The short-term effect of the government of Ghana's decision to open borders at the early-onset of the COVID-19 pandemic

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ABSTRACT

Non-Pharmaceutical Interventions (NPI) are used in public health to mitigate the risk and impact of epidemics or pandemics in the absence of medical or pharmaceutical solutions. Prior to the release of vaccines, COVID-19 control solely depended on NPIs. The Government of Ghana after assessing early NPIs introduced at the early stage of the pandemic began to ease some restrictions by the opening of international borders with isolation and quarantine measures enforced. It was argued by some experts that this was a hasty decision. In this study, we assessed the impact of the opening of borders to ascertain if this action caused a surge or otherwise in cases in the country. Using data from the database on Africa's records of COVID-19 from the John Hopkins University, the Generalized Linear Model (GLM) time-series regression model for count data was applied to study effects in Ghana during a 4-month and 8-month period post-opening of borders. The study showed that after the decision of the government to open international borders, Ghana's expected case count declined by 72.01% in the 4-month period and 54.44% in the 8-month period. This gives an indication of the gradual reversal of the gains made due to the early implementation of NPIs. Notably, this may not only be attributed to the opening of borders but the relaxation of the strict enforcement measures that were put in place at the onset of the pandemic in Ghana. There is therefore the need for continuous enforcement of intervention measures to reduce case counts, particularly with the emergence of new COVID-19 virus strains. The study provides some recommendations for policy and improvements in model building such as developing better data collection system in Ghana, investigating more control variables, estimating the decaying effect of interventions, and ensuring better preparations prior to easing of public health restrictions.

Introduction

The absence of proven medical cure for Covid-19 virus at the early stages of the pandemic made the threat posed by the virus to all nations quite direr. The World Health Organization (WHO) in their first situational report on the Novel Coronavirus (2019-CoV) on January 21, 2020, reported 282 cases in four countries, namely, China, Thailand, Japan, and the

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Republic of Korea, indicating a spread into countries other than China in less than a month of the virus emerging [31]. Prior to the release of the vaccines in existence now, control of the COVID-19 solely depended on the enforcement of measures which are termed as Non-Pharmaceutical Interventions (NPI). These interventions are generally employed to reduce contact between the infected and uninfected persons. Examples of such measures include social distancing, isolation of suspected cases, quarantine of infected persons, avoiding overcrowding, school and workplace closures, among others. NPIs are effective where pharmaceutical and pharmacology are unavailable or cannot work in isolation. Notably, these measures are considered disruptive to the normal way of life and as such, it is highly recommended that countries weighed their impact before implementation. A strategy recommended by the WHO Director-General was for countries to test, detect, isolate, trace, and mobilize people to prevent cases so that they do not promote wide community spread [32].

Several studies have researched the effectiveness of NPIs in various jurisdictions [6,10,21,24,26]. For example, Bo [6] conducted a study on the effectiveness of NPIs to contain the time-varying reproductive number of the coronavirus disease in 190 countries between January 23, and April 13, 2020, while Silva [26] studied the effects of the lockdown implementation on the cases and deaths recorded in some regions of Brazil. Bonardi [7] researched how lockdown policies affect the spread and severity of COVID-19 in various countries. A recent study by Askitas et al. [5] assessed the impact of NPIs on COVID-19 incidence in over 175 countries highlighted the importance of focusing on restrictions that prevented mass gatherings rather than restrictions like travel control which ceased to be effective after a period. To access the effectiveness of lockdown policies on the incidence and mortality rates of COVID-19 in China, [24] conducted a similar study, specifically in Hubei and Guangdong provinces. The study showed the effectiveness of social distancing and suggested time periods for which effects are to be expected or otherwise escalate. In Ghana, [12] proposed a susceptible-infectious-quarantine-hospitalized-recovered-susceptible model to predict the trajectory of the pandemic to help in future planning purposes. Important in their finding were that cases and deaths were reduced with respect to the interventions introduced, however, interventions studied independently could not help reduce the reproductive number. This indicated the need for more well-coordinated interventions as they reduce the intensity of the spread of COVID-19 in Ghana. A study by [19], on Ghana's response to COVID-19, showed that although the partial lockdown was lifted in three weeks, post lockdown measures were strongly enforced to control the spread of the virus. The stance of managing the COVID-19 pandemic in poor urban neighbors was researched by [11] in the Accra and Johannesburg jurisdictions during the lockdowns periods. They found that most people in Accra and Johannesburg did not comply with government regulations during the citywide lockdown. However, the study showed that the challenge was not the willingness of the population to cooperate but the ability to do so. This lack of ability is attributed to a lack of space and infrastructure due to highly dense neighborhoods. Other published work by Asamoah et al. [3,4] and Acheampong, et al. [1] formulated compartmental mathematical models to study the dynamics of COVID-19 in Ghana, and evaluate optimal control measures as well as perform sensitivity analyses of these models. These modeling approaches are useful for informing effective intervention strategies by governments and policy-makers to reduce disease transmission and spread.

Afulani et. al[2]., studied the preparedness of Ghana to respond to the COVID-19 pandemic focusing on health care workers. They observe in their study that health care systems across Africa were generally limited due to debt, poor governance, and economic instability. Bukari et al. [9] studied the impact of COVID-19 on poverty and living standards in Ghana, and Iddi et al. [18] focused on coping strategies of individuals during the COVID-19 pandemic and the period of lockdown in Ghana. Many other researchers have attempted to investigate virus strains. A typical example of such a study was by the West African Centre for Cell Biology of Infectious Pathogens (WACCBIP) with assistance from the Noguchi Memorial Institute for Medical Research (NMIMR) at the University of Ghana. They sequenced genomes of the SARS-Cov-2 virus to obtain information about the genetic composition of the virus in some confirmed cases in Ghana. This was an important achievement as it was a means to track and observe mutations of the virus and discover if any novel variations have been produced locally [29]. Owusu et al. [25], contributed to research on COVID-19 by providing a detailed epidemiological profile of cases in Ghana. The study described the socio-demographic features and patterns of COVID-19 spread and dynamics of the virus of persons residing in the northern, middle, and part of the southern parts of the country.

Ghana was one of the first countries in sub-Saharan Africa to begin enforcement of WHO's COVID-19 recommended social interventions. After the first reported cases of COVID-19 in the country on March 12, 2020, Ghana began implementation of social distancing, border closure, and partial lockdown on March 16, March 23, and March 30, 2020, respectively as the cases started to soar. To strengthen the initial restrictions, a legal act, Imposition of Restriction Acts 2020 (Act 1012) was gazetted on the 21st of March 2020 to further pose as a deterrent for non-compliance with restrictions imposed. Offenders were liable to payments of fine, not less than one thousand penalty units and not more than five thousand penalty units or a term of imprisonment of not less than four years and not more than ten years [17].

As these interventions run simultaneously, cases began to go higher until the country started experiencing some decline between August and September 2020. The government after assessing the situation announced the easing of some restrictions by the opening of borders to international flights with isolation and quarantine measures enforced. While some experts argued that the decision of the government could be catastrophic, the government insisted that the decision was taken after careful consultation with experts. It is important to assess the impact of the opening of the border to ascertain if this government action caused a surge or otherwise in cases after the gains the country began to experience due to earlier implementation of NPIs. The main objective of this study was therefore to assess the effectiveness of the critical government decision of the opening of borders on the spread of COVID-19 in Ghana. Given that the observed data was a time-series,

Table 1
Pre-post Opening number of time points (in days) for the two periods.

	March - December, 2020	March, 2020 - April, 2021
Pre-opening	171	171
Post-opening	122	242

time-series methodology was employed. Specifically, we employed a generalized linear model time-series regression model. The version of this model to assess the effect of intervention through segmentation of time was used.

As threats to public health are endless, having continuous research into measures that can contribute to making more informed decisions is extremely relevant. Informed decisions should be based not just on rhetoric but on substantial evidence which research provides. Just as COVID-19 took the world by surprise revealing many loopholes in the country's health care systems, this study amongst others aids in ensuring preparedness for unforeseen future outbreaks.

The rest of the paper is organized as follows. Section 2 describes the data and the source of data. Section 3 contains description of the statistical methodology employed in this research. Exploratory and further analyses are conducted in Section 4. Section 5 contains the discussions, concluding remarks, and recommendations.

Data source, description, and ethics

The data used for this study was obtained from the COVID-19 database compiled by the John Hopkins University. The data was acquired from the website: https://raw.githubusercontent.com/CSSEGISandData/COVID-19/master/csse_covid_19_data/csse_covid_19_time_series/time_series_covid19_confirmed_global.csv. In line with the objective of the study, we used data on Ghana's daily case count of COVID-19. The data set included the date of record, the number of confirmed cases, and the cumulative case count from March 15, 2020 to April 30, 2021.

The analysis focused on two defined periods, namely from the first reported cases until the end of the year 2020 and the period going until April 2021. The total number of time points for both pre- and post-opening of borders for the two periods are given in Table 1.

Since the data is publicly available, we did not require ethical approval for its use.

Methodology

There are several methodologies commonly and frequently used to conduct intervention analysis. Of particular mention are the Box-Jenkins approach of Autoregressive integrated moving averages (ARIMA) modeling [8], the extended logistic regression model [20], segmented regression for interrupted time-series [16,27,30], and several extensions to these models [13,14,23]. In this study, we employed the generalized linear model for time-series intervention analysis for count outcomes.

A time-series data is a collection of a sequence of observations taken at successive points in time. Observations may be in many forms such as continuous, count, or binary. Statistical models used for the analysis of time series are designed to reflect the dependencies that are inherent in time-series. Time-series methodology for continuous responses are quite common. In recent times, the ideas for continuous type data have been extended for time-series count data, under the generalized linear model framework. The model relates the conditional mean of the count time-series to past observations of the response, past conditional means, and covariates. To formulate the model, we define a set $P = i_1, i_2, \ldots, i_p$ and integers $0 < i_1 < i_2 < \ldots < i_p < \infty$ with $p \in \mathbb{N}_0$ which allows to regress on lagged observations, $Y_{t-i_1}, Y_{t-i_2}, \ldots, Y_{t-i_p}$. Similarly with a set $Q = j_1, j_2, \ldots, j_q$ and integers $0 < j_1 < j_2 < \ldots < j_p < \infty$ with $q \in \mathbb{N}_0$ the model regress on lagged conditional means, $\mu_{t-j_1}, \mu_{t-j_2}, \ldots, \mu_{t-j_q}$. The general form of models is posited as:

$$g(\mu_t) = \beta_0 + \sum_{k=1}^{p} \beta_k \tilde{g}(Y_{t-i_k}) + \sum_{l=1}^{q} \alpha_l g(\mu_{t-j_l}) + \eta^T X_t \tag{1}$$

where $g : \mathbb{R}^+ \to \mathbb{R}$ is the link function and $\tilde{g} : \mathbb{N}_0 \to \mathbb{R}$ is the transformation function. The vector η^T corresponds to the covariate effects with X_t being the covariate process. The parameters, $\alpha_1, \ldots, \alpha_l$ and $\beta_0, \ldots, \beta_k$ are the regression coefficients that explain the size of the effect on the response variable [22]. Apart from extending the model to include covariates, the model can be used to assess the effects of an intervention introduced in the course of the time series. This can be done by introducing a deterministic covariate of form $\delta^{t-\tau} (t > \tau)$, where τ is the time of occurrence and δ is the rate of decay which is a known constant. Fakianos et. al [15]., developed a model that included the effects of a process on the linear model when an intervention is included. The linear predictor with some s types of interventions according to parameters $\delta_1, \ldots, \delta_s$ occurring at time points $\tau_1, \ldots, \tau_s$ is given as

$$g(\mu_t) = \beta_0 + \sum_{k=1}^{p} \beta_k \tilde{g}(Y_{t-i_k}) + \sum_{l}^{q} \alpha_l g(\mu_{t-j_l}) + \eta^T X_t + \sum_{m=1}^{s} \omega_m \delta_m^{t-\tau_m} I(t \geq \tau_m) \tag{2}$$
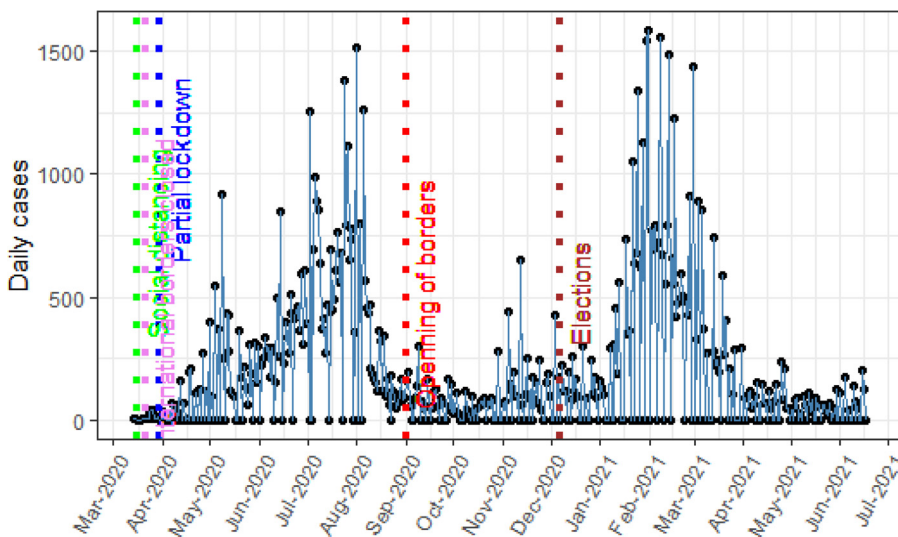
Fig. 1. Time Plot of Ghana's Daily COVID-19 Cases.

The effect of the intervention is tested by testing if the coefficient ω_m is different from zero. The value of δ_m determines different types of intervention effect. For example, $\delta = 1$, represents a permanent change of location (level shift) of the intervention, and values ranging from $(0,1)$ indicate an exponentially decaying change in location.

For count data, the random variable $Y_t|F_{t-1}$ is assumed to follow either a Poisson or negative binomial (NB) distribution. In both cases, the log-link function is used as the link function. For example, assuming $Y_t|F_{t-1} \sim Poisson(\mu_t)$, then equation (2) becomes

$$\log(\mu_t) = \beta_0 + \sum_{k=1}^{p} \beta_k \log(Y_{t-i_k}) + \sum_{l}^{q} \alpha_l \log(\mu_{t-j_l}) + \eta^T X_t + \sum_{m=1}^{s} \omega_m \delta_m^{t-\tau_m} I(t \geq \tau_m) \tag{3}$$

The maximum likelihood estimation (MLE) was adopted for estimating the model parameters. A vector of the regression parameters is denoted by $\theta = (\beta_1, \ldots, \beta_k, \alpha_1, \ldots, \alpha_l, \eta_1, \ldots, \eta_r, \omega_1, \ldots, \omega_s)^T$ and is estimated by the conditional maximum likelihood $\hat{\theta}_n$, which is obtained by

$$\hat{\theta}_n = arg \, max_{\theta \in \Theta} \ell(\theta; Y_t) \tag{4}$$

For the case where the observed time series $(Y_1, \ldots, Y_n)^T$ follows the Poisson distribution, the conditional log-likelihood function is given by

$$\ell(\theta; Y_t) = \sum_{t=1}^{n} [Y_t \ln \mu_t(\theta) - \mu_t(\theta) - \ln(Y_t)]. \tag{5}$$

The Akaike Information Criterion (AIC) is good way to assess model adequacy. The AIC is computed by

$$AIC = -2\ell(\hat{\theta}; Y_t) + 2m \tag{6}$$

where m is the total number of parameters in the model and n is the sample size. Usually, models with the smallest AIC are preferred.

To determine an appropriate GLM time-series model for our data, we considered both the Poisson and Negative Binomial distribution for the count outcome. Diagnostics analyses such as the test for serial dependency are performed to check for appropriateness of the models. Marginal calibration approach, scoring techniques, and AIC is used to aid in the selection of the best-fitting model to the data. Furthermore, appropriate lag-effects for both past observation and past conditional means are determined and the intervention effect assessed on the selected model. These procedures are followed for determining the border opening effect across the two periods.

Data analysis

Exploratory analysis

We begin the analysis by exploring the data for trends and patterns. The plot in Fig. 1 shows the trend of the time series of Ghana's daily case count along with government interventions that were implemented at various time points.
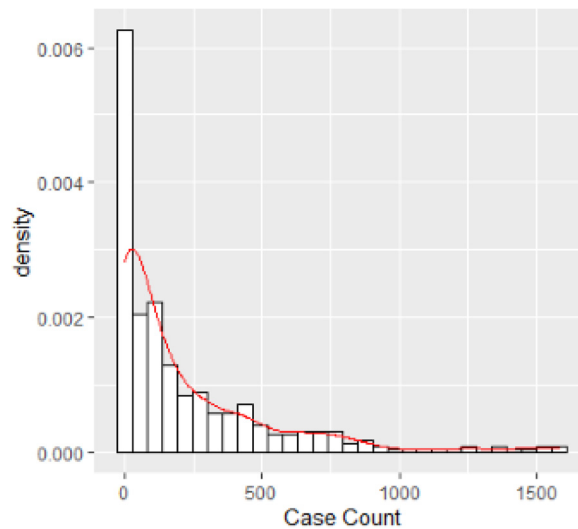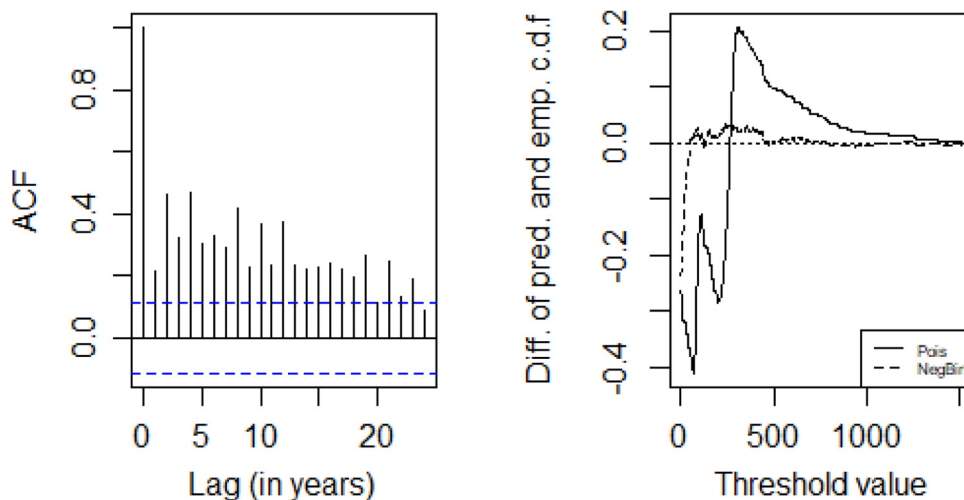
Fig. 2. Histogram of Observed Data.

Fig. 3. Serial dependence and Calibration Diagnostic.

Fretheim et al. [16], recommended that a minimum of 50-time points is required before and after implementation of interventions to conduct an intervention analysis. In the light of this, we observed that interventions such as social distancing, closure of borders, and partial lockdown occurred very early in the pandemic and so there was insufficient pre-intervention data to conduct meaningful inference. Therefore, this study focused on studying the impact of the opening of air border on the COVID-19 case count.

A visualization of the data using a histogram of the case count is shown in Fig. 2. The histogram clearly shows that the data is not normally distributed. The plot can be said to be right-skewed which is very common with Poisson distributed data. Further checks on the plausibility of this distribution are carried out in the next section.

Further analysis

Selecting the best distributional assumption

The first step in our model building process was to check for serial dependency. We expected a lack of independence to motivate the use of the Poisson or negative binomial series models. An autocorrelation function (ACF) plot was examined together with a formal test of independence using the Durbin-Watson test. The ACF plot in Fig. 3 showed that there was serial dependence (autocorrelation which is common in count data) in the residuals of the suggested negative binomial and Poisson models for the response variable.

The follow-up Durbin-Watson test gives a statistic < 2 which indicates the existence of positive autocorrelation in the residuals of both the Poisson (Value $= 1.5761$) and NB (Value $= 1.8856$) models.

Table 2

Scoring Rules for Poisson and Negative Binomial.

	logarithmic	quadratic	spherical	rankprob	dawseb	normsq	sqerror
Poisson		0.017	− 0.009	201.283	439.942	434.542	95,248.990
NegBin	5.769	− 0.026	− 0.204	134.987	12.508	0.993	95,248.990

Table 3

Time Series GLM coefficient of Poisson against Negative Binomial.

Distribution	Cases Recorded	Estimate	Std.Error	CI(lower)	CI(upper)
Neg-Binomial	Intercept(β_0)	5.4002	0.1564	5.0937	5.7068
	Lagged past values(β_1)	0.0377	0.0278	-0.0168	0.0922
	Lagged conditional mean(α_1)	-0.2384	0.1444	-0.5215	0.0446
	Overdispersion(σ^2)	2.0431			
Poisson	Intercept(β_0)	5.4002	0.0074	5.3858	5.4147
	Lagged past values(β_1)	0.0377	0.0066	-0.2514	-0.2254
	Lagged conditional mean(α_1)	-0.2384	0.0066	-0.2514	-0.2254

Table 4

Bootstrapping standard errors for NB time-series model.

	Estimate	Std.Error	CI(lower)	CI(upper)
Intercept(β_0)	5.400	0.203	5.000	5.743
Lagged past values(β_1)	0.038	0.039	-0.031	0.112
Lagged conditional mean(α_1)	-0.238	0.144	-0.502	0.059
Overdispersion(σ^2)	2.043	0.238	1.602	2.595

Next, marginal calibration and scoring methods were carried out to investigate which of the two distributions were appropriate for the data. From Fig. 3, the plot of marginal calibration points to the fact that the negative binomial was much better choice than the Poisson in terms of predictability. This is shown by the closeness of the plot to the zero lines. However, this observation was inconclusive, and therefore we employed the use of scoring techniques to help provide numerical evidence. The results of the scoring method as shown in Table 2 suggested that the negative binomial was a better approximation as it has much lesser estimates compared to that of the Poisson. The normal square error was again close to one(1) showing that the Negative Binomial model was much adequate and preferable for predictive purposes.

Furthermore, we examined the fit for the two distributions by modeling the count as time series GLM assuming both a Poisson and Negative Binomial distributions with a log-link. The results of the model fits are shown in Table 3.

From the results, the negative binomial includes a coefficient σ^2 that gives information on the overdispersion parameter. Failure to account for overdispersion, when present, results in bias and underestimation of precision. Notably, we observed that the parameter estimates are quite similar between the two models, however, the Poisson version underestimates precision in terms of having smaller standard errors. Note further that, because there are no analytical approximation for the dispersion parameter, the standard errors of the overdispersed parameter are not available from the results in Table 3. An approach to obtain a precision estimate for the overdispersed parameter was to apply the bootstrap method [22]. We applied a parametric bootstrap method to obtain the standard error estimates. From the estimates in Table 4, we observed that the overdispersion parameter was significant, indicating that it can not be excluded from the model. Thus, we observed that all diagnosis analyses support the use of the NB distribution as appropriate to model the count series and for testing the effect of the opening of borders in subsequent analyses.

Determination of lagged effects

Typically, the effects of intervention may not be immediate and have some lagged effects. This was implicitly indicated by the results of serial dependence. Taking the number of days (14 days) one can be infectious when they have COVID, we tested for the most significant lag effect that will help make the best prediction of the impact of the intervention, by modeling a log-linear at all the time periods and using the AIC selection criteria to select the model with the best fit. Table 5, shows the AIC values for the different lags to the 14th order. The value written as (1,5) is interpreted as estimates of the regression on the previous observation (first-order correlation) and regression on the values of the conditional mean five units back in time. The model of best fit was that which had the lowest AIC value.

It was observed that for the model covering the period until December 2020, effects of past conditional mean was expected at the 12th lag while effects of the past conditional mean was expected at lag 10 for the model using data up until April 2021. Therefore we carried out all subsequent analyses with a lag of 12 and 10 effects, respectively.

Table 5
AIC values for different lagged models.

AIC values		
Lagged period	Cases until Dec 2020 (Case 1)	Cases until April 2021 (Case 2)
(1)	3389.292	4773.072
(1,2)	3328.512	4736.477
(1,3)	3372.888	4750.099
(1,4)	3340.952	4686.495
(1,5)	3394.79	4755.2
(1,6)	3322.245	4681.836
(1,7)	3369.113	4744.682
(1,8)	3360.102	4733.716
(1,9)	3357.95	4753.079
(1,10)	3319.748	**4672.01**
(1,11)	3392.952	4753.252
(1,12)	**3307.889**	4711.801
(1,13)	3382.966	4768.241
(1,14)	3377.29	4755.916

Table 6
Coefficients of the Time Series Log-linear GLM model.

Period	Cases Recorded	Estimate	Std.Error	CI(lower)	CI(upper)
	Intercept(β_0)	4.8318	0.2260	4.3889	5.2747
Cases until	Lagged past value(β_1)	0.0005	0.0385	-0.0749	0.0760
Dec 2020	Lagged conditional mean(α_{12})	0.1550	0.0377	0.0812	0.2289
(Case 1)	Time-trend(η_1)	0.0053	0.0037	-0.0019	0.0125
	Border Decision (ω)	-1.2734	0.2783	-1.8188	-0.7279
	Overdispersion(σ^2)	1.8481			
	Intercept(β_0)	4.8432	0.2141	4.4236	5.2629
Cases until	Lagged past value(β_1)	0.0186	0.0315	-0.0432	0.0803
Apr 2021	Lagged conditional mean(α_{10})	0.1395	0.0309	0.0789	0.2000
(Case 2)	Time-trend(η_1)	0.0047	0.0015	0.0018	0.0077
	Border Decision (ω)	-0.7861	0.2433	-1.2629	-0.3093
	Overdispersion(σ^2)	2.2813			

Assessing the effect of the opening of borders

Next, we investigated the effects of the opening of international borders on case count COVID-19 in Ghana. We defined an indicator for the opening of international borders. This variable was coded '0' for the periods when borders were closed, and '1' when borders were open (level shift). The decision of the government to open borders was treated as the 'intervention' and time trend treated as a covariate in the time series GLM model with lag for the observation and conditional mean count as determined earlier.

Table 6 shows the results of the model fit. From this result, we specify the time-series log-linear model for the 4 month period till December 2020, $Y_t|F_{-1} \sim NegBin(\mu_t)$ as

$$log(\mu_t) = 4.8318 + 0.0005Y_{t-1} + 0.1550\mu_{t-12} + 0.0053X_{1t} - 1.2734 \times I(t \geq \tau)$$

and that of the 8 month period to be

$$log(\mu_t) = 4.8432 + 0.0186Y_{t-1} + 0.1395\mu_{t-10} + 0.0047X_{1t} - 0.7861 \times I(t \geq \tau)$$

The time-trend, (η_1), showed that in the short term period of 4-months, a unit increase in time has 0.53% influence on the rise of cases experienced after the decision to open the international borders. In Case 2, a unit increase in time increased expected number of cases by 0.47%. These indicated that, over time, cases have decreased marginally. The border opening effect, ω in the 4-month period was -1.2734 which gives an exponential value of 0.2799. This indicated that we witnessed about a 72.01% reduction in cases recorded after the opening of international borders. The long-period effect gave a factor of 0.4556. This showed that in the long term, we experienced a 54.44% reduction in cases after the opening of borders. So whereas the reduction was relatively higher in the short period (4 months), there was a dip in the rate of reduction for the longer period (8 months) post opening of borders. This indicated a gradual reversal of the gains due to the early introduction of NPIs in Ghana.

Discussion and conclusions

The easing of restrictions, specifically the opening of international borders of Ghana on September 1, 2020, saw the Ministries of Information, Health and Aviation, and respective agencies spell out measures to be taken, including the compulsory

possession of negative PCR test results from the country of origin [28], to mitigate the impact of such a critical government decision. Despite this, data showed spikes in COVID-19 cases particularly towards the December 2020 elections.

In this research, we studied the effect of the opening of the borders on the COVID-19 case count in Ghana. The data was modeled using a negative binomial time-series GLM model. Data from March 2020 to December 2020, and also up to April 2021 were considered. For both time periods, we find that the opening of borders on September 1st, 2020, was a significant predictor in the daily case count of COVID-19 recorded in the country. The impact of critical decisions such as non-pharmaceutical interventions, on infectious diseases often do not take immediate effect. The study identified 12 and 10-day lag effects when the data was analyzed considering the period between onset of reported cases and end of the year 2020, and when analyzed from onset to the end of April 2021, respectively. A unit change in time resulted in a marginal decline in the expected case count across both periods. The period after the opening of borders saw a reduction in the number of reported cases, for both periods studied. The rate of the decline reduced for the extended period, an indication that the opening of borders was beginning to show negative repercussions. This could also be due to the effect of the increase in political activities towards the December 2020 elections.

In summary, this study showed that earlier intervention measures were somewhat effective and informed the government decision to open borders. The government's desire to mitigate the economic impact of the pandemic also motivated this critical move. However, the relaxation of the strict enforcement measures explains the waning of impact gained by these earlier interventions. It is therefore important for continuous enforcement of interventions enacted at the onset and in the course of the pandemic to reap desire benefits. This research is therefore relevant as it can guide policies during future outbreaks in the country.

This scope of this research did not cover investigating the individual effect of NPIs such as social distancing, closing of borders, partial lockdown, etc. due to the insufficient pre-intervention data points. We assumed in this study that these interventions were having a positive effect, informed by the decline in cases prior to the opening of international borders. This might be a strong assumption that can be investigated further. The study is also limited in that it did not control for other important factors such as mobility, climatic and economic indicators. We emphasize the need to develop and establish good databases in the country for impactful statistical analyses to inform decision-making. Given that the objective of this study was inferential and not forecasting, the choice of the best fitting model or model validation was based on an in-sample approach using AIC. For studies targeted at predicting cases, an out-of-sample model validation approach could be used to check for the best predictive model. Finally, we recommend future studies to explore other approaches that finds δ_m, the decaying effect, that may reflects a different data-driven behaviour of the 'intervention' either than a level shift.

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Declaration of Competing Interest

The authors have no competing interests to declare.

CRediT authorship contribution statement

Karen N.B. Clottey: Conceptualization, Data curation, Methodology, Formal analysis, Writing – original draft, Writing – review & editing. **Godwin Debrah:** Supervision, Writing – review & editing, Validation. **Louis Asiedu:** Methodology, Supervision, Writing – review & editing. **Samuel Iddi:** Conceptualization, Supervision, Methodology, Validation, Writing – review & editing.

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