ARIMA models for P_t and the produced residual series (ε_t) can then be written as

$$\varepsilon_t = \begin{cases} w_A \pi(B) I_t + e_t & for\ AO \\ w_s c(B) I_t + e_t & for\ LS, \\ w_I I_t + e_t & for\ IO \end{cases} \tag{3}$$

where e_t is a white noise disturbance term; w_A, w_S and w_I are AO, LS and IO coefficients, respectively. The $\pi(B)$ and $c(B)$ are time-lag series of π-operators and c-operators respectively defined as

$$\pi(B) = 1 - \pi_1 B - \pi_2 B^2 - \cdots = \tfrac{\varphi(B^s)\varphi(B)\nabla_s^D \nabla^d}{\theta(B^s)\theta(B)} \text{ and}$$
$$c(B) = 1 - c_1 B - c_2 B^2 - \cdots = \nabla^{-1}\pi(B)$$

Test of null hypothesis that no AO, LS or IO occurs at time i may be performed with the following likelihood ratio statistic (Pankratz, 1991)

$$L = \begin{cases} w_A k_A^{-1/2}/\sigma_e & for\ AO \\ w_s k_s^{-1/2}/\sigma_e & for\ LS, \\ w_I/\sigma_e & for\ IO \end{cases} \tag{4}$$

where $k_A = (1 + \pi_1^2 + \pi_2^2 + \cdots + \pi_{n-i}^2)^{-1}$,
$k_s = (1 + c_1^2 + c_2^2 + \cdots + c_{n-i}^2)^{-1}$ and
σ_e is the residual standard deviation.

Practically we use the sample estimate of w_A, w_S, w_I, k_A, k_s and σ_e. The critical value for the likelihood ratio statistic L is similar to a critical standard normal value or t-value. However, it is not feasible to determine the exact repeated sampling distributions of likelihood ratios in(4). Some simulation experiments are reported by Chang et al. (1988) The common practice to choose critical value is within 3 to 4 (Pankratz., 1991). If outliers more than one type are detected in the same point, we consider that type for which the L-statistic gives higher value.

3 Model Building

To construct a time series model, the stationarity of the time series variable, to be forecasted, must be verified. The sample autocorrelation function (ACF) and partial autocorrelation function (PACF) of share index data for Banks and other Financial Institutions are given in Fig.1 and Fig.2, which lead us to check for a unit root. The ADF test recommends for a unit root. Therefore, we take first difference to make the series stationary. Checking the sample ACF (Fig.3) and PACF (Fig.4), of the differenced data, we made the following ARIMA model.

$$\nabla Y_t = -0.358 \nabla Y_{t-15} \tag{5}$$

$$t = (-2.841)$$

$$R^2 = 0.332$$

$$\sigma_e = 63.2024$$

The ACF (Fig.5) and PACF (Fig.6) of residuals for model in eq. (5) are stationary. The normal probability plot (Fig.7) rejects the normality assumption of residuals. The standardized residuals (Fig.8) show no inadequacy except a very high residual, which lead to construct an intervention model. To check the existence of external event in each point, the primary job is now to compute the π-weights and c-weights (Table 1). Application results of the outlier detection procedure to the differenced data (not shown here) identified only one innovational outlier. With this innovational outlier the estimated intervention model is

$$\begin{aligned} \nabla Y_t \quad &= \quad -0.383\ B^{15}\ \nabla Y_t + 457.331\ I_t \\ t = \quad & \quad (-6.836) \qquad\qquad (16.249) \end{aligned} \tag{6}$$

$$R^2 = 0.909$$

$$\sigma_e = 27.0862,$$

where $I_t = 1$ for $t = 45$ and 0 otherwise.

The sample ACFs (Fig.9) and PACFs (Fig.10) are within the limits of two standard deviation and the normal probability plot (Fig.11) is nearly a straight line. The standardized residuals (Fig.12) show no inadequacy. That is our fitted intervention model is adequate.

4 Forecasting

The table below shows the 8 periods ahead forecast values, forecast errors, root mean squared forecast error (RMSFE) and MAPE for the constructed models

5 Result and Discussion

Since significant change at a point in the data level indicates effect of external event, intervention model is fitted. This intervention point can be explained in the following way.

In the last week of September 1998 the Federal Reserve moved to stimulate the US economy. The Fed Chairman Alan Greenspan gave a speech in which he appeared to signal his intention of moving in the direction of lower interest rates. Greenspan told lawmakers that foreign economic activity, notability in Asia, was likely to act as drag on the seven years US expansion and curb inflation. Thus easing US credit cost would encourage business and consumers to invest and spend more, with effect not only domestically but also in Asian economic trying desperately to export their way out of recession.

The reflection of Greenspan's voice was also found in Asian's investors. They thought, a rate cut in the US is likely to prompt local banks to speed up a cut in their own rates. As a result, most of the Asian stock market got upward. The effect of this external event is noted by the intervention point in our model.

We observed that ARIMA model gives lower RMSFE and MAPE than those of intervention model. But intervention model has lower residual variance and higher R^2 value. Moreover, the standardized residuals of intervention model are adequate and approximately normal whereas that of ARIMA model is not. Therefore, our realization is that intervention model can fit the data appropriately.

6 Conclusion

Our study with share index data was to obtain a better model considering external events. Our findings established that DR model with intervention analysis have lower residual variance and fits the data better than the ARIMA model.

We conclude that if the time series variable seems to be affected by some external events or if the outliers are detected in the data series, it is a good practice to build a DR model with intervention analysis. The model, developed in this research work, would be useful for the investors or the researchers to determine the future values of share indices and thereby take decision for their valuable investment.

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