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Intervention time series modeling with parametric and nonparametric approach: comparative study on Corporation tax in Togo

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Abstract. Time series are often subject to structural changes caused by external events such as strikes, new fiscal measures, or policy changes. In the current paper, we conduct a comparative study of a parametric and nonparametric approach to intervention time series modeling to model the impact, on corporate tax, of the important tax reform in December 2012 in Togo (the establishment of a Togolese Revenue Office).The comparison of the two models has led us to conclude that the non-parametric approach is superior in terms of predictive quality as well as the measurement of the effect of the reform.

Key words: intervention analysis; central mean subspace in time series; Nadaraya-Watson kernel estimator.
AMS 2010 Mathematics Subject Classification Objects : 62P20; 62M10; 91B84; 62G08

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Résumé. (Abtsract in French) Les séries temporelles sont souvent sujettes à des changements structurels causés par des événements externes tels que des grèves, de nouvelles mesures fiscales ou des changements de politique. Dans cet article, nous menons une étude comparative des approches paramétrique et non-paramétrique de l'analyse d'intervention afin de modéliser l'impact de l'importante réforme fiscale de décembre 2012 au Togo (mise en place de l'Office Togolais des Recettes) sur l'impôt sur les sociétés. La comparaison des deux modèles nous a amené à conclure que l'approche non-paramétrique est meilleure en terme de qualité prédictive ainsi que la mesure de l'effet de la réforme.

1. Introduction

Intervention analysis is a powerful and increasingly popular tool for evaluating structural change in times series caused by external events. It has been widely applied in many disciplines such as economics, biology, environmental science, and social science. Firstly, introduced by Box and Tiao (1975) and further developed by many other researchers such as Larcker *et al.* (1980) and Enders *et al.* (1992), intervention models combine an ARIMA noise model with a causal specification as a parametric model. Shao (1997) proposes an extension of parametric intervention analysis by using multiple interventions time-series analysis to evaluate the impact of promotional strategies on sales. The approach involves the clustering of similar interventions. As in real life, nonlinearity is very often characteristic of time series, whether derived from socio-economic or environmental phenomena, the majority of research has focused on the development of nonlinear solutions for time series analysis. Sarkar and Kartikeyan (1993) present methods to study nonlinear time series with three different kinds of interventions using the parametric Quadratic Volterra Type (QVT) model.

Parametric models provide a powerful tool for time series analysis provided that they are correctly specified. However the issue of modeling biases always arises in parametric modeling and a natural alternative is to use a nonparametric approach. Dombrow *et al.* (2000) apply Theil's nonparametric regression technique in the estimation of abnormal returns and conclude to superiority of nonparametric test statistics in detecting abnormal performance. Recently, Park *et al.* (2009) constructed a formal dimension reduction in time series as a viable and meaningful nonparametric alternative for traditional time series analysis. Park (2012) extends the resulting central mean subspace in time series to a nonparametric intervention analysis.

This paper conducts a comparative study of a parametric and nonparametric approach to intervention time series modeling to model the impact, on corporate tax, of the important tax reform in December 2012 in Togo (the establishment of a Togolese Revenue Office). Indeed, in December 2012, a Togolese government decree reformed the former Tax and Customs departments into a single entity (Togolese Revenue Office). The objective is twofold, firstly to capture and quantify the impact of the reform on the collection of tax revenues, and secondly to show the effectiveness of the nonparametric intervention models in the evaluation of tax policies.

The remainder of this paper is organized as follows. In Section 2, the corporate tax data used are described. In section 3, the parametric approach and its results are given. Section 4 is concerned with the nonparametric approach and corresponding results. Section 5 gives a brief discussion of the results. The summary and conclusions are addressed in the last section.

2. Data Description

The data relating to corporation tax are part of tax data, collected before by the General Tax Directorate and now by the Togolese Revenue Office (OTR). They are published periodically in the form of T.O.F.E (Table of Financial Operations of the State) on the website togoreforme. For convenience, the corporate tax data are given in billions of CFA francs in Table 1.

The data set is divided into two categories belonging to the pre and post intervention periods. Figure 1 shows a set of corporation tax data. These are monthly data collected from January 2008 to December 2017. The vertical line indicates the date when the intervention took place. Although the law on tax reform was taken in December 2012, the said reform actually began in February 2013.

Table 1: **Corporate tax data, from January 2008 to December 2017. Source : Ministère de l'Economie et des Finances/OTR**

YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
2008	1,24	1,33	0,08	0,24	0,69	2,81	0,86	3,30	0,91	1,03	2,23	2,04
2009	1,72	2,31	0,10	0,32	0,76	1,23	3,05	3,88	0,73	1,41	0,73	0,21
2010	2,58	1,26	0,31	1,28	2,59	1,67	1,61	1,68	0,94	1,62	1,20	1,55
2011	1,82	2,37	0,43	2,89	4,26	2,94	3,81	2,29	1,11	2,75	2,09	1,00
2012	3,31	1,51	0,34	1,72	4,29	2,65	3,35	2,07	0,33	3,01	1,58	0,76
2013	3,54	2,90	0,33	3,49	9,41	3,71	4,08	5,18	1,67	5,43	1,11	1,30
2014	5,62	2,81	1,19	3,45	6,07	1,60	6,74	2,46	1,29	6,24	1,95	11,08
2015	7,04	1,38	0,68	7,84	7,67	3,13	7,95	2,00	1,16	8,13	1,22	2,97
2016	8,38	0,77	1,31	10,40	12,13	1,17	10,89	2,85	3,04	10,30	1,83	1,49
2017	9,82	0,76	0,59	2,60	11,40	0,78	8,90	1,30	0,41	7,64	0,72	0,57

3. Interrupted ARIMA model

3.1. Empirical stochastic intervention model

We recall that for a stochastic process $\{Y_t\}$, the **mean function** is defined by $m_t = \mathbb{E}(Y_t),\ t \in \mathbb{Z}$. Now, it is assumed that the intervention affects the process by changing the mean function or trend of a time series. Resuming the box and

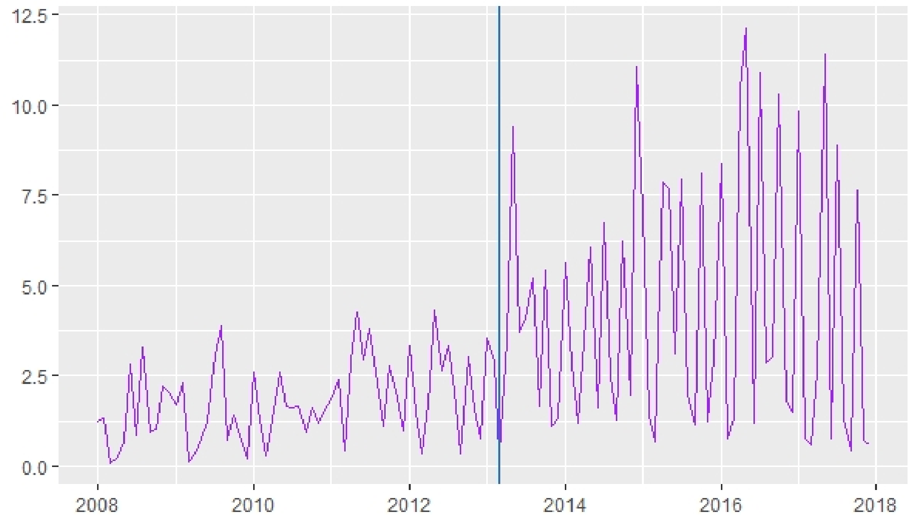


Fig. 1: Corporate tax (C.T) data, from January 2008 to December 2017

tiao model and for a time series $\{Y_t\}$ characterized by a natural or man-made intervention, the general model is given by

$$Y_t = f(\delta, \omega, \zeta, t) + N_t$$

where Y_t represents the value of the series at time t or its value after a suitable transformation. The function $f(\delta, \omega, \zeta, t)$ denotes the deterministic effects of time t, the exogenous variables ζ with the set of unknown parameters δ and ω. N_t is the stochastic background variation or dependent noise variation. That is, the underlying time series where there is no intervention and it may be seasonal or nonseasonal, stationary or nonstationary. The function $f(\delta, \omega, \zeta, t)$ can be characterized as follows:

$$f(\delta, \omega, \zeta, t) = \frac{\omega(B)B^b\zeta_t^{(T)}}{\delta(B)}$$

where

$\delta(B) = 1 + \delta_1 B + \ldots + \delta_r B^r$ (Slope parameter)
$\omega(B) = 1 + \omega_1 B + \ldots + \omega_s B^s$ (Impact parameter)
$b =$ delay parameter
$B =$ Backshift operator i.e. $B^i Y_t = Y_{t-i}$
$\zeta_t^{(T)}$ is an indicator variable. it can be coded either using

a **step function** $\zeta_t^{(T)} = S_t^{(T)} = \begin{cases} 1, & \text{if } t \geq T \\ 0, & \text{otherwise} \end{cases}$

or by

a **pulse function** $\zeta_t^{(T)} = P_t^{(T)} = \begin{cases} 1, & \text{if } t = T \\ 0, & \text{otherwise} \end{cases}$

with T the time of the occurrence of intervention.

The noise N_t can be modeled as an $ARIMA$ process, that is

$$\phi_p(B)\Phi_P(B^L)\,(1-B)^d\left(1-B^L\right)^D N_t = \theta_q\,(B)\,\Theta_Q\left(B^L\right)\varepsilon_t$$

where $\phi_p(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p$ and $\theta_q(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q$ are nonseasonal, autoregressive and moving average polynomials in B of degrees p and q respectively; $\Phi_P(B) = 1 - \Phi_1 B^L - \Phi_2 B^{2L} - \cdots - \Phi_P B^{PL}$ and $\Theta_Q(B) = 1 - \Theta_1 B^L - \Theta_2 B^{2L} - \cdots - \Theta_Q B^{QL}$ are seasonal autoregressive and moving average polynomials in B of degrees P and Q respectively, with seasonality of period L; D and d are respectively, seasonal and nonseasonal differences numbers and ε_t is a white noise.

3.2. ARIMA intervention model fitting for Corporate tax data

In order to make the data normal, we use the log transformation. Based on the preintervention data, an $ARIMA(4,0,0) \times (1,1,0)_{12}$ model is tentatively specified for the underlying intervention-free series N_t. The first three autoregressive parameters are fixed at 0.

Figure 2 displays the differences between the forecasted values (using the preintervention model) and the actual values, for the postintervention period. Whereas, the reform is a permanent intervention and that it actually took place from February 2013, we opt for a specification with the step input of value 0 before February 2013 and 1 from February 2013 .

From the examination of the figure, we model the intervention effect (tax reform

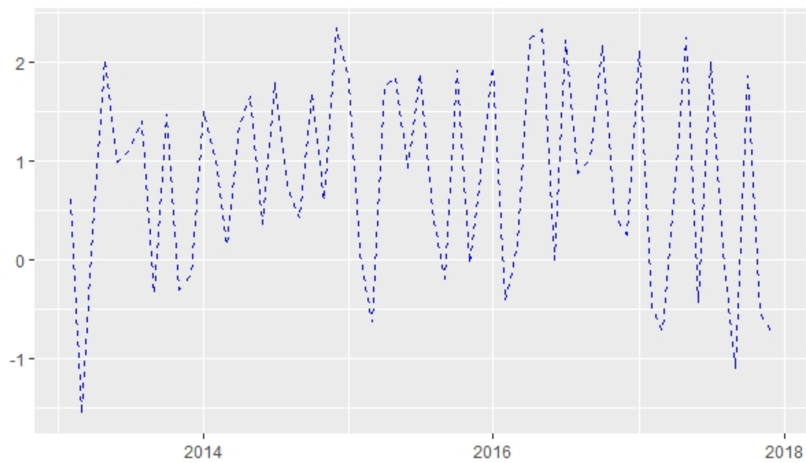


Fig. 2: Times series plot of differences

01/2013 effect) as

$$f(\delta,\omega,t) = \frac{\omega B}{1-\delta B} S_t^{(T)}$$

Table 2: **Summary of statistics for model**

Parameter	Estimate	Standard error	p-value
ϕ_4	-0.187	0.099	0.057
Φ_1	-0.204	0.103	0.047
Dec 09	-1.117	0.309	0.000
Dec 14	1.024	0.287	0.000
Sept 16	0.836	0.311	0.007
Dec 10 (LS)	0.389	0.124	0.002
Mar 17 (LS)	-0.661	0.152	0.000
δ	0.427	0.240	0.076
ω	0.401	0.181	0.027
σ^2 estimated as 0.2714, log-likelihood = -82.39 , AIC = 182.78			

where T denotes February 2013.

We recall that outliers may be regarded as interventions of unknown nature that have a pulse response function. An additive outlier occurring at time T thus takes the form $f(\delta,\omega,t) = \omega P_t^{(T)}$ and Level Shifts (outliers) are modeled as $f(\delta,\omega,t) = \frac{\omega B}{1-B} P_t^{(T)}$. Outliers are detected through specific statistical tests on the data. Now, Model diagnostics of the fitted model suggested the existence of three *Additive Outliers* (December 2009, December 2014 and September 2016) and two *Level Shifts* (December 2010 and March 2017). Table 2 summarizes the fitted model. Figure 3 graphs the estimated tax reform effects on corporate tax against the data. The fitted model estimates that the tax reform intervention increases revenue from corporate tax by around a $102\% = \left\{\exp(\frac{0.401}{1-0.427}) - 1\right\} \times 100\%$ as ultimate gain for the mean function.

4. Non-parametric approach of the intervention model

4.1. Estimation method

Active research in the treatment of high-dimensional data has given rise to a family of diverse statistical methods, including Sufficient Dimension Reduction (SDR) in regression.The latter performs a linear reduction of a group of p regressors, in a more small group of d variables while maintaining a link function that is not necessarily linear. The link with the time series comes from the article by Park *et al.* (2009), opening another horizon on the non-parametric approach in time series modeling.

Consider a time series y_t characterized by a natural or man-made intervention and let ℓ_t be an intervention at specific time t. Following the approach in Park (2012), let's $\mathbf{Y}_{t-1} = (y_{t-1}, \cdots, y_{t-p})^T$, with $p \geq 1$, the number of lags, and

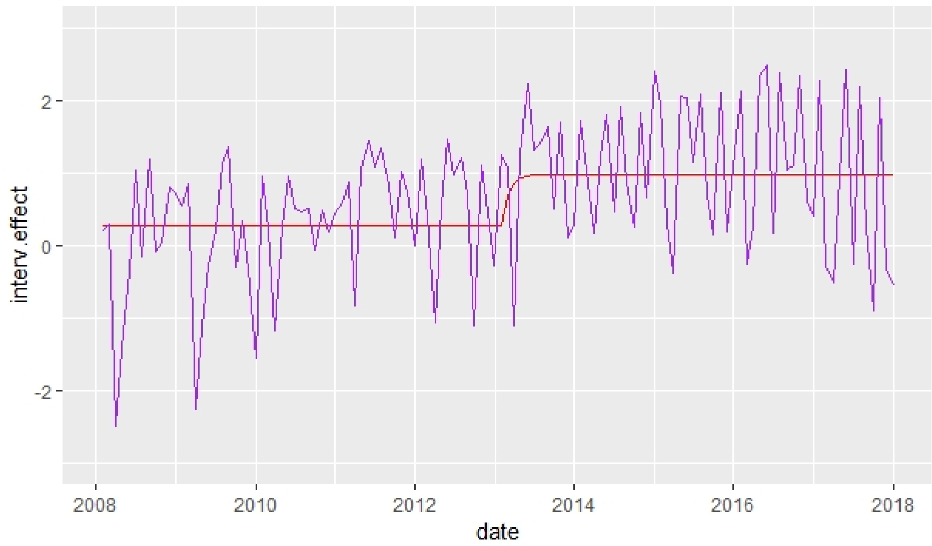


Fig. 3: Tax reform effects on corporate tax

$\mathbf{Z}_t = (\ell_{1t}, \ell_{2t}, \cdots, \ell_{kt})^T$, with k, the number of interventions (including several interactions of interventions). The challenge in dimension reduction method is to estimate a $(p+k) \times q$ matrix $\mathbf{B}_q = (\beta_1, \ldots, \beta_q)$, $q \leq (p+k)$ which satisfies the relation

$$y_t = g[\mathbf{B}_q^T(\mathbf{Y}_{t-1}, \mathbf{Z}_t)] + \varepsilon_t, \quad (1)$$

where $\varepsilon_t \perp\!\!\!\perp (\mathbf{Y}_{t-1}, \mathbf{Z}_t)$. It is then assumed that the $q \times 1$ vector $\mathbf{B}_q(\mathbf{Y}_{t-1}, \mathbf{Z}_t)$ contains all the information about y_t that is available from $\mathbb{E}(y_t|(\mathbf{Y}_{t-1}, \mathbf{Z}_t))$. A vector space $\mathcal{S}_q$ such that each of its bases satisfies the model (1) is called the intervened time series mean dimension reduction subspace $(TSMDRS)$ for y_t on $(\mathbf{Y}_{t-1}, \mathbf{Z}_t))$. When there is a single minimal intervened $TSMDRS$, this is called the intervened time series central mean subspace $(TSCMS)$, and will be denoted $\mathcal{S}_d$. We have in this case

$$\mathcal{S}_d = \bigcap \mathcal{S}_q.$$

The intervened $TSCMS$ does not always exist, but under mild assumptions, we can have it.

To estimate the basis vectors $(\beta_1, \ldots, \beta_d)$ of the intervened $TSCMS$ when its dimension is d, the number of lags is p, and interventions are all known, Park (2012) proposes to minimize an objective function

$$\mathbf{\Pi}(\mathbf{B}_d) = \mathbb{E}\left\{y_t - g\left[\mathbf{B}_d^T(\mathbf{Y}_{t-1}, \mathbf{Z}_t)\right]\right\}^2$$

with respect to $\mathbf{B}_d$ such that $\mathbf{B}_d^T\mathbf{B}_d = \mathbf{I}_d$, and where $g[\mathbf{B}_d^T(\mathbf{Y}_{t-1}, \mathbf{Z}_t)] = \mathbb{E}[y_t|\mathbf{B}_d^T(\mathbf{Y}_{t-1}, \mathbf{Z}_t)]$. It is proved that $\mathbb{E}[y_t|(\mathbf{Y}_{t-1}, \mathbf{Z}_t)] = \mathbb{E}[y_t|\mathbf{B}_d^T(\mathbf{Y}_{t-1}, \mathbf{Z}_t)]$ (see Park (2012)) and we have $\mathbf{\Pi}(\mathbf{B}_d) \geq \mathbf{\Pi}(\mathbf{I}_d) = \mathbf{\Pi}(\mathcal{B}_d)$ for any $\mathbf{B}_d$, where $\mathcal{B}_d = \arg\min_{\mathbf{B}_d} \mathbf{\Pi}(\mathbf{B}_d)$.

For estimation of the unknown mean function, Park (2012) used a Nadaraya-Watson kernel estimator.

$$\hat{g}_{\gamma_n}(\mathbf{B}_d^T(\mathbf{Y}_{t-1}, \mathbf{Z}_t)) = \sum_{i=1}^{n} \mathcal{R}_i y_i, \tag{2}$$

where

$$\mathcal{R}_i = \frac{G[(\mathbf{B}_d^T(\mathbf{Y}_{t-1}, \mathbf{Z}_t) - \mathbf{B}_d^T(\mathbf{Y}_{t-1}, \mathbf{Z}_t)_{i-1})/\gamma_n]}{\sum_{j=1}^{n} G[(\mathbf{B}_d^T(\mathbf{Y}_{t-1}, \mathbf{Z}_t) - \mathbf{B}_d^T(\mathbf{Y}_{t-1}, \mathbf{Z}_t)_{j-1})/\gamma_n]},$$

G is a Gaussian kernel function and $\gamma_n > 0$ is a sequence of nonincreasing bandwidths. The sample version of the objective function is given by $\hat{\mathbf{\Pi}}(\mathbf{B}_d) = \sum_{t=1}^{n} \left\{ y_t - \hat{g}_{\gamma_n}\left[\mathbf{B}_d^T(\mathbf{Y}_{t-1}, \mathbf{Z}_t)\right] \right\}^2$ for $\mathbf{B}_d$ such that $\mathbf{B}_d^T \mathbf{B}_d = \mathbf{I}_d$.

In practice, if the number of interventions is known, this is not the case for the number of lags p and the dimension d. Hence the need to estimate them. Park (2012) proposes an estimation method based on the modified Bayesian information criterion (MBIC) adopted by Park *et al.* (2009). The procedure and formulations for MBIC are as follows: First, given the number of interventions k, $\hat{d}_{p,k}$ is determined with respect to p:

$$\hat{d}_{p,k} = \underset{1 \le d \le (p+k)}{\arg\min} \left\{ n \log\left(\frac{\hat{\mathbf{\Pi}}_n(\hat{\mathcal{B}}_{p+k,d})}{n} \right) + d(p+k)n^{0.375} \right\}. \tag{3}$$

Second, given k and estimate $\hat{d}$, p is estimated using the following MBIC:

$$\hat{p} = \underset{p}{\arg\min} \left\{ n \log\left(\frac{\hat{\mathbf{\Pi}}_n(\hat{\mathcal{B}}_{p+k,\hat{d}})}{n} \right) + \hat{d}(p+k)n^{0.375} \right\}. \tag{4}$$

4.2. Data analysis

Our analysis procedure begins with the determination of the delay parameters p and dimension d, followed by the estimation of basis vectors of $\mathcal{S}_d$ in a univariate time series with one intervention.The intervention noted ℓ_t is coded 0 for all the values before February 2013 and coded 1 for all other values. Objectively, we estimate y_t versus $(\mathbf{Y}_{t-1}, \mathbf{Z}_t) = (y_{t-1}, \cdots, y_{t-p}, \ell_t)^T$.

To estimate d, we use equation (3). Therefore we compute the MBIC values for $d = 1,\ 2$ with $p = 1$, then $d = 1,\ 2,\ 3$ with $p = 2$, and $d = 1,\ 2,\ 3,\ 4$ with $p = 3, \ldots, 13$. The results are recorded in Table 3 . The analysis of the table with regard to the criterion in (3) gives us the value of $\hat{d}_{p,1}$ for each p and $\hat{d}_{p,1} = 1$ for all $1 \le p \le 13$. Using the MBIC criterion in equation (4) and for $\hat{d}_{p,1}$ set to 1, we estimate p and Table 3 indicates $\hat{p} = 12$. Therefore, we set $\hat{d} = 1$ and $\hat{p} = 12$ for the rest. The estimation of the $13 = (p + k) \times 1$ basis vector $\mathcal{B}_1$ through the *fmincon* function in MATLAB led us to the following results:

$\hat{\mathcal{B}}_1^T$= (-0.0610, 0.2233, -0.0735, 0.0603, 0.0246, -0.1747, -0.0124, 0.0060, -0.2779, 0.1976, -0.1233, -0.8311, -0.2895). The intervention effect are related to the last values. Figure 4 displays time series plot of t versus $d_{1,t}$ (with $d_{1,t} = \hat{\mathcal{B}}_1^T(\mathbf{Y}_{t-1}, \mathbf{Z}_t)$) and t versus y_t. After examining the two-dimensional plot of y_t versus $d_{1,t}$, we conducted a regression of y_t on the predictor series $d_{1,t}$, which led us to the following linear regression model:

$$y_t = 0.18782 - 0.63484 d_{1,t} + \varepsilon_t, \quad (5)$$

where ε_t is a noise, and autocorrelation check of the residuals indicates that it is white noise.

The coefficients in the model (5) are found to be significant with standard error of estimates 0.0763 and 0.053, respectively. Indeed the p-value is 0.015 and 2.10^{-21} respectively for the intercept and slope parameter.In addition, the model shows approximately $120\% = \exp\{-0.63484 \times (-0.2895)\} \times 100\%$ increase in corporate income tax revenues.

Table 3: **Detecting d and p for Corporate tax data**

p	$d = 1$	$d = 2$	$d = 3$	$d = 4$
1	$-547.3195^{\star}$	-513.3887		
2	$-541.4949^{\star}$	-506.0810	-466.7477	
3	$-555.0723^{\star}$	-516.7231	-476.6332	-430.7961
4	$-555.8242^{\star}$	-514.1801	-470.0038	-428.7987
5	$-550.9040^{\star}$	-504.7885	-459.2041	-416.6254
6	$-558.4799^{\star}$	-519.8747	-471.0858	-424.9538
7	$-553.2602^{\star}$	-511.5387	-462.1139	-412.6744
8	$-547.0470^{\star}$	-499.9099	-445.1456	-391.3705
9	$-543.7122^{\star}$	-492.2358	-437.7208	-383.8667
10	$-539.5347^{\star}$	-486.6224	-422.1025	-365.1012
11	$-534.4476^{\star}$	-476.5057	-410.9253	-359.8144
12	$-573.6355^{\star\blacklozenge}$	-507.9588	-440.8337	-388.8505
13	$-568.3210^{\star}$	-498.9870	-424.7697	-371.9811

Note: * Indicates the smallest value of $\hat{d}_{p,1}$ for each value of p. $^{\blacklozenge}$ Denotes the smallest value of p for d set to 1

5. Discussion

The parametric model has qualities that are indisputable. It offers the advantage of appreciating or understanding how the intervention affects the mean function, and this by means of a parametric model supposed to describe or approach the mean function. The difficulty in this approach lies in the model to be defined. When the latter is poorly specified, there is a significant bias in the estimated parameters and the quality in terms of model accuracy suffers. This is the

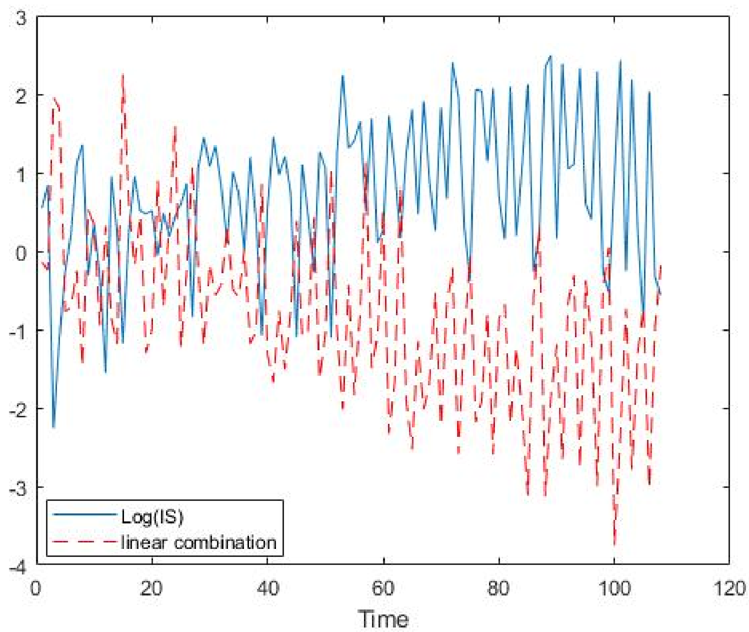


Fig. 4: Corporate tax: Time series plot of t versus y_t (solid line) and t versus $d_{1,t}$ (dashed line)

challenge raised by the non-parametric approach presented in this study.

In terms of predictive quality, the two approaches are compared, based on the mean square relative error ($\mu = \frac{1}{n}\sum_{t=1}^{n}[(y_t - \hat{y}_t)^2/y_t]$). From the residuals, this one is calculated and is 0.319 for ARIMA intervention model (parametric model) and 0.079 for non-parametric approach of the intervention model. We note immediately the superiority in terms of prediction of the non-parametric approach over the traditional model of intervention (parametric model).

Furthermore, model (5) (non-parametric model) easily captures the effect of the reform and on this point, it is estimated at 120%, much higher than the estimate of the parametric model (102%). Likewise, the non-parametric approach has the advantage of being less complex and more intuitive compared to the parametric approach which requires modeling for the preintervention data. There is also the possibility in this kind of approach to take into account the interactions of several interventions during the analysis (see Park (2012)).

Thus the non-parametric approach of the intervention model provides a viable alternative to the traditional ARIMA intervention model. And this article aims among other things, to promote such an approach.

6. Conclusion

In this article we conducted two modeling approaches to capture and estimate the impact of the major tax reform in Togo (the establishment of O.T.R.) on corporate tax revenues. Firstly, the Box and Tiao (1975) intervention model was fitted to the data. Secondly, a non-parametric approach introduced by Park (2012) was conducted on the data.
The comparison of the two models led us to conclude that the non-parametric approach is superior in terms of predictive quality as well as the measurement of the effect of the reform. Thus according to this study, the tax reform has resulted in an increase in corporate income tax receipts in the order of 120%. In addition, the value of the slope parameter δ in the parametric model reveals a symptom of a reform whose effect is quickly felt in its full strength.
On the other hand, the evolution of corporation tax-to-GDP ratio since 2008 (Table 4) already foreshadowed such an impact. Indeed, this ratio increased from an average of 1.45% of GDP between 2008 and 2012 to 2.38% of GDP over the 2013-2017 period, a growth rate of 64%.

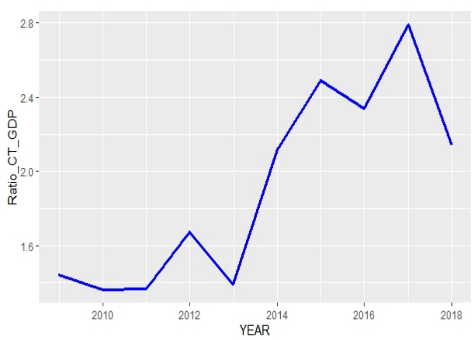
The results that emerged from our analysis reveal that tax reform, as established, is a real success and its contribution to the government's self-financing capacity is remarkable. We hope ultimately that these results serve as an incentive for many African countries to move in the same direction.

Annex

Table 4: Evolution of corporation tax-to-GDP ratio since 2008

YEAR	GDP	C.T	C.T (%GDP)
2008	1 482,36	21,40	1,44
2009	1 589,24	21,66	1,36
2010	1 696,83	23,20	1,37
2011	1 824,89	30,54	1,67
2012	1 977,54	27,54	1,39
2013	2 134,46	45,21	2,12
2014	2 258,93	56,27	2,49
2015	2 471,78	57,87	2,34
2016	2 618,08	73,09	2,79
2017	2 774,19	59,39	2,14

Source: *Authors'calculations based on world bank data*



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