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Intervention Time Series Modeling of Infant Mortality: Impact of Free Maternal Health Care

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Authors' contributions

This work was carried out in collaboration among all authors. JK designed the study, performed the statistical analysis, wrote the protocol, and wrote the first draft of the manuscript. JO and EO verified the analytical methods of the study and supervised the findings of this study. All authors read and approved the final manuscript.

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Abstract

Infant mortality is an important marker of the overall society health. The 3rd goal of the Sustainable Development Goals aims at reducing infant deaths that occur due to preventable causes by 2030. Due to increased infant mortality the Kenyan government introduced Free Maternal Health Care as an intervention towards reducing infant mortality through elimination of the cost burden of accessing medical care by the mother and the infant. The study examines the impact of Free Maternal Health Care on infant mortality using Intervention time series analysis particularly the intervention Box Jenkins ARIMA (Autoregressive Integrated Moving Average) model. There was significant support that Free Maternal Health Care had a significant impact on infant mortality which was estimated to be a decrease of 10.15% in infant deaths per month.

Keywords: Infant mortality; maternal health care; intervention time series analysis; Box Jenkins ARIMA model.

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1 Introduction

Infant mortality gives key information about the infant health. The infant mortality is an important markers of the overall society health. Infant mortality refers to the death of an infant before his/her first birthday, Center for Disease Control [1]. There has been a decrease in infant mortality rate globally from 64.8 deaths per 1000 live births in 1990 to 30.5 deaths per 1000 live births in 2016 accounting for annual decline in infant deaths from 8.8 million in 1990 to 4.2 million in 2016, WHO[2]. According to Bourbonnaires [3], Kenya had experienced high infant mortality rates due to lack of access to quality maternal health services such as ante-natal, delivery and post-natal services. The Kenya government therefore introduced the Free Maternal Health Care (FMHC) on 1st June 2013 in all public hospitals as an intervention towards reducing infant mortality rate, an initiative that was to be effected immediately. In July 2013 the government allocated Ksh95 billion to health services with Ksh3.8 billion committed to Free Maternal Health Care provision, Ksh700 million for free access to health centers and dispensaries, Ksh3.1 billion for recruitment of 30 community nurses for every constituency, Ksh522 million for recruitment of 10 community health workers per constituency, Ksh1.2 billion for provision of housing units for health workers and Ksh60 billion was given to the county governments for provision of health services at the county level. According to a comprehensive report by Ministry of Health [4], the FMHC was to help increase access to skilled delivery services with the aim of reducing infant mortality which in effect would help Kenya in moving towards the 3rd Sustainable Development Goal of ending preventable infant mortalities, UNICEF [5].

1.1 Intervention time series analysis

Time series is a set of observations x_t, each one of them recorded at a specific time t, Brockwell & Richard [6]. Intervention time series analysis is the application of modeling procedures with the inclusion of the impact of changes or forces such as policy changes, price changes, strikes e.t.c known as interventions which may occur at a known point in time T, Box et.al [7]. The intervention models first introduced by Box and Tiao [8] has two main components: 1) The intervention component which measure the effect of the event (Free Maternal Health Care) on a time series (infant mortality); and 2) the noise component that accounts for residual variability in the observed infant mortality data when the effect of Free Maternal Health Care is modeled. Based on Box and Tiao [8] an intervention model is given as,

$$X_t = N_t + \frac{\omega(B)B^b}{\delta(B)} I_t^{t_0} \tag{1}$$

Where B is the backshift operator such that $B^b I_t^{t_0} = I_{t-b}^{t_0}$, $I_t^{t_0}$ is the deterministic input of 0's and 1's that specifies when the intervention event occurred and whether the event produces a temporary or permanent event, B^b represents the time delay or backshift of b time units in the model (If b=0 then the intervention effect is felt instantaneously but if $b \geq 1$ the intervention effect is felt after one period and so on) and

$$N_t = \frac{\theta(B)\epsilon_t}{\varphi(B)} \tag{2}$$

with $\varphi(B) = \phi(B)(1-B)^d$ where $\phi(B) = 1-\phi_1 B-\phi_2 B^2.....-\phi_p B^p$ and $\theta(B) = 1-\theta_1 B-\theta_2 B^2....-\theta_q B^q$.

Where θ is the Moving Average model parameters and φ is the Autoregressive model parameters. The impact of intervention of Free Maternal Health Care on infant mortality in this study is modeled as a step function given as

$$f_t = \frac{\omega(B)B^b}{\delta(B)} S_t^T \tag{3}$$

Where intervention impact with r+1 parameters is given as,

$$\omega(B) = \omega_0 + \omega_1 B + ... + \omega_r B^r \tag{4}$$

and the the slope at the point of intervention with s parameters has the form,

$$\delta(B) = 1 - \delta_1 B, -...., -\delta_s B^s \tag{5}$$

with r and s being non negative integers.

The presence of the denominator variable in the intervention component indicates whether or not the process returns to the pre-vent levels gradually or not. In this study the presence of a damping operator in the intervention component indicates that the infant mortality returns to pre-intervention time abruptly while the absence of the damping operator in the intervention component indicates that the infant mortality returns to pre-intervention time gradually, Box and Tiao[8]. The intervention ARIMA model was use in this study where the Box Jenkins modeling procedure was used to fit the models before and after intervention.

2 Literature Review

Okereke et.al [9] carried out a study on the impact of needs on inflation rate in Nigeria using the intervention ARIMA model where the resultant model was

$$X_t = \frac{4.521}{1 - 0.508B} l_t + 0.986 X_{t-1} \tag{6}$$

The study found that needs had significant negative effect on inflation rates in Nigeria and the effect was abrupt and temporary. The study applied intervention analysis on inflation data whereas the study under consideration applied the intervention ARIMA model on infant mortality data.

Su J. amd Deng G.[10] carried out a study on application of Intervention Analysis Model in Yu Ebao (monetary fund) Yield Prediction and found out that the effect of Niu's comment on decline in the yield was significant (0.148% decline in Yu Ebao's yield). The intervention model was given as

$$X_t = 6.774 - 0.013t + \frac{-0.014}{1 - 0.928B} S_t^T \tag{7}$$

The study applied intervention time series analysis on monetary fund data while the study under consideration sought to use intervention time series analysis on infant mortality data.

ITSA has not been applied much in public health data analysis. Moreover it has not been applied in Kenya in modeling infant mortality.

3 Materials and Methods

The infant mortality sample data was obtained from the Kakamega county Public Health office between January 2010 to December 2017 on monthly basis. The available data was that collected from all the health facilities in the county. The data was then subdivided into two:1) the pre-intervention data between January 2010 to June 2013; 2) the post intervention data between July 2013 and December 2017.

However the collected data had missing data for some months in the year 2010. These were intrapolated using the Zoo package in R software. The intervention component was then identified using the following intervention time series modeling procedure; Using the data before intervention to fit a model, Using the model fitted to the data before intervention to estimate the after intervention model,using the data after intervention to fit the after intervention model,obtaining the difference between the estimated intervention model and the actual intervention model and lastly Observing the later difference to obtain the intervention effect model, STAT 510[11]. In this study the Box Jenkins modeling procedure was used to fit both the models before and after the intervention,Box and Tiao[8]. Model identification was done using the sample ACF and sample PACF where the best fit was that regarded to have the minimum AIC, AICc and BIC. For parameter estimation the maximum likelihood method was used and the Box Ljung test and the residual ACF were analysed to check for non zero autocorrelations in the forecast errors as evidence for model adequacy, Box et.al[7]. In addition the forecasting performance of the models was compared using the Mean Absolute Error where the model with the minimum MAE was the best forecasting model for infant mortality data with intervention, Rob J.H.[12].

4 Results and Discussion

4.1 Model construction for infant mortality before and after intervention

In Fig. 1 and Fig. 2 below there is presence of non stationarity in the time series data which was accertained by the Augumented Dickey Fuller (ADF) test (Data before intervention;Dickey Fuller=-2.5577, Lag order=3, p-value=0.3538, Ha: Stationary and Data after intervention; Dickey Fuller=-2.256, Lag order=3, p-value=0.4714, Ha: Stationary). To stablize the time series differencing was carried out which helped in obtaining the order of differencing 'd'.

Fig. 3 and Fig. 4 provided sufficient evidence that the time series data before and after the intervention had been stationarized which was confirmed by the ADF test (Data before intervention; Dickey Fuller=-4.303, Lag order=3, p-value=0.01, Ha: Stationary and Data after intervention;Dickey Fuller=-4.2291, Lag order=3, p-value=0.01, Ha: Stationary).

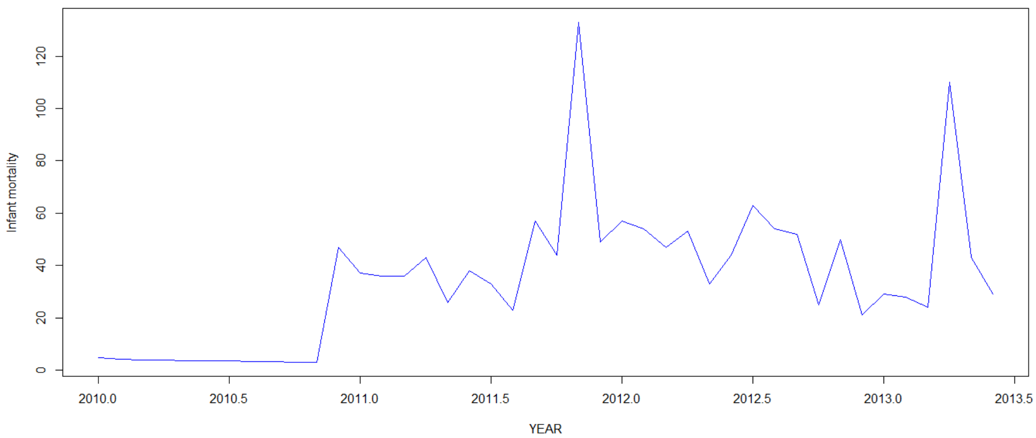

Fig. 1. Time series plot for the infant mortality data before intervention

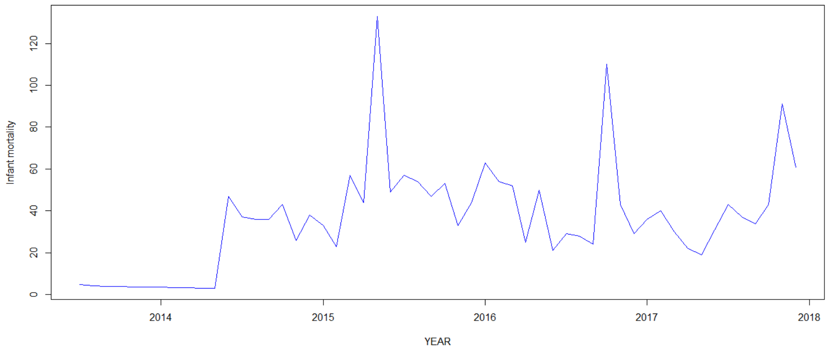

Fig. 2. Time series plot for the infant mortality data after intervention

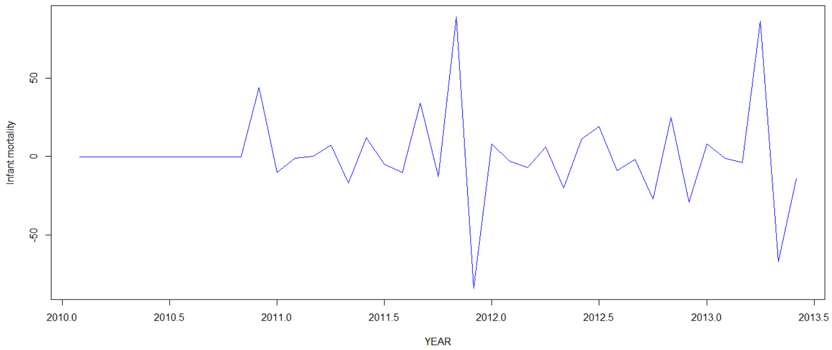

Fig. 3. Time series plot of the differenced infant mortality data before intervention

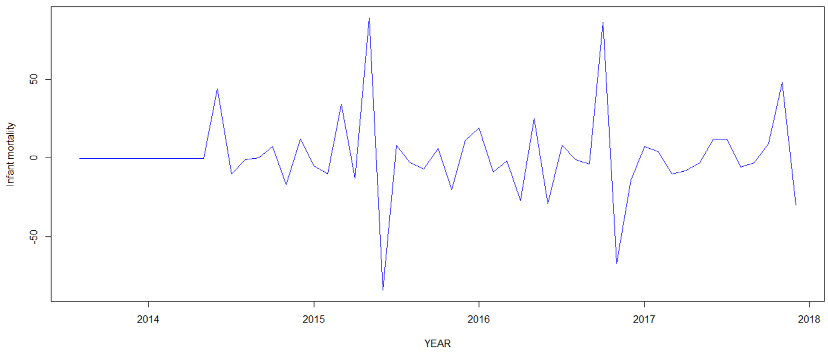

Fig. 4. Time series plot of the differenced infant mortality data after intervention

The ACF and PACF plots in Fig. 5 and Fig. 6 respectively were examined to obtain the order for AR and MA for the differenced infant mortality data before intervention. From the ACF plot the autocorrelation at lags 0 and 1 were significant while the others were within bounds. For PACF plot the autocorrelation was significant at lags 0 and 1 and tailed off after lag 1. This resulted to; ARMA(0,1), ARMA(1,0) and ARMA(1,1).

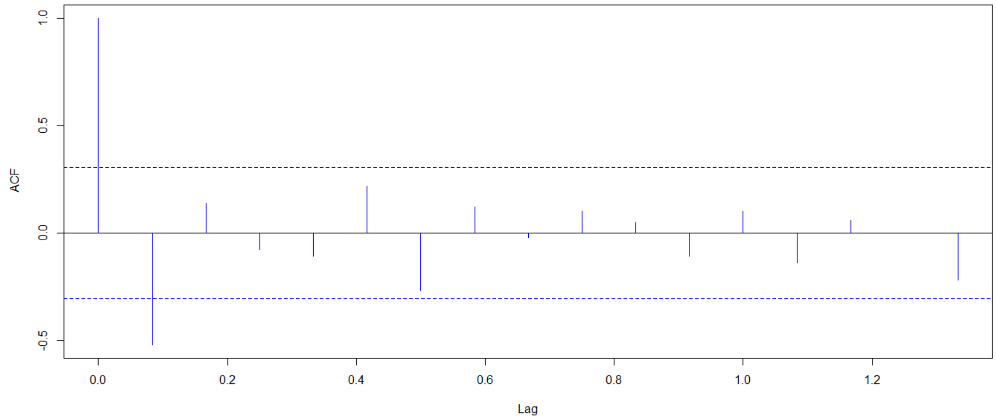

Fig. 5. The ACF plot

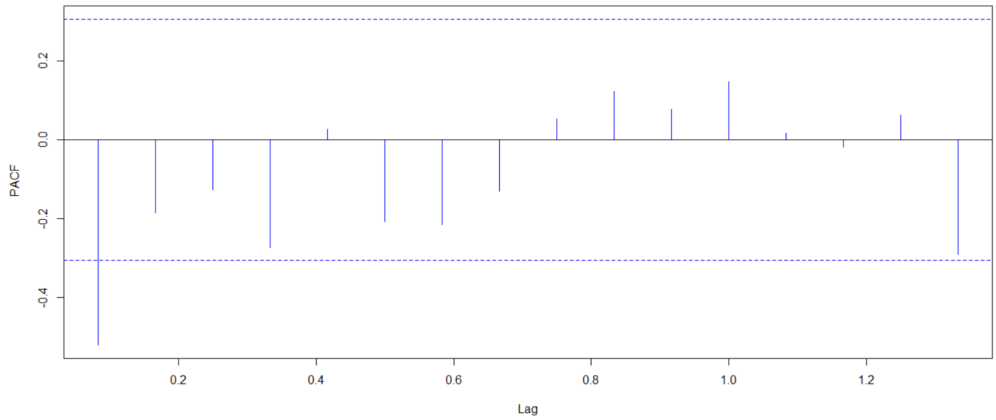

Fig. 6. The PACF plot

The ACF and PACF plots in Fig. 7 and Fig. 8 respectively were also examined to obtain the order for AR and MA for the differenced infant mortality data after intervention. From the ACF plot the autocorrelation were insignificant thus we tested for significance at lag 1. For PACF plot the autocorrelation were within the bounds but we tested for any significance at lags 1, 2 and 3. This resulted to; ARMA(0,1), ARMA(1,0), ARMA(1,1), ARMA(2,0), ARMA(2,1), ARMA(3,0) and ARMA(3,1).

Thus the model identified for before intervention was ARIMA(0,1,1) with AIC=369.82,AICc=370.47 and BIC=374.96 and which was the best forecasting model for future infant mortality data with

MAE=12.22501. Table 1 also shows that the after intervention ARIMA(1,1,1) with AIC=433.73, AICc=434.56 and BIC=441.61 was the best forecasting model for infant mortality data with a MAE=10.69036.

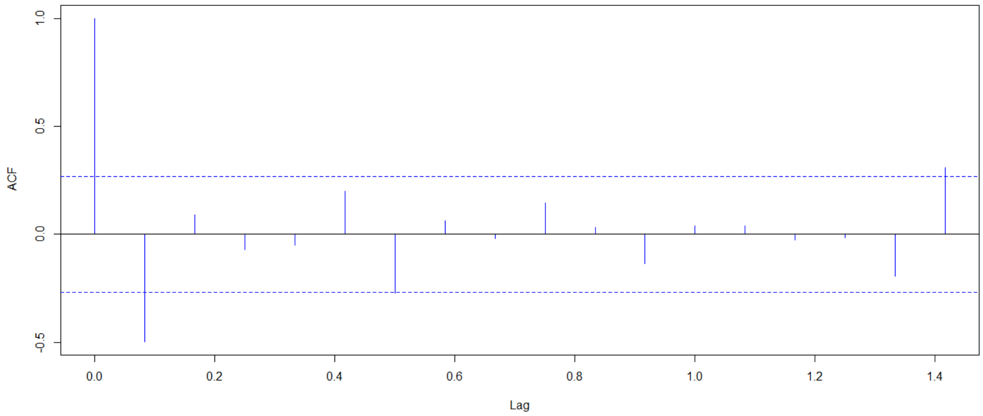

Fig. 7. The ACF plot

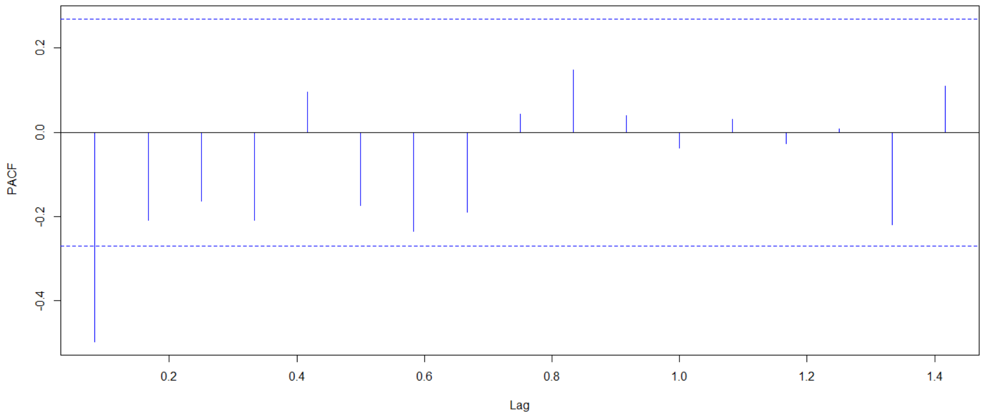

Fig. 8. The PACF plot

The correlogram for the before intervention ARIMA(0,1,1) model showed that none of the sample autocorrelations for lags 1-20 exceeded the significance bounds and the Box Ljung p-value =0.1982 was large, both suggesting that the residuals are white noise. In addition the correlogram for after intervention ARIMA(1,1,1) model indicated that none of the sample autocorrelations for lags 1-20 exceeded the significance bounds and the Box Ljung p-value =0.9049 was large both suggesting that the residuals are white noise.

Table 1. Model statistics

Model	AIC	AICc	BIC
Before intervention ARIMA(0,1,0)	429.16	429.26	430.85
ARIMA(0,1,1)	369.82	370.47	374.96
ARIMA(1,1,0)	398.1	398.43	401.48
ARIMA(1,1,1)	377.05	377.72	382.12
After intervention ARIMA(0,1,0)	480.72	480.8	482.67
ARIMA(0,1,1)	441.89	442.14	445.8
ARIMA(1,1,0)	468.26	468.51	472.16
ARIMA(1,1,1)	433.73	434.56	441.61
ARIMA(2,1,0)	460.13	460.63	465.99
ARIMA(2,1,1)	441.37	442.22	449.17
ARIMA(3,1,0)	453.95	454.8	461.75
ARIMA(3,1,1)	442.63	443.93	452.38

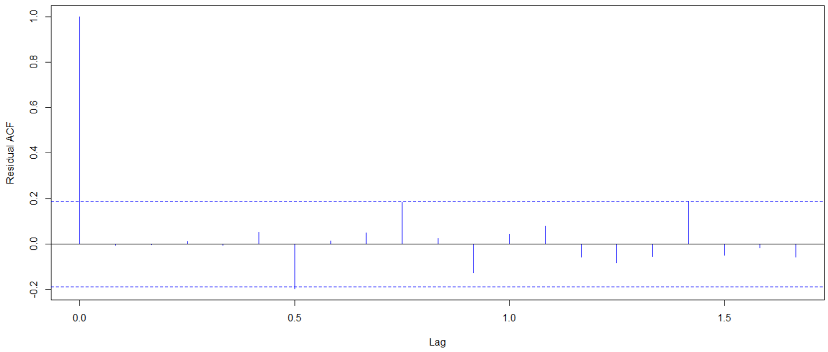

Fig. 9. The Residual ACF plot for ARIMA(0,1,1)

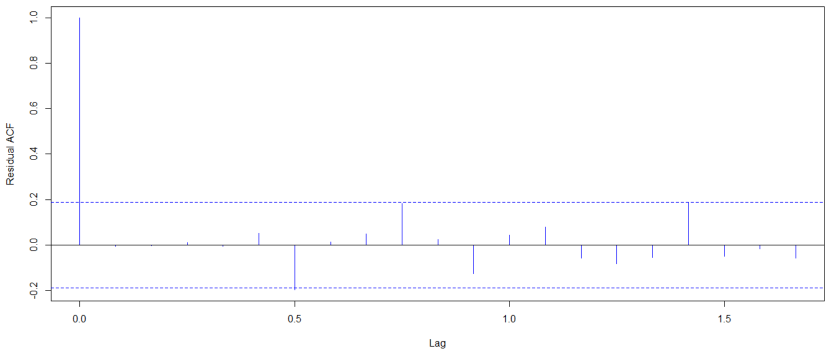

Fig. 10. The Residual PACF plot for ARIMA(1,1,1)

The before intervention model was given as

$$X_t = (1 - 0.7557B)\epsilon_t \quad (8)$$

while the after intervention model was

$$X_t = \frac{1 - 0.8600B}{1 - 0.5258B}\epsilon_t \tag{9}$$

4.2 Purified Series Model

The purified series model was fitted from a series of infant mortality data without putting the inclusion of the Free Maternal Health Care intervention. The model was given as

$$X_t = (1 - 0.6158B)\epsilon_t \tag{10}$$

With the model parameters being significant at 0.05 level of significance. Thus this implied that the model fitting was adequate. This model shows the residual variability in the purified series of infant mortality.

4.3 Intervention model construction

The intervention effect model was fitted from the intervention value obtained by getting the difference between the actual intervention data and the forecasts of the before intervention model ARIMA(0,1,1). The intervention effect model was

$$X_t = \frac{0.1015}{1 - B} \tag{11}$$

Where the intervention impact ω=0.1015 and δ was constrained as 1 so that there is a temporary change in infant mortality and that it falls back to the pre-intervention time after a given period of time. The model parameters were significant at 0.05 level of significance implying that the model fitting was adequate. The full intervention model was given by combining the intervention effect model and the purified series model as

$$X_t = \frac{0.1015}{1 - B} + (1 - 0.6158B)\epsilon_t \tag{12}$$

5 Conclusion

This study considered intervention Box Jenkins ARIMA model in assessing the impact of Free Maternal Health Care. Substantial evidence was obtained from the intervention time series analysis that Free Maternal Health Care has had a significant impact on infant mortality with a mean reduction of 10.15% infant deaths per month between July 2013 and December 2017. Model adequacy was checked using residual analysis which was intended to check for significance in autocorrelations at different time lags of the forecasting errors of the fitted model.

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Competing Interests

Authors have declared that no competing interests exist.

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