Estimating the Impact of the Cocoa Hi-Tech and Mass Spraying Programmes on Cocoa Production in Ghana: An Application of Intervention Analysis

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Abstract

Using the intervention time series analysis of Box and Tiao, this paper presents an estimate of the level and nature of impact of the national mass spraying and the cocoa hi-technology Government intervention programmes, implemented in 2002 and 2003 respectively, on cocoa production in Ghana. An annual time series cocoa production data covering the period from 1948 to 2011 was obtained from the Monitoring, Research and Evaluation Department of Ghana's COCOBOD. Results from the study indicate that the preintervention period could best be modeled with an AR(1) process. The effects of both intervention programmes were found to be abrupt and permanent. The impact of the mass spraying programme was estimated to have had a significant increase of 182,398.2 metric tonnes. It was also found that the cocoa hi-technology programme significantly increased production by 266,515.1 metric tonnes per annum.

Keywords: intervention time series analysis, mass spraying, hi-technology, abrupt, permanent

1.0 Introduction

Ghana's cocoa production sector has over the decades faced major challenges which have adversely contributed to the country losing her position as the world's leading producer of cocoa beans. The key challenges facing the cocoa sector include; diseases and pests infestation, climate and soil quality, and the setting of cocoa producer price (Pilot survey of labour practices in cocoa production in Ghana, 2006).

In a committed attempt to capture the decline in cocoa production levels and the quality of yields, the Government in collaboration with Ghana Cocoa Board (COCOBOD) instigated a nationwide cocoa disease and pests control programme popularly known as 'mass spraying', and the cocoa hi-technology programme in 2001/2 and 2002/3 cocoa seasons respectively. These two programmes were purposely to assist all cocoa farmers to fight against diseases and pests plaque, and also to improve soil quality. The objective of this paper is to estimate the level and nature of impact of these two recent control measures using intervention time series analysis, originally introduced by Box and Tiao (1975).

After the development of this intervention technique by Box and Tiao, many analysts have used it in a wide variety of applications. For example, Bhattacharyya and Layton (1979) and Harvey and Durbin (1986) have both applied the intervention analysis technique to analyze the effects of seatbelt laws on road fatality rates in Australia and Britain, respectively. The technique has then being applied in many key areas such as health (Cristina et al., 1998; Stuart et al., 2006; Ferrand et al., 2011), terrorism activities (Enders et al., 1990; Carlos, 2003; Ismail, et al., 2009), and in disaster cases (Fox, 1996; Min, 2008a, 2008b). Other vital areas include transportation (Ming-Chan, 2003; Narayan and Considine, 1989; Chen, 2006), environmental issues (Sharma and Khare, 1999; Kuo and Sun, 1993) and the financial sectors (Chung et al., 2009; Shittu, 2009; Valadhkhani and Layton, 2004).

In the context of the agriculture subsectors, not much literature exists on the use of intervention analysis to assess programmes or events in the sectors. Nonetheless, Sathiananda et al. (2006) evaluated the impact of an introduction of crafts with outboard engines on marine fish production in Kerala and Karnataka. Based on their estimated intervention models, the effect of the intervention was estimated at 2.26 lakh tonnes and 88 thousand tonnes per annum respectively for Kerala and Karnataka. Examples of other papers in the agriculture subsectors are the evaluation of California's Brucellosis Eradication Campaign (Morales et al., 1988); and the changes in cow heart rate affected by programmed audio and environmental/physiological cues (Remenyi et al., 2010).
However, to the best of our knowledge no published study has being extended to assess programmes in the cocoa subsectors using the intervention analysis technique, and for that matter, this paper pioneers the literature on the application of the technique in the cocoa subsectors.

The remaining sections of the paper are organized as follows: In the second section, we describe the methodology and modeling procedure of the ARIMA-Intervention technique. Section three present results and analysis; section four gives summary of conclusion statements and the last section acknowledges person who helped in diverse ways.

2.0 Research Methodology

2.1 Box-Jenkins ARIMA modeling

The Box-Jenkins ARIMA models actually builds upon an earlier work put forward by Yule (1927), Slustky (1937) and Wold (1938). These analysts are highly credited for pioneering an investigation into the Autoregressive (AR) and Moving Average (MA) processes. However, Box and Jenkins (1970) developed a new model which combines the AR and MA processes with an integrated term, and also provided a cohesive framework for building these models. Their model was simply denoted as ARIMA (*p*, *d*, *q*), and can be decomposed into two main components. The *d* in the ARIMA model is the integrated term which takes care of nonstationary processes. The second component is in the form of an ARMA model, where AR represents the correlation between the immediate value and some past values of a time series, whereas the MA part gives the influence of the error series (random shocks). Most often, the ARMA model could be rendered stationary through differencing, and by so doing it is known as an ARIMA model.

Generally, the Box-Jenkins process of fitting and analyzing univariate time series models can primary be categorized into three iterative stages: identification, estimation and diagnostics.

2.1.1 Identification

The first step under the identification stage is to undertake a graphical analysis of the observed time series to verify whether the series is stationary or otherwise. Correlograms and objective tests such as the ADF and the KPSS statistics may be use to ascertain stationarity or nonstationarity of a series. Generally, an ADF test with hypothesis $H_0: \rho_1 = 0$ and $H_1: \rho_1 < 0$ is tested in the regression model $Y_t = \alpha_0 + \rho_1 y_{t-1} + \sum_{i=2}^{p} \beta_i \nabla y_{t-i} + bt + \varepsilon_t$ for serial correlation. An alternative to the ADF unit root test is the KPSS stationarity test. The null hypothesis of this test does not depend on the existence of a unit root as the ADF does, but instead a stationary series. The initial point of the KPSS test is given as $Y_t = \alpha_t + \beta_t + \mu_t$. Instead of the commonly used constant term, a random walk, $\alpha_t = \alpha_{t-1} + \varepsilon_t$ is allowed, where ε_t are assumed to be i.i.d.
After achieving stationarity in the time series, the analyst then examine the ACF and the PACF patterns to identify the form and order of tentative models. A pure AR or MA model or a mixture of the two may be revealed. In summary, the characteristics of the ACF and PACF for identifying simple tentative models are presented in Table 1.

2.1.2 Estimation

After identifying a tentative ARIMA model, the next stage would be to estimate the parameters in the model. The most popular methods for estimation are the least square estimates, the method-of-moments estimates and the maximum likelihood estimates.

For each parameter estimate, there will be a reported standard error for that particular parameter. From the parameter estimate and its standard error, a test for statistical significance can be conducted. Over here, a *t*-test, which is a test of whether a parameter is significantly different from zero, is used. Again, the estimated AR and MA parameters must also conform to certain boundary conditions. For these estimated parameters to be stable, it is deemed appropriate for the coefficients of the AR and MA parameters to lie within the bounds of stationarity and invertibility.

2.1.3 Diagnostic

The main objective under the diagnostic stage is to examine whether the residuals of the fitted model follows a white noise process. The modified Ljung-Box portmanteau test is usually used to achieve this objective. The test statistic is given by:

$$Q = n(n+2)\sum_{k=1}^{h}\frac{r_k^{\ 2}}{(n-k)} \tag{1}$$

where n denote the sample size, $r^2{}_k$ is the square of the autocorrelation at lag k, h is the maximum lag being considered and Q is asymptotically a χ^2 distribution with a certain significant level on $h-p-q$. The decision is to accept an adequate model if $Q < \chi^2{}_{\alpha,(h-p-q)}$ and to reject inadequate model if $Q > \chi^2{}_{\alpha,(h-p-q)}$. These iterative stages of identification, estimation and residual diagnostics are repeated in a cycle until an adequate model is obtained.

2.2 Intervention Time Series Analysis

Intervention analysis is a special case of dynamic regression models which is mainly use by time series analysts to assess the impact of external events such as economic policy changes, strikes, political events, sales promotions and many similar events which are commonly referred as intervention events. It is also called impact analysis. According to Robert and McGee (2000), the impact response model is formulated as a regression function where the independent variables consist of an ARIMA noise model and an intervention function, whereas the dependent variable represents the response series. It is generally formulated as:

$$Y_t = \sum_t \Sigma f(I_t) + N_t \tag{2}$$

where $f(I_t)$ is an intervention function of a dichotomous deterministic intervention indicator at time t, and N_t is the ARIMA preintervention model or the noise model.

Box et al. (1994) outlined two common types of deterministic input variables that have been found useful to represent the impact of intervention events on a time series. Such input variables can be coded as either a step function or a pulse function depending on the onset and duration of the input event. If the deterministic intervention function is that of a step function, then the intervention indicator is coded 0 prior to the beginning of the event and as 1 at both the onset (T) and for the entire duration of the presence of the event.

$$f(I_t) = s_t^{(T)},\ when\quad s_t^{(T)} = \begin{cases} 1, & if\ \ t \geq T \\ 0, & if\ \ t < T \end{cases} \tag{3}$$

In the other situation the deterministic intervention function can also be modeled as a pulse function. In such circumstances, the intervention indicator is coded as 0 prior to the event and immediately after the event, and as 1 at the onset of the event.

$$f(I_t) = p_t^{(T)},\ when\quad p_t^{(T)} = \begin{cases} 1, & if\ \ t = T \\ 0, & if\ \ t \neq T \end{cases} \tag{4}$$

There are two major dimensions characterized by impact assessment. These are observed through the duration and the nature of impacts. The most common of these dimensions include; (a) sudden and constant changes (abrupt permanent); (b) sudden and instantaneous changes (abrupt temporary); (c) gradual and permanent effects; and (d) gradual and temporary changes (pulse decay). Step functions are mainly used to model permanent changes in the response series, whereas temporary effects are modeled with pulse functions.

The abrupt onset and permanent duration effects are popularly called a simple step function. A step function with a first-order decay rate may be formulated as;

$$Y_t = \frac{w_0}{(1-\delta_1 L)} I_{t-b} + N_t \tag{5}$$

If after fitting the model in (5) the denominator reduces to unity $(\delta_1 = 0)$, the model will then be called a simple step function with a zero-order decay, where $f(I_t) = s_t^{(T)} = w_0 I_{t-b}$. Also, if there are no time delays $(b = 0)$, the simple step function model will now be of the form;

$$Y_t = w_0 I_t + N_t \tag{6}$$

Due to the occurrence of the cocoa mass spraying and the hi-technology programmes, we considered the two intervention events as step intervention functions. It was then hypothesized that each programme produces a positive impact with respect to production levels. In line with their known onset and duration, the intervention events were postulated as;

$$Y_t = c + w_1 I_{1t} + w_2 I_{2t} + \frac{\theta(L)}{\phi(L)} \varepsilon_t \tag{7}$$

where

$$I_{1t} = S_t^{(2002)} = \begin{cases} 1, & t \geq 2002 \\ 0, & otherwise \end{cases}$$

$$I_{2t} = S_t^{(2003)} = \begin{cases} 1, & t \geq 2003 \\ 0, & otherwise \end{cases}$$

c is a constant and Y_t is the level of change with respect to gains or losses made in the volume of production. The intervention variable I_{1t} is a step function which corresponds to the mass spraying exercise and I_{2t} represents another step function for the cocoa hi-technology event.

3.0 Results and Analysis

The data used in this paper was obtained from the Monitoring, Research and Evaluation Department of Ghana's COCOBOD. The data is made up of sixty-four (64) consecutive annual readings of cocoa production levels in Ghana, spanning from 1948 to 2011. The data was accessed on January 18th, 2012.

3.1 Results and Analysis of the Preintervention model

In a process of assessing the degree of dependence in any series and selecting a model for such series, the most important tools time series analysts normally use are the sample ACF and PACF of that particular series. The ACF can be used to detect stationary and nonstationary series. If a series is stationary, its ACF rapidly die out to or near zero. A nonstationary series mainly have high positive lags which slowly decay to or near zero.

Critical observation from Figure 2 shows that the autocorrelation function of the preintervention series attenuates at a quicker rate to nearly zero, whiles the partial autocorrelation function shows a significant non-zero spike at the first lag and thereafter geometrically decays to zero. This depicts a clear situation of a series which is stationary in the mean and does not require any form of differencing or transformation. Results from the ADF and KPSS tests presented in Table 2 also conferred stationarity in the preintervention cocoa production series.

Based on the correlogram and the partial correlogram in Figure 2, the appropriate noise model to represent the period prior to the intervention events (1948-2001) could reasonably be seen as an AR(1) process.

The parameters of the selected AR(1) model were estimated using the maximum likelihood estimation method, with the R statistical software package. The estimated ar1 (ϕ_1) coefficient of 0.7966(0.0804) was statistically different from zero, and strictly conforms to the bounds of parameter stationarity. Symbolically, the estimated model can be written as:

$$Y_t = 0.7966 y_{t-1} + 313689.72 + \varepsilon_t \qquad (8)$$

Moreover, the estimated noise model was checked for adequacies. The left panel of Figure 3 shows a time plot of the unstandardized residuals for the fitted AR(1) model. The plot generally shows no clear pattern, and may be conceived of as an i.i.d sequence with a constant variance and a zero mean. From the right panel of Figure 3, the ACF of the residuals follows a white noise process with evidence of no significant spike in the plot. The Ljung-Box test in Table 3 does not reject randomness of the residuals based on the first 24 autocorrelations of the residuals. Again, the Shapiro-Wilk normality test failed to reject normality for the residuals of the fitted noise model as shown in Table 3. In considering these reported diagnostic checks, we strongly confirm that the fitted noise model for the preintervention series is convincingly adequate of a good fit.

3.2 Results and Analysis of the Intervention model

Prior to the fitting of the intervention model, the Zivot and Andrews test of no data break point as its null hypothesis, was used to ascertain a structural change or a possible break in the entire cocoa production series. Results from the test as shown Table 4 reported a potential break point at position 55 of the dataset which corresponds to the year 2002, where, the mass spraying intervention event took off. This obviously confirms the appropriateness of the use of impact analysis for this series, and also shows an indication that, the onset of the mass spraying intervention was characterized by an immediate impact, hence the break at the year of onset. Also, there were no time delays for the impact of the hi-technology intervention event since the size of the spike at the onset of the event is more pronounced, as observed in Figure 1.

Thereafter, the fitted AR(1) noise model of the preintervention series was estimated together with a dichotomous intervention function and presented in Table 5. In notation, the estimated intervention model is written as:

$$Y_t = 315435.3 + 182{,}398.2 I_{1t} + 266{,}515.1 I_{2t} + (1 - 0.6777L)\varepsilon_t \qquad (9)$$

Generally, the full-fitted intervention model exhibits a stationary process, and all its estimated coefficients are significantly different from zero. The adequacy of the fitted intervention model was also checked based on the residual plots shown in Figure 4 and the Ljung-Box Q statistic test. The residual plots in Figure 4 do not show any clear anomalies for the fitted intervention model. From Table 6, the Ljung-Box test was not significant with a recorded *p*-value of 0.9586 at 5% significance level. These observations attest to the fact that the residuals left after fitting the intervention model were considerably white noise, and for that reason, our intervention model fits the series quite well. In all, the results from the estimated intervention model in Table 5 indicate that the mass spraying event significantly increased production by 182,398.2 metric tonnes annually. The table also shows that the cocoa hi-technology programme had a significant impact by increasing production by 266,515.1 metric tonnes per annum.

4.0 Conclusion

This study aims at using intervention analysis in estimating the impact of the national mass spraying and the cocoa hi-technology intervention programmes, initiated by the Government of Ghana to help boost its annual cocoa production outputs. Result from the study revealed that the intervention effect of the mass spraying and the cocoa hi-tech programmes could best be fitted to a simple step function with zero-order decays. Moreover, the two intervention events showed abrupt and permanent nature of impact on the response cocoa production series. It can then be generally concluded that the mass cocoa spraying and the cocoa hi-tech intervention programmes, have had significantly positive impact on increasing Ghana’s cocoa production levels by 182,398.2 and 266,515.1 metric tonnes per annum respectively.

5.0 Acknowledgement

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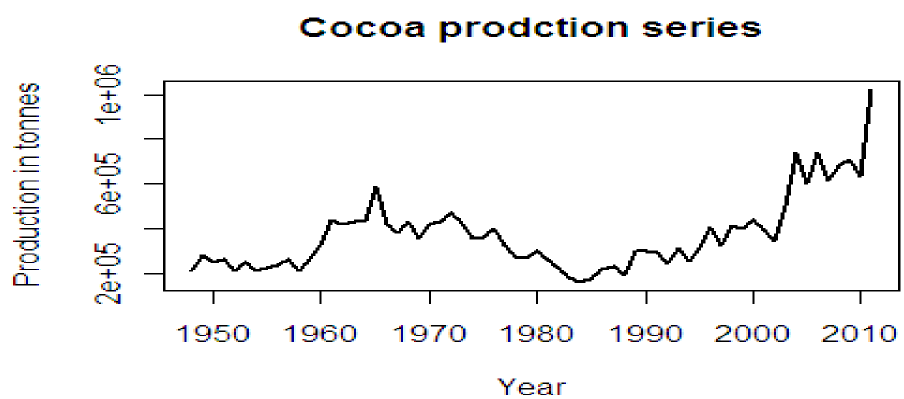

Figure 1: Ghana's annual cocoa production time plot from 1948 to 2011

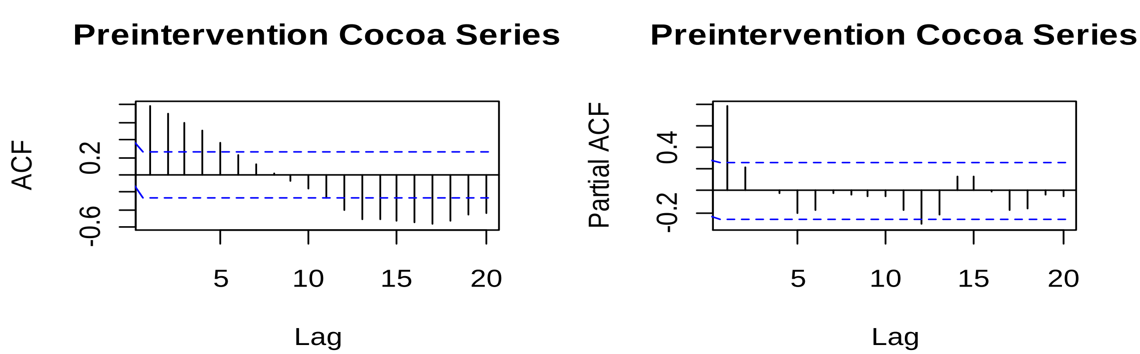

Figure 2: ACF and PACF of the preintervention part (1948-2001) of the cocoa series

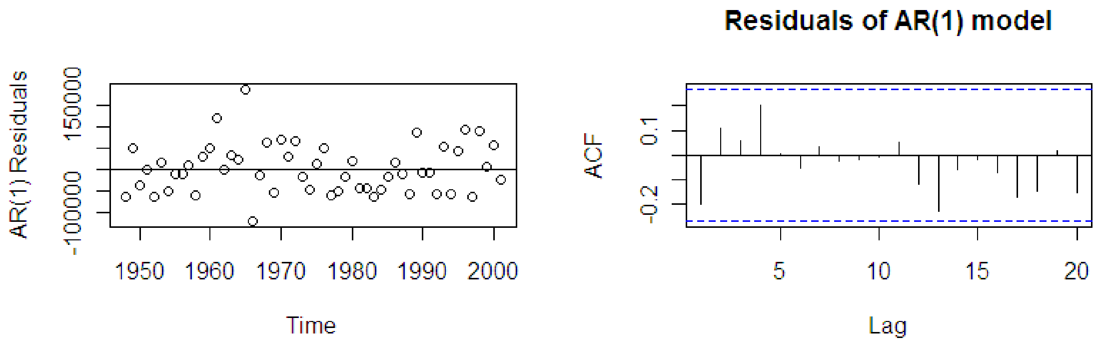

Figure 3: Diagnostic residual plots of the noise model

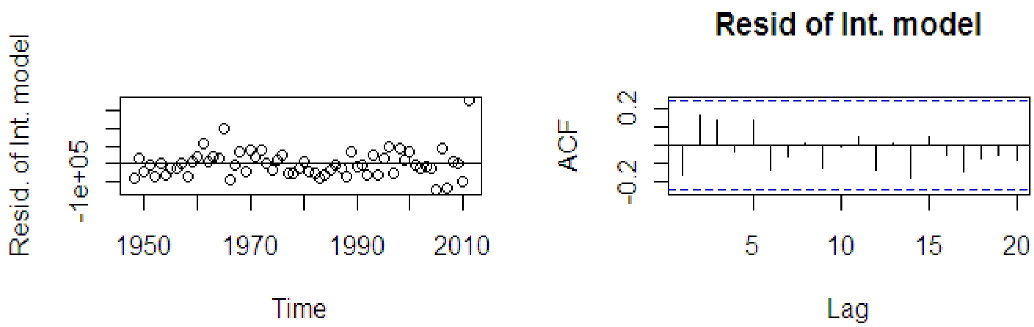

Figure 4: Diagnostic residual plots of the intervention model

Table 1: Characteristics of the ACF and PACF for identifying pure AR and MA models

Process	**ACF**	**PACF**
AR(p)	Tails off as exponential decay	Spikes at lag 1 to p, then cuts off to zero
MA(q)	Spike at lag 1 to q, then cuts off to zero	Tails off as exponential decay
AR(1)	Quickly tails off as exponential decay	Spike at 1, then cuts off to zero
MA(1)	Spike at lag 1, then cuts off to zero	Quickly tails off as exponential decay

Table 2: Unit Root and Stationarity Tests for the cocoa preintervention series

	Summary of Test Statistic		
Test Type	Test Statistic	Lag order	*p*-value
ADF	-4.164	12	0.01
KPSS	0.2853	1	0.1

Table 3: Parameter Estimates for ARIMA(1, 0, 0) model

		Model Fit Statistics			
	AIC	AICc	BIC		
	1339.9	1340.4	1345.9		
Coefficients	Estimate		Std Error	t - value	
ar1	0.7966		0.0804	9.90796	
Intercept	313689.72		35313.86	8.88291	
Shapiro-Wilk Test Statistic			Ljung-Box Test Statistic		
W	p-value		Chi-Square	df	p-value
0.9582	0.05728		20.3258	24	0.6781

Table 4: Za Test for possible break point position

	Summary of Test Statistics		
	Test statistic	Critical values	p-value
Test Type	-3.6517	0.01 = -5.57	2.20E-16
		0.05 = -5.08	
Za		0.10 = -4.82	
potential break in data at position 55			

Table 5: Parameter Estimates for the hypothesized Intervention model

		Model Fit Statistics		
AIC	AICc	BIC		
1596.3	1597.0	1604.9		
		Estimate	STD. Error	*t*-value
Coefficients				
ar1		0.6777	0.1007	6.729891
I1t-MA0		182398.2	70061.35	2.603406
I2t-MA0		266515.1	71671.58	3.718561
Intercept		315435.3	30113.68	10.47482

Table 6: Ljung-Box Test for the Intervention model

	Summary of Test Statistic		
Test Type	Chi-square	df	p-value
Ljung-Box	13.4239	24	0.9586