Exploring the Impact of Government Interventions on COVID-19 Pandemic Spread in Kuwait

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ABSTRACT

To model the trajectory of the pandemic in Kuwait from February 24, 2020 to February 28, 2021, the authors used two modeling procedures—auto regressive integrated moving average (ARIMA) with structural breaks and multivariate adaptive regression splines (MARS)—and then mapped the key breakpoints of the models to the set of government-enforced interventions. The MARS model, as opposed to the ARIMA model, provides a more precise interpretation of the intervention's effects. It demonstrates that partial and total lockdown interventions were highly effective in reducing the number of confirmed cases. When some interventions, such as enforcing regional curfews, closing workplaces, and imposing travel restrictions, were combined, their impact became significant. MARS method is recommended when exploring the impact of interventions on the spread of a disease. It does not require any prior assumptions about the statistical distribution of data, does not affect data collinearity, has simple and transparent functions, and allows for a more accurate analysis of intervention results.

KEYWORDS

ARIMA, COVID-19, Interrupted Time Series, Interventional Analysis, MARS Modeling, Precautionary Measures

1. INTRODUCTION

After the first novel coronavirus infection case was detected in Wuhan, China, in December 2019 (Zhu et al., 2020), the virus widely and rapidly spread across the world, leading the World Health Organization (WHO) to declare COVID-19 a pandemic on March 11, 2020 (Cucinotta & Vanelli, 2020). Since then, the pandemic has become the most serious challenge for human societies and has negatively affected the world's healthcare and financial systems (McKibbin & Fernando, 2020). By May 20, 2021, more than 165 million confirmed cases and 3.4 million deaths were reported globally (WHO Coronavirus Disease [COVID-19] Dashboard, 2021).

To slow down the spread of the virus and relieve health systems, health authorities adopted clinical practices, such as applying robust testing programs and, lately, speeding up vaccination. In addition, government authorities enforced physical nonpharmaceutical interventions (NPIs) and measures, such as mask-wearing, social distancing, quarantines, and lockdowns. However, applying these measures for long periods of time have social and economic consequences, such as high unemployment rates and bankruptcy (Policy Brief, 2020).

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Kuwait started to suffer from the COVID-19 pandemic after its first infection case was detected on February 24, 2020. Since then, the government of Kuwait has enforced several precautionary measures, including banning flights; closing workplaces, schools, and shopping malls; and applying total and partial lockdowns. As of May 20, 2021, Kuwait reported 295,861 confirmed infections, 281,920 recovered cases, and 1,711 deaths (WHO Coronavirus Disease [COVID-19] Dashboard, 2021).

Several studies have shown that interventions considered by health and government authorities are important and effective in controlling previous outbreaks (Leach, 2008; World Health Organization, Food and Agriculture Organization of the United Nations & United Nations Children's Fund [UNICEF], 2012; Funk et al. 2017; Turner et al., 2020; Bernal et al., 2017). The interrupted time series (ITS) study design was widely and successfully used in some of these studies (Turner et al., 2020; Bernal et al., 2017). Several research studies used various statistical techniques to explore the impact of government precautionary measures on the spread of COVID-19 in different countries, such as China (Al-Rousan & Al-Najjar, 2020), the UK (Ferguson et al., 2020), the US (Ferguson et al., 2020), Taiwan (Hsieh et al., 2020), Bahrain (Al Dallal et al., 2021), and Kuwait (Almeshal et al., 2020). These studies considered the pandemic at its early stage when its trajectory had a single wave. Therefore, it is not clear whether the same techniques are still applicable for analyzing current pandemic trajectories that contain multiple waves. In addition, the study of the case in Kuwait (Almeshal et al., 2020) only considered government precautionary measures enforced during the early pandemic days.

The present paper analyzes the impact of precautionary measures enforced since the beginning of the pandemic until February 28, 2021, on the spread of COVID-19 in Kuwait. During this period, the pandemic in Kuwait went through several subwaves. We used two modeling procedures: autoregressive integrated moving average (ARIMA) and multivariate adaptive regression splines (MARS). The models were constructed and compared, and the interpretation of their relationship to the precautionary measures were highlighted. The findings showed that some of the precautionary measures, such as complete lockdowns, were significantly effective in reducing the number of confirmed cases (referred to as "Cases" in the rest of this paper), thus containing the disease's spread. Other precautionary measures, such as partial lockdowns and travel restrictions, became effective only when they were combined. The findings showed that opening interventions caused the disease to resurface. Precautionary measures, such as a strict quarantine for arriving travelers, were found to be effective in preventing COVID-19's spread. The ARIMA model was found to be slightly better than the MARS model in terms of quality of fit measures. The results, however, showed that the latter model provided a more accurate interpretation of the interventions' effects.

The remainder of this paper is organized as follows. Section 2 provides an overview of the related work. Section 3 explains the applied methodology. Section 4 discusses the relationship between the trajectory of the pandemic, in terms of the number of cases, and the enforced interventions. Section 5 discusses the results of the two modeling procedures applied. Finally, in Section 6, we present the conclusions.

2. RELATED WORK

In this section, we review related literature on exploring the impact of precautionary measures on containing the spread of COVID-19. We provide an overview of the statistical techniques applied in this research.

2.1. Literature Review

Several studies investigated the effect of enforced precautionary measures on the spread of COVID-19. Al-Rousan and Al-Najjar (2020) applied time series forecasting models, including ARIMA, simple, Holt, and Brown, to model the pandemic in China and assess the impact of government interventions on containing the spread of COVID-19. The results showed that the growth rate for new infections

decreased from 4.43% to 2.64% after applying the government interventions, and the growth rate for recovered cases increased from 3.86% to 4.91%.

Ferguson et al. (2020) used models previously used to model the spread of influenza pandemic to explore the effect of several NPIs on reducing the level of demand on the healthcare system and the number of deaths caused by COVID-19 in the UK and the US. They found that the impact of NPIs on reducing the number of predicted deaths is limited when the NPIs are considered individually and significant when they are considered in combination. A study of the COVID-19 pandemic in Taiwan showed that the NPIs reduced the respiratory disease cases by 50% (Hsieh et al., 2020).

Al Dallal et al. (2021) proposed a methodology that considers the percentage of change in the values of the daily estimated reproduction number and the percentage of change in the number of performed tests before and after applying a precautionary measure. The methodology was considered to explore the impact of the precautionary measures applied and religious occasions celebrated in the Kingdom of Bahrain on the spread of COVID-19 pandemic. The results showed that most of the enforced precautionary measures were effective in reducing the spread of the disease by a percentage ranging from 20.2% to 41.8%, whereas a religious occasion involving large gatherings caused the spread of the disease to increase by 28.7%.

Almeshal et al. (2020) used compartmental and logistic regression models to predict the pandemic's future trajectory in Kuwait and to assess the effectiveness of the Kuwait government's interventions on containing the spread of the virus for a relatively short period of time from February 24, 2020, to April 19, 2020. To study the impact of an intervention, the authors applied their prediction models with and without considering the cases reported after the intervention. They also compared the prediction results in terms of the estimated pandemic size and end dates.

Vokó and Pitter (2020) used the ITS analysis to explore the impact of social distance measures implemented in 28 European countries on the spread of COVID-19. The results proved that social distancing meaningfully contributed to containing the spread of COVID-19 in Europe.

2.2. Applied Statistical Techniques

In this section, we provide a brief overview of some of the statistical methods on which our proposed models are based.

2.2.1. ARIMA Models

ARIMA is a model used to understand past data or predict future data in a time series (Tandon et al., 2020). The response variable Y_t is measured at regular intervals (minute, hour, day, month, etc.). A univariate time series uses only previous values in times (Y_{t-1}) to predict future values, whereas the series is a multivariate when other predictors are included in the model. The term “autoregression” (AR) refers to a model that regresses the dependent variable on its own lagged or past values. The difference between raw observations is represented by integrated (I). To make it stationary, data values are replaced by the difference between the data values and the previous values. A stationary model demonstrates that the data are consistent over time. The moving average (MA) denotes that forecasting errors are linear functions of previous errors.

An ARIMA(p,d,q) is a standard notation for a nonseasonal ARIMA, where p (lag order) is the number of lag observations, d is the number of times that the raw observations are differenced, and q is the order of the MA. The steps for fitting an ARIMA model to a (nonseasonal) time series data (PennState, 2021) are as follows: Identify any outliers by plotting the data first and then using a Box–Cox transformation to stabilize the variance if necessary. The Box–Cox method considers a family of transformations on a strictly positive response variable and is defined as

$$g_{\lambda}(y) = \begin{cases} \frac{y^{\lambda} - 1}{\lambda} & \lambda \neq 0 \\ \log(y) & \lambda = 0 \end{cases} \quad (1)$$

The λ parameter is chosen by maximizing the log-likelihood,

$$L(\lambda) = -\frac{n}{2} \log(RSS_{\lambda} / n) + (\lambda - 1) \sum \log(y_i), \quad (2)$$

where RSS is the residual sum of squares and log is the natural logarithm.

If the time series is nonstationary, take the first differences and repeat differencing as needed until the data become stationary. The autocorrelation function (ACF) and partial autocorrelation function (PACF) plots are used to examine the series' residual time errors. Out of the appropriate models found, select the best model based on the Akaike information criterion (AIC). The final model can be used for forecasting. The “auto.arima” procedure does not cover all of these steps, and a manual check must therefore be considered. For a seasonal time series, the data should be corrected to reflect the differences between the seasons.

2.2.2. MARS Algorithm

The MARS algorithm is a nonlinear and nonparametric regression model. It was first introduced by Friedman (1991). This model estimates the relationships between the dependent and independent variables using piecewise linear splines. The power of the MARS model over other competitive models has been addressed in various publications (Boehmke & Greenwell, 2019; Lee et al., 2006; OEB, 2017). Traditional statistical analyses, such as mixed linear models, struggle to perform well when the number of possible predictors is extremely high. The MARS model is formulated as

$$y_t = f(x_t) = \beta_0 + \sum_{i=1}^k \beta_i B_i(x_t) + \varepsilon, \quad (3)$$

where β_0 is a constant representing the model intercept, $B_i(x_t)$ is a basis function (BF, spline function), k is the number of BFs, β_i is the constant coefficient of the i th BF, and ε is the unexplained variation.

MARS generates knots or cut points for the different variables in the model. The algorithm searches through all possible knot locations and through all variables and their interactions. It accomplishes this through the use of variable combinations known as BFs (spline functions). MARS builds the model with these BFs. Each BF in MARS models consists of a constant (i.e., the intercept) and a hinge function, as well as a product of two or more hinge functions, to model variable interactions if they exist. Hinge functions are an important part of MARS models and take the form of $\max(0, x-c)$ or $\max(0, c-x)$, where c is a constant called a knot (i.e., a breakpoint value) and $\max(0, x-c)$ and $\max(x-c, 0)$ refer to hinge functions where $\max(0, x-c)$ is 0 if $x-c < 0$, else $x-c$.

The MARS algorithm can be summarized as follows. It begins by locating a single point (knot) c across a spectrum of x_t values, where two separate linear relationships between y_t and x_t achieve the lowest error (i.e., smallest error sum of squares [SSE]). Consequently, a BF is developed. MARS continues until many knots are discovered using the forward stepwise algorithm, which results in an overestimated model with a large number of BFs. Although many knots would match a good relationship with the training data, it would not be good at predicting new observations. As a result,

once the entire set of knots has been found, MARS employs a backward stepwise algorithm to eliminate knots that do not significantly contribute to predictive accuracy. Cross-validation is used to find the optimum number of knots in this operation, which is known as “pruning.” Based on the SSE criterion, BF_s are extracted one by one from the overfit model during the pruning stage. After each deletion, the model is refitted, and each reduced model is evaluated using the generalized cross-validation (GCV) criterion, which is a weighted mean squared error (MSE) criterion used to avoid overfitting. A model with a GCV R^2 score near 1 is considered good, while one with a GCV R^2 score near zero is considered poor. The GCV R^2 of an optimal model is maximized. MARS can also multiply modeling parameters to include variable interaction terms. This is the second tuning parameter and is measured in terms of degrees of freedom, abbreviated as “degree.” MARS can generally only add parameters to the model if they increase the model’s GCV value.

2.2.3. Quality of Fit Criterion

When models are built, specific criteria must be used to determine and choose the best among them. Models can be used to describe relationships and forecast outcomes in general. It is preferable to use a small and interpretable model to describe relationships. If the aim is to make predictions, models with the fewest errors and no overfitting are preferred.

The coefficient of determination (R^2) and MSE, two well-known metrics for determining the model fit, have a drawback in that their values do not worsen when an additional variable is applied to the model even though that predictor has no significance to the model. Therefore, if we just consider these measures, we will still choose the largest model, and our fitting will lead to noise. Since it is often better to have a small model with a good fit, we must follow other model criteria that consider the size of the model (i.e., model terms) even if we sacrifice a small amount of quality-of-fit in exchange for having a small model. Following that, we’ll go through some quality criteria that consider the model’s size. Extensive statistical explanations of these criteria are given in Dalpiaz (2020). With the exception of adjusted R-squared (Adj. R^2), the smaller the criterion value, the better for model selection.

Akaike information criterion (AIC): This criterion is a measure of the quality of the model and is defined as $2\log(\text{maximum log-likelihood of a regression model})$.

Bayesian information criterion (BIC): Just like AIC, the BIC quantifies the balance between a model that fits well and the number of model parameters. However, it usually selects a smaller model than AIC for a reasonable sample size.

Adjusted R-squared (Adj. R^2): It is a modified coefficient of determination (R^2) that has been adjusted for the number of predictors in the model. It can decrease as predictors are added.

Cross-validation criterion (CV): The idea is to create a train/test split of the data, including some sample observations not included in the model-building process and will be used to test the performance of the fully trained model. It provides a prediction error estimate.

Cross-validated RMSE: It is mainly used to measure the model’s performance during cross-validation by means of a root mean squared error (RMSE). The RMSE is a measure of the model’s average prediction error when predicting the outcome of an observation.

Mean absolute error (MAE): It is an alternative to the RMSE that is less sensitive to outliers. It corresponds to the average absolute difference between observed and predicted outcomes. During cross-validation, MAE is also used to assess model performance.

3. METHODOLOGY

3.1. The Data

We collected COVID-19 data for Kuwait from the official website of the Ministry of Health of Kuwait (Ministry of Health, Kuwait, 2021). The reported daily data, including Cases, recovered cases, deaths, ICU patients, and number of performed PCR tests. In this research, we are interested in the daily

number of cases since the first case was reported on February 24, 2020, until February 28, 2021, when we collected the data. We estimated the positivity rate as 100 times the ratio of daily new cases to daily PCR tests for each of the dates studied. It is an important metric because it indicates how widespread the infection is in the area where testing is taking place and whether testing levels are keeping up with disease transmission levels (Dowdy & D'Souza, 2020).

3.2. Adopted Interventions and Major Related Events in Kuwait

Government and health authorities in Kuwait enforced several precautionary measures to slow down the spread of COVID-19 in Kuwait. The major ones are summarized in Table 1. These measures started by enforcing travel restrictions (E1) on March 7, 2020, followed by a series of graduating lockdown restrictions, including E2, E3, and E4, and ending with a total lockdown (E6) enforced on May 10, 2020, for three weeks. These restrictions started to be relaxed by a series of reopening interventions, including E7, E8, and E9, which were followed by a complete termination of the lockdown (E10) on August 30, 2020, and a partial resumption of the commercial flights (E11 and E13). By the end of December 2020, Kuwait started vaccinating people with two approved vaccines, including Pfizer/BioNTech and Oxford/AstraZeneca. When the second main pandemic wave started at the beginning of February 2021, the government resumed some partial lockdown decisions, including E14 and E15.

3.3. COVID-19 Interventional Study Models Proposed

Our objective in this work was to investigate and quantify the effects of nonpharmaceutical interventions (Table 1) implemented in Kuwait during the pandemic period under consideration. Two modeling procedures were used to achieve this goal. The first model was based on ARIMA, which displayed the time series' greatest breakpoints with a structural fit (Garziano, 2017). This model was constructed in three major steps. First, we applied structural change analytics to the original time series data. Throughout this analysis, the main breakpoints and their respective break dates were identified. The minimum BIC was used to select the optimal number of breakpoints m . Second, we plotted the original time series against the structural breaks and the associated confidence intervals. Third, the fitted multiple-level changes of the structural breaks could be used as an intervention component in the ARIMA model. The final version of the model must go through a residual analysis to ensure that the stationary and other model assumptions were satisfied.

The MARS model, including both quantitative (day) and qualitative (interventions) predictors, was used in the second method. The BF's of the mixed model were expressed differently for each type of variable. The two modeling procedures were compared using RMSE, MAE, and result interpretability. In all of our analyses, we used R version 4.0.2, 2020.

4. INVESTIGATING CASES IN TIME VS. INTERVENTIONS

The progression of the pandemic, as measured by the daily number of cases (positive PCR test), is graphically depicted in Figure 1, as well as the activation of the 14 interventions mentioned in Table 1 from February 24, 2020, to February 28, 2021. Table 2 shows the number of days that each intervention was absent or active during the study period. E1 was triggered at a very early stage of the pandemic and is still active, so its effect is likely to be masked by subsequent interventions. Even though interventions E13–E14 were initiated at the end of the study period, there is insufficient evidence to allow a reliable comparison of their effects afterward.

The time series of Cases by E2 (chain of lockdown interventions) and by E4 (regional ban) are very similar in terms of activation periods (Figure 1). Therefore, we performed a chi-square test of independence between the two events E2 and E4. The resulting chi-square of 219.843 ($df=1$, $p\text{-value} < 0.001$) is highly significant, and the estimated effect size (Cramér's V) = 0.77 is also very high. Cramér's V is an effect size measurement for the chi-square test of independence. It assesses how

Table 1. Major government precautionary measures

Effective Date	Code	Intervention Description	Status/Ended
7-Mar-20	E1	Outbound and inbound flights are banned for certain affected countries.	Ongoing*
12-Mar-20	E2	Chain of interventions: Vacation for employees. No gatherings in restaurants and coffeehouse. Closing mosques, shopping malls, and gyms. Banks closed for 2 weeks. Closing Kuwait stock market.	30-Jun-20
22-Mar-20	E3	Partial curfew: 5 PM to 4 AM	9-May-20
6-Apr-20	E4	Applying regional total ban	9-Jul-20
19-Apr-20	E5	Evacuating citizens who are outside of Kuwait until May 6, which includes 500,000 Kuwaiti citizens	6-May-20
10-May-20	E6	Lockdown (total ban, stopping the delivery of orders)	30-May-20
31-May-20	E7	Total lockdown switched to a partial curfew for 12 hours, resume online ordering and delivery, more regions added to regional ban	30-Aug-2020
10-Jun-20	E8	Permission to pray in mosques while maintaining health regulations	Ongoing*
30-Jun-20	E9	Partial opening for workplaces and malls with certain criteria	29-Aug-20
30-Aug-20	E10	Terminating partial curfew and resuming normal life but limited to banning some commercial activities and gathering including making feasts gathering and weddings	7-Mar-21
1-Oct-20	E11	Resuming some commercial flights from and to Kuwait	Ongoing*
24-Dec-20	E12	Starting vaccinating people	Ongoing*
17-Jan-21	E13	Allowing housekeepers to fly to Kuwait under certain regulations including quarantine for two weeks and presenting negative PCR result.	Ongoing*
7-Feb-21	E14	All commercial activities are banned from 8:00 PM until 5:00 AM except Co-ops and pharmacies - Gyms and Spas shops closed completely	7-Mar-21

*By the end of the study, it was still ongoing.

strongly two categorical variables are associated (Sheskin, 2011). These results most likely indicate a confounding effect in a sense we will not be able to distinguish between the effects of the two events.

In a similar way, the test of independence for E2 and E3 (partial curfew) is significant (chi-square=128.418 with df=1, p-value<0.001), and the estimated effect size (Cramér's V) is 0.588, indicating a strong association between these two events. In addition, E3 and E4 are strongly associated (chi-square=54.19, with df=1, p-value<0.001, Cramér's V=0.382). Overall, it appears that each of the three events E2, E3, and E4 has an impact that is mixed (confounded) with the effects of the other two.

It is also noticeable from Figure 4 that after the total ban (E6), the curve obviously decreased. The two interventions, E5 (citizens' evacuation from abroad) and E6 (total ban), were found to have no relationship (chi-square=0.0294, with df=1, p-value=0.587). Also, E7 (partial curfew) and E8 (allowing mosques prayer with precautions) were found to have a very weak relationship (chi-square=4.17, with df=1, p-value=0.041, Cramér's V=0.106).

The progression of Cases remained relatively low compared to those lately reported until the E11 (resuming commercial flights) after the partial opening (E9) and the termination of the partial curfew (E10), which results in returning to a normal life. After these interventions, the second wave of the pandemic has begun to spread. It is found that E10 and E11 are strongly associated (chi-square=258.191, with df=1, p-value<0.001, Cramér's V=0.834). This most likely means that we won't be able to tell the difference between the two events' outcomes.

The vaccination campaign (E12) began in late December 2020, but the curve continued to rise two months later until the end of this study period.

Figure 1. Time series of cases vs. interventions ($\circ$ days absent, Δ days active)

Figure 2 shows the data distribution by the most recent interventions in this study, E13 and E14. The second wave of the pandemic, as well as the activation of E13, began in January 2021. Before and after this period, the mean and median have risen significantly. When comparing cases before and after January 21, the mean increased from 479.9 to 778.0, and the median increased from 526.5 to 840.0. Similarly, when comparing cases before and after February 21, the mean increased from 487.2 to 946.2, and the median increased from 530.0 to 977.5 cases.

Table 3 provides overall descriptive measures for the data from February 24, 2020, to February 28, 2021. The median number of daily cases is 553, which is greater than the mean of 514.4 because the

Table 2. Intervention frequency table E1–E14

Events	E1	E2	E3	E4	E5	E6	E7	E8	E9	E10	E11	E12	E13	E14
Absent (0)	12	260	322	276	353	350	312	107	310	188	220	304	328	349
Active (1)	359	111	49	95	18	21	59	264	61	183	151	67	43	22

Figure 2. Cases by E13 and E14 **Table 3.** Summary Statistics of Cases and Positivity Rate

Variable	N	Min Max	Q1 Q3	median	Mean (sd)	95% CI
Cases	371	0 1073	284.5 732	553	514.4 (293)	(484.5, 544.3)
Positivity rate	275	2.8 27.7	7.8 17.4	12.96	12.84(5.77)	(12.2, 13.5)

latter is sensitive to very small values at the start of the series. The median positivity rate is 12.96%, which is higher than the recommended threshold of 5%. The WHO recommended in May 2020 that the positivity rate remain below 5% for at least two weeks before governments consider reopening. If we are successful in controlling coronavirus transmission, this threshold may be lowered over time to loosen social restrictions even more and allow for very large gatherings or meetings of people traveling from all over the world (Dowdy & D'Souza, 2020). Figure 3 depicts the positivity rate beginning on May 30, 2020, when Kuwaiti officials started announcing the number of daily PCR tests.

5. INTERVENTION ANALYSIS

In this section, we used nominal predictors, the interventions listed in Table 1, and day number as a time trend to fit Y (Cases). The goals were to determine which NPIs have a significant effect on the curve of cases and to quantify this effect.

5.1. Intervention Analysis Using Arima Models

A Box–Cox transformation with an optimal $\lambda=0.3$ was applied to the response variable of interest (Cases) in our modeling procedures in this section and in the following section. This transformation

Figure 3. Positivity rate by month

Figure 4 Plot of breakpoints against BIC and RSS

resulted in obtaining Cases^t values. The goal of this transformation was to stabilize the time series' nonhomogeneity of variance and make the pattern more consistent across the entire data set. Simpler patterns tend to produce more accurate forecasts.

The best breaks at $m=3$ is achieved with minimum BIC value=1,809, as shown in Figure 4 where BIC is presented on the left y-axis and RSS on the right y-axis. The plot of the original time series against its structural breaks and their confidence intervals is given in Figure 5. It can be observed that there are three major changes on the structural level on April 23, 2020, November 10, 2020, and January 4, 2021.

Table 4 presents the optimal breakpoints represented in terms of day number and corresponding break dates in addition to 95% confidence interval (CI). The value for $m=1$ corresponds to the first breakpoint, which occurs at observation number 60 (on April 23, 2020), with confidence interval ranges between observation numbers 59 and 61. It was similar for the second and third breakpoints, as shown in the table.

Figure 5. Plot of actual cases' values versus its structural breaks (breakpts)

To translate the effect of the structural breaks on the original time series, we performed a back-transformation of the Box–Cox transform and calculated the difference in means between the cases before and after a breakpoint using the Welch two sample t-test. The mean difference (μ_d) and its 95% CI corresponding to each of the three breakpoints are as follows. A mean difference of $\mu_d=611.7$ indicated an average increase of 612 cases after the first breakpoint on April 23, 2020, with 95% CI of mean difference between (583.9, 639.4) cases. An average decrease of about 318 cases ($\mu_d=-318.3$) occurred after the second breakpoint on November 11, 2020, with 95% CI of mean difference between (-364.7, -271.9). Lastly, an average increase of 378 cases ($\mu_d=378.2$) after the third breakpoint on January 4, 2021, with 95% CI of mean difference between (305.4, 451.0).

Table 4 . Breakpoints of cases' time series

	Breakpoints at observation No. with 95% CI			
	m	Lower 2.5%	Breakpoint	Upper 97.5%
Breakpoint (Break date)	1	59 (April 22, 2020)	60 (April 23, 2020)	61 (April 24, 2020)
Breakpoint (Break date)	2	258 (Nov. 9, 2020)	261 (Nov. 10, 2020)	264 (Nov. 11, 2020)
Breakpoint (Break date)	3	313 (Jan. 1, 2021)	316 (Jan. 4, 2021)	319 (Jan. 7, 2021)

Notably, the first breakpoint occurred after applying a set of lockdown interventions, including E1–E4. The breakpoint is observed after about two weeks from applying the total ban intervention (E4) for regions, including crowded housing for workers, where implementing strict social distancing measures is potentially difficult. The decrease in the number of cases observed at the second breakpoint is potentially due to the effectiveness of the preceding complete lockdown intervention (E6), which was followed by a set of partial opening interventions (i.e., E7–E11) accompanied with strict precautionary measures. The decline in the number of cases proved that these precautionary measures were successfully implemented. Finally, the third breakpoint observed on January 4, 2021, showing an increase in the number of cases, occurred after the coronavirus UK variant (B.1.1.7) globally spread. The breakpoint potentially showed that this coronavirus variant significantly affected Kuwait at that time.

The fitted multiple levels (breaks in Figure 5) can be used as an intervention variable to fit an ARIMA model. This variable was inserted into the Arima() function in R as an xreg argument (sfrit as a predictor). Next, we searched for the best ARIMA model. The auto.arima function in R suggested the model Arima(1,1,4). Nevertheless, the residual analysis of this model did not reveal white noise residuals, indicating that this model does not capture all the structures of the original time series. Therefore, we performed a manual search for the best model based on the quality-of-fit criteria in addition to the model residual analysis using ACF/PACF plots. The results are listed in Table 5.

Table 5. Comparison of different ARIMA models of cases'

Model ARIMA(p,d,q)	Criteria		
	AIC	AICc	BIC
Model_1: ARIMA(5,1,2)	1316.1	1316.2	1351.3
Model_2: ARIMA(5,1,3)	1318.1	1318.7	1357.2
Model_3: ARIMA(4,1,2)	1319.6	1320.0	1350.9

Model_1 is the top candidate since it provides the best AIC and AICc metrics. Using the checkresiduals() function within the forecast package and the sarima() within the astsa package, the assumptions of Model_1 were examined and presented in Figure 6. We also tested the autocorrelation of the residuals using the Ljung–Box test within the FitARMA package. The desirable result is to have a nonsignificant (p-value>0.05) test. That was achieved for Model_1 with test values $Q^*=64.6$, $df=66$, and $p\text{-value}=0.5258$, as anticipated. Hence, the predicted COVID-19 model (ARIMA(5,1,2) for Cases' with a structural fit) is represented as

$\text{Cases}^t = 0.64 \text{ ar1} - 0.61 \text{ ar2} - 0.29 \text{ ar3} - 0.18 \text{ ar4} - 0.14 \text{ ar5} - 1.21 \text{ ma1} + 0.94 \text{ ma2} + 0.15 \text{ sfit}$, where the response variable Cases^t is the Cox-Box transformation of Cases. The terms (ar1, ar2, ..., ar5), (ma1, ma2), and sfit terms in the model represent the five autoregressive terms, the two MA terms, and the structural break fit, respectively. All the model coefficients were tested and found to be significant. The model RMSE=1.39 and MAE=1.03.

5.2. Intervention Analysis Using MARS

Four models were built as part of our MARS modeling procedure. The first involved using binary interventions E2–E14 in addition to a quantitative variable “day” as predictors. The second MARS model used day and curfew as predictors. In this model, we combined the lockdown interventions (E3, E6, and E7) into a single binary intervention called curfew because they all referred to a lockdown but at different times. In the third MARS model, curfew was represented as a quantitative variable in terms of hours of lockdown. The final model quantified E4, the regional ban, as occupancy (percent) in the total shutdown areas. The last two models produced the same results. The second model with predictors (day, E2, E4, E5, E8, E9, E10, E11, E12, E13, E14, and curfew) was chosen and is presented in this section.

When building the MARS models, we applied the forward and backward steps explained in Section 2.2.2. We found that the best MARS model for COVID-19 data has 12 additive BF. The best cross-validated RMSE and MAE values are 1.48 and 1.17, respectively.

Figure 6 . Residual analysis plots for the ARIMA(5,1,2) with structural breaks

Our optimal model has 13 terms (with intercept) based on four predictors, as shown in Figure 7. Any additional terms retained in the model, over and above the optimal terms, resulted in less than 0.001 improvement in the GCV R2 (GRSq). Day, curfew, E5, and E9 were the four predictors chosen to fit the best model for Cases^t .

Figure 7. MARS model selection plot for COVID-19 in Kuwait

Table 6 explicitly presents the selected BF_s with the most relevant variables contributed as additive terms in the model. The first three BF_s correspond to binary interventions E5, E9, and curfew when activated. The remaining nine BF_s involve breakpoints or knots of the time trend at days 12 (March 6, 2020), 84 (May 17, 2020), 108 (June 10, 2020), 204 (September 14, 2020), 216 (September 26, 2020), 246 (October 26, 2020), 306 (December 25, 2020), and 318 (January 6, 2021). The final model is expressed as a linear combination of the BF_s as follows:

$$\text{Cases}^t = -23.406 - 1.737 \text{ BF}_1 + 1.186 \text{ BF}_2 - 3.071 \text{ BF}_3 + 0.684 \text{ BF}_4 + 0.312 \text{ BF}_5 - 0.812 \text{ BF}_6 + 0.106 \text{ BF}_7 - 0.182 \text{ BF}_8 + 0.325 \text{ BF}_9 - 0.273 \text{ BF}_{10} + 0.515 \text{ BF}_{11} - 0.226 \text{ BF}_{12}.$$

Table 6. Model coefficients and BF_s

Model term	Coeff.	Basis functions
Intercept	-23.406	
E5 ₁ [§]	-1.737	BF ₁ = I(E5=1) ^{§§}
E9 ₁ [§]	1.186	BF ₂ = I(E9=1) ^{§§}
Curfew ₁ [§]	-3.071	BF ₃ = I(Curfew=1) ^{§§}
h(Day-12)	0.684	BF ₄ = max(0, Day-12)
h(84-Day)	0.312	BF ₅ = max(0, 84-Day)
h(Day-84)	-0.812	BF ₆ = max(0, Day-84)
h(Day-108)	0.106	BF ₇ = max(0, Day-108)
h(Day-204)	-0.182	BF ₈ = max(0, Day-204)
h(Day-216)	0.325	BF ₉ = max(0, Day-216)
h(Day-246)	-0.273	BF ₁₀ = max(0, Day-246)
h(Day-306)	0.515	BF ₁₁ = max(0, Day-306)
h(Day-318)	-0.226	BF ₁₂ = max(0, Day-318)

[§]intervention at level 1 (Active);^{§§}I is an indicator function, I = 1, if condition (.) is satisfied

Figure 8. Actual cases' time series against its MARS fit

The model GCV, generalized R^2 (GRSq), and R^2 statistics were, respectively, 2.24, 0.95, and 0.94.

Figure 8 plots the actual values of the time series against the MARS estimated values. Remember that a BF $\max(0, x-c)$ (or $\max[0, c-x]$) is defined as the maximum value of two elements, 0 and $x-c$, where c is a breakpoint. It has no effect on Y unless $x-c$ is positive. In this sense, $\max(0, \text{day } 12)$ became positive after the 12th day. A breakpoint at day 84 is indicated by the model terms $0.312 \max(0, \text{day } 84)$ and $-0.812 \max(0, \text{day } 84)$. By that point, essential interventions E1–E6 had occurred, which might explain the decline in the curve after this point. The term $0.106 \max(0, \text{day } 108)$ increased the curve after breakpoint 108. This happened about two weeks after E7 was implemented, when the total lockdown was changed to a partial curfew. The curve rose after breakpoint 204 and then fell after breakpoint 216, which occurred about two weeks after E10, when the partial curfew was lifted, and normal life resumed with restrictions. After breakpoint 246, the term $-0.273 \max(0, \text{day } 246)$ significantly decreased the curve. This occurred after at least 11 interventions had been implemented. The contribution of the terms of the last two breakpoints increased the curve at day 306 and decreased the curve at day 318. The latter occurred approximately two weeks after the vaccination campaign began. We also noticed that the most influential breakpoints in terms of decreasing the curve occurred on May 17 and October 26, 2020.

Figure 9 depicts a partial dependence plot for each predictor individually while keeping the other predictors at fixed levels. This will show the effect of that specific predictor on the model prediction. We used the “plotmo” package, which also allows us to visualize the effect of Y across the range of two predictors at the same time if interaction exists. The individual plots showed that our model found one knot in each of the interventions (E5, E9, and curfew) that provided the best fit, in addition

Figure 9. Partial dependence plots

to the breakpoints in the time trend (day) predictor. Curfew activation (at level 1) results in a greater marginal decrease in Cases. Similarly, there is a slight decrease in the curve for E5 (evacuating citizens). Citizens were subjected to a 14-day special quarantine regardless of the results of PCR tests. When E9 (partial opening for workplaces and malls) was activated, there was a marginal increase.

6. CONCLUSIONS

The effect of a nonpharmaceutical intervention is considered in a novel application of intervention analysis to model the number of infected COVID-19 cases in Kuwait between February 24, 2020, and February 28, 2021. Our goal in this work was to investigate and quantify the effects of nonpharmaceutical interventions carried out in Kuwait during the pandemic period under study. To achieve this goal, two modeling procedures were used. The first method was to use intervention analysis with Arima modeling by fitting a structural break variable to the time series that reflected the major change points. The variable was then induced in the Arima model to obtain the best fit. The second method was to employ the MARS model, which included both quantitative (day) and qualitative (interventions) predictors. The mixed model's BF's are expressed differently for each type of variable. The nonparametric MARS method has the advantage of not requiring any prior assumptions about the statistical distribution of the data. Furthermore, MARS was not adversely affected by data collinearity, which is a common problem in interventional analysis. Also, its functions are clear and transparent, particularly when compared to other methods.

The main findings of our interventional analysis using ARIMA(5,2,1) showed a significant multiple-level shift caused by structural breaks with three breakpoints. The first occurred between days 59 and 61, indicating a 95% confidence interval increase in the mean number of cases between (584, 639). Although the five interventions E1–E5 were already in place, this was the start of the pandemic's first wave. The second breakpoint occurred between days 258 and 264, reproducing a 95% confidence interval decrease in the mean number of cases between (272, 365). Following the implementation of the 11th intervention E11, there is a significant decrease in the mean number of cases. This model's last breakpoint occurred between days 313 and 319, resulting in an average increase in the mean number of cases between (305, 451) with a 95% confidence level. This was at the start of the pandemic's second wave, which occurred after increasing commercial flights (E13) from certain countries with a high pandemic rate.

The first three BF's in the MARS model correspond to binary interventions E5, E9, and curfew. As the curfew is activated, there is a greater marginal decrease in Cases. Similarly, there is a slight

decrease in the curve for E5 (evacuating citizens). It should be noted that citizens were subjected to a 14-day special quarantine regardless of the PCR test results. When E9 (partial opening of workplaces and malls) was activated, there was a marginal increase. The remaining nine BFs involved time trend breakpoints or knots at days 12, 84, 108, 204, 216, 246, 306, and 318. The two most influential breakpoints occurred at days 84 (May 17, 2020; E1–E6 were implemented) and 246 (October 26, 2020; post E11), where the cases were decreased in both incidences. Although the ARIMA(5,1,2) model's metrics (RMSE=1.39 and MAE=1.03) were slightly lower than those of the MARS model (RMSE=1.48 and MAE=1.17), the latter offers a more precise interpretation of the intervention's effects.

The findings of this research are generally in line with those of previous studies in terms of reducing the spread of the disease by implementing lockdown interventions. The impact of opening interventions differs from one country to another based on the effectiveness of and adherence to the precautionary measures through these openings.

The only pharmaceutical intervention in this study is vaccination (E12), which began in late December 2020. However, it is difficult to see the effect of the binary variable E12 within two months. To describe the effect of this pharmaceutical intervention, a quantitative measure of vaccination would be more appropriate.

DATA/CODE AVAILABILITY STATEMENT

Data and R codes for this study are available with the first author.

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