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REVIEW ARTICLE

Forecasting Construction Tender Price Index in Ghana using Autoregressive Integrated Moving Average with Exogenous Variables Model

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Abstract

Prices of construction resources keep on fluctuating due to unstable economic situations that have been experienced over the years. Clients knowledge of their financial commitments toward their intended project remains the basis for their final decision. The use of construction tender price index provides a realistic estimate at the early stage of the project. Tender price index (TPI) is influenced by various economic factors, hence there are several statistical techniques that have been employed in forecasting. Some of these include regression, time series, vector error correction among others. However, in recent times the integrated modelling approach is gaining popularity due to its ability to give powerful predictive accuracy. Thus, in line with this assumption, the aim of this study is to apply autoregressive integrated moving average with exogenous variables (ARIMAX) in modelling TPI. The results showed that ARIMAX model has a better predictive ability than the use of the single approach. The study further confirms the earlier position of previous research of the need to use the integrated model technique in forecasting TPI. This model will assist practitioners to forecast the future values of tender price index. Although the study focuses on the Ghanaian economy, the findings can be broadly applicable to other developing countries which share similar economic characteristics.

Keywords

Forecasting, tender price index, ARIMAX, Ghana

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Introduction

Tender price indices are comparable to output price indices. It is an output index demarcating the average building prices within a specific period, i.e. the agreed price to be paid by the clients/owners. It then reflects the common market conditions (Ng, et al., 2000). Forecasting the movement of the TPI is never a straightforward process, as it could be influenced by a series of socio-economic factors such as interest rate, gross domestic product (GDP), unemployment rate and the varying challenges in tender appraisals rising from current trend of complex designs (Fitzgerald and Akintoye, 1995; Ng, et al., 2000; Wong and Ng, 2010). Similarly, Wong, Bai and Chu (2010) posited that the rate at which one can precisely forecast the tender price of a construction project has been a subject of research a few decades ago, as tender prices could influence the ideas of clients, contractors, property investors, financial institutions, etc. Hassanein and Khalil (2006) argued that a perfect forecast of indices in any way is arduous. In addition, the development of TPI is highly unstable in the building industry as there is an extensive inconsistency between the annual rate of tender price and building cost (Akintoye, 2000). Hassainein and Khalil (2006) further posited that there are many variables in a business environment that cannot be implied with certainty. However, TPI is vital in the successful delivery of projects and is more imperative in decision-making right from the beginning of any project as it ensures effective cost planning practices. Tender Price Indices (TPI) is, therefore, employed to track the historical inclinations in the movement of tender price levels of construction contracts throughout the respective stages.

The establishment of an appropriate tool for predicting TPI is still evolving and in developing countries, this is now gathering momentum due to the recent economic recession. Consequently, in developed countries, there has been several models that have been developed forecasting TPI (McCaffer, McCaffrey and Thorpe, 1983; Runeson, 1988; Fellows, 1991; Akintoye, Bowen and Hardcastle, 1998; Ng et al., 2000; Ng, et al., 2004; Wong and Ng, 2010). The need for more unbiased methods and the benefits of quantitative predictive price models, in general, have been recognised in the construction industry (Li and Love, 1999; Ng, et al., 2000,2004). However, the search for more concrete model remains debatable among researchers as new statistical and econometric methods keep on revolving. As a result, diversity of cost models of varying complexities has been devised by researchers. Based on this, the paper seeks to forecast TPI in the Ghanaian Building Industry (GBI) using autoregressive integrated moving average with exogenous variables (ARIMAX) models. Previous research argues that ARIMAX has a better predictive ability when compared to autoregressive integrated moving average (ARIMA) (Kongcharoen and Kruangpradit, 2013).

The paper first looks at previous works on TPI modelling, followed by research methodology and data analysis and discussions. Lastly, the conclusion underscored the need for using the integrated approach in forecasting TPI.

Previous Studies

Statistical methods have been widely applied in forecasting TPI, which includes Regression Analysis (RA) and Time Series (TS) Vector Error Correction (VEC), Fuzzy Sets (Chang *et al.,* 1997), Structural Equation (Akintoye and Skitmore, 1999) and Artificial Neural Network approaches (Williams, 1994).

Regression is mostly used to examine the relationship between variables. These variables are either dependent or independent and such their measuring effects are hooked on the estimated regression equation. Regression method was the first approach used in predicting

TPI and remains the most popular technique in the modelling of TPI (Bowley and Corlett, 1970; McCaffer, McCaffrey and Thorpe, 1983; Runeson, 1988; Akintoye and Skitmore, 1994; Ng, et al., 2004). Regression models provide an accurate prediction of TPI movement when price levels are steady, that is, moving constantly upward or downward. However, construction prices are mostly affected by market conditions and can fluctuate radically. This is evident in recent world economic crisis, for instance in Ghana, it is very vivid as the credit remains very unstable. Several studies have also shown that the weakness of current models is due to changes in economic situations, which always lead to substantial errors (Taylor and Bowen, 1987; Akintoye and Skitmore, 1994; Wong and Ng, 2010), and so have not produced satisfactory results in terms of prediction (Ng, et al., 2000). Consequently, Wisnowski, et al. (2001) and Yu (2014) argued that the candid causal relationships between the TPI and the associated variables cannot be revealed in regression analysis.

In addition, time series analysis involves the identification of the nature of phenomenon represented by a sequence of observation and forecasting. Box-Jenkins approach is the most commonly used because it offers a more structured way of choosing the specification of the model and estimating the parameters. It has been used in forecasting tender price index by several authors (Fellows, 1991; Ng, et al., 2000). It must be noted that statistical methods can be classified into two classes: univariate and multivariate models. However, current statistical methods, such as univariate time series models, do not have expounding capability and suitability for short-term prediction (Goh and Teo, 2000; Wong and Ng, 2010). In addition, the univariate time series modelling assumes that current trends to remain relatively steady, might produce high forecasting errors when the trend discontinues within the projected timeframe (Tong and Lim, 1980). Multivariate Discriminant Analysis is similar to regression analysis; however, the dependent variables consist of classifications that are related to the linear combination of independent variables. Thus, to advance the accuracy of TPI forecasts, Ng, et al. (2000) in Hong Kong adopted the multivariate discriminant analysis for forecasting directional changes of the TPI. However, under closer examination, the study was uncertain on many fronts. Firstly, the definition of the "constant movement" category of tender price movement changes over time. Consequently, there was constant movement when the value of the tender price index is the same as the previous quarter (Yu, 2014). The holdout sample selected the best lag periods for the economic indicators in the model. Therefore, the 'holdout sample' is not really held out from the model construction. Yu (2014) further argued that the prediction power of the model can be regarded as poor.

Furthermore, econometric models were developed for predicting various economic and financial variables, and little has been done in the construction industry especially in forecasting the tender price using the VEC modelling approach. It is thus found that the VEC model outperforms the Box– Jenkins and regression models and proved to be efficient and reliable in forecasting the short-to-medium-term tender price movements (Yu, 2014). Wong and Ng (2010) in similar studies use vector error corrections by integrating the correlation of co-integration non-stationary variables, which gave better results. Akintoye and Skitmore (1994) derived a structural equation model for forecasting TPI. This model produces inaccurate results as changes in the coefficients of the structural demand and supply equations will change the coefficients of the equation. On the other hand, a study done by Asano et al. (2008) using the equation data based on Akintoye and Skitmore (1994) model showed that some values of some coefficients differ, and some variables were less statistically significant.

Li, et al. (2006) observed that the main problem associated with existing methods being used for forecasting the TPI is the limited consideration of market conditions, particularly when the market is unstable. Furthermore, Ho (2013), to forecast TPI for under incomplete information of the building project, proposed the grey system theory. The grey system forecasting is based on a statistical method, which is similar to time-series method. The forecasting power of this model depends on the identification of appropriate leading variables. However, the temporal relations of variables were ignored in these models. Notwithstanding, Ng, et al. (2004) in attempting to improve the accuracy, developed a building tender price index (TPI) forecasting model by combining the multivariate regression model with univariate ARIMA model.

Following the previous model's review in the above, data span adopted for the assorted studies were not the same. Although in some cases, similar data were used, the results differ from one model to another due to the statistical tools used. In addition, a lot of models hinged on time series or other techniques, with a major problem of being non-stationary. Furthermore, the use of integrated approach by Ng, et al. (2004) showed the robustness of combining two methods. The study was therefore carried out using an integrated approach in line with the Granger (2001) postulation that an integration of techniques enhances the predictive ability of models. This study, therefore, adopts the integration techniques approach in modelling. Hence, autoregressive integrated moving average with exogenous variables (ARIMAX) model would be utilised. This is because ARIMAX model has a better prediction ability than the Autoregressive Integrated Moving-Average (ARIMA) models (Anggraeni, 2015; Andrew, et al., 2013; Kongcharoen and Kruangpradit, 2013). Thus, the aim of this paper is to examine how ARIMAX can be used in forecasting TPI in the Ghanaian Building Industry.

Research Method

EXPLORATORY VARIABLES

The establishment of appropriate economic indicators for the development of any TPI is essential because indices are forecast based on economic patterns. Several researchers have stated different economic parameters for the determination of reliable TPI and its forecast (McCaffer, McCaffrey and Thorpe, 1983; Runeson, 1988; Fellows, 1991; Akintoye, Bowen and Hardcastle, 1998; Ng, et al., 2000; Wong and NG, 2010). Hoptroff, Bramson and Hall (1991) argued that the best method for determination of economic indicators is the establishment of the leading economic indicators which have an influence on the pricing of construction resources. The identification of appropriate leading indicators includes a mixture of theoretical considerations and derived analysis. On the theoretical stands, Berk and Bikker (1995) and Ng, et al. (2000) indicated that in choosing the potential indicators for forecasting it is relevant to consider the economic likelihood of their leading characters. McCaffer, McCaffrey and Thorpe (1983) opined that economic indicators are imperative in TPI development due to the relevance of changing market conditions. However, the list of leading indicators is accumulated on basis of paper review, availability of data and significance of candidate indicators to pricing (Wong, 2001). Based on the comprehensive literature review, 23 economic indicators were identified to have influence on tender price indices prediction. However, six (6) out of the twenty-three (23) indicators were available and were deemed to be significant to tender price indices prediction in the Ghanaian Building Industry. These are Composite consumer price indices (CCPI), gross domestic product – construction (GDPC), exchange rate (ER), gross domestic product (GDP), interest rate (IR) and producer price indices (PPI). On this basis, the function of influence is given as:

$$\text{TPI} = f\,(CCPI, GDPC, ER, GDP, IR, PPI)$$

DATA SET

The variables for the analysis, therefore, consisted of TPI and six exploratory variables (Economic Indicator-EI). These economic indicators were obtained from the Ghana Statistical Service and Bank of Ghana while the TPI was obtained from previous studies. The data covered a total of 32 quarters ranging from 2009Q1to 2016Q4

ARIMAX MODEL

Basically, ARIMAX is a combination of regression and ARIMA models (Andrew, et al., 2013). In ARIMAX model, the exogenous variable (s) is the independent variable(s) in linear regression equations. Although the ARIMAX model has not been widely used in forecasting in construction economics it provides good predictor variables that affected pricing. It is an extension of the ARIMA that has the ability to identify the underlying patterns in time series data. ARIMAX model provides flexibility in model building with time series data as it can be simply reduced to ARIMA model if historical behavior is to be examine by making projections through employing only statistically identified historical relationships.

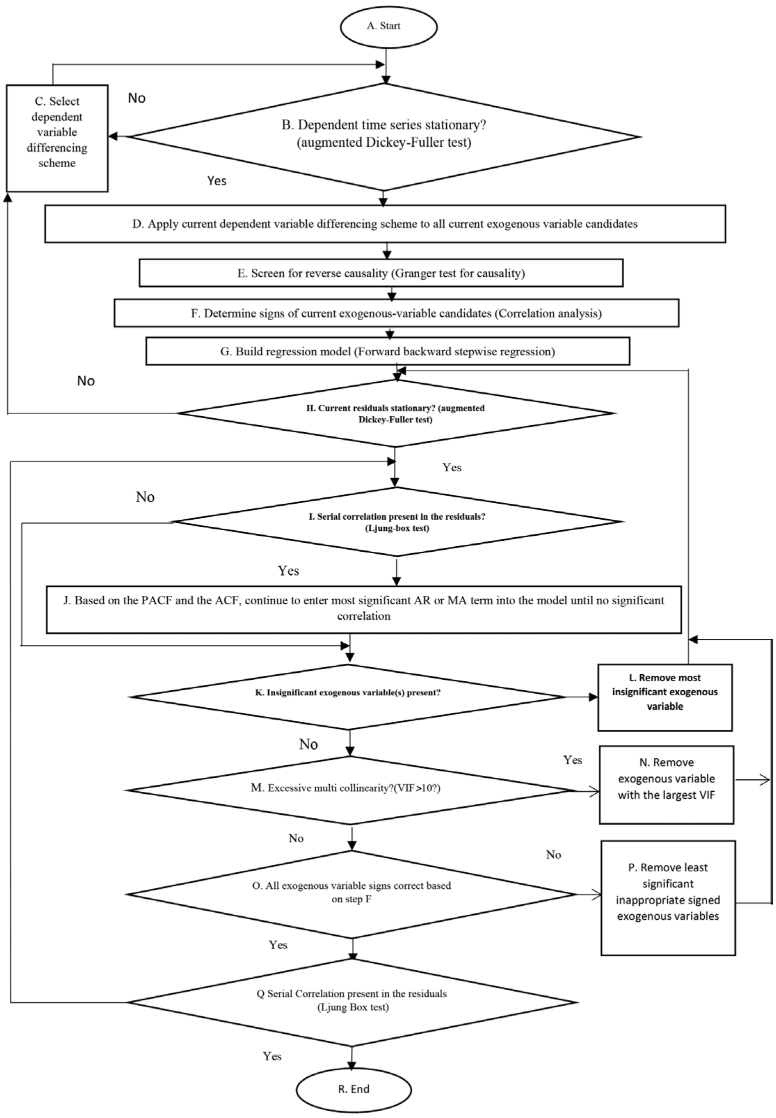

Figure 1 Processes for arimax model development (Adopted form Andrew et al.,2013)

In building ARIMAX model, time-series model techniques must be used involving two phases (see **Figure 1**: Processes for ARIMAX model development). The first phase deals with a linear regression model. This helps in maintaining independent variables that are significant (exogenous variables). The second phase deal with iterative searching process, thus, searching the order of ARIMA part of the model. There are various assumptions that must be satisfied to ensure that the resulting ARIMAX model is valid. ARIMAX model building may not commence until the time series is stationary. In addition to stationarity, the residuals from the model must not exhibit significant serial autocorrelation and must be white noise. For a given dependent variable and exogenous variable the ARIMAX model can be denoted as:

$$y_t = \hat{\beta}_1 x_t + \hat{\emptyset}_1 y_{t-1} + \hat{\emptyset}_2 t_{t-2} \dots + \hat{\emptyset}_n \varepsilon_{t-n}$$

Where

$\hat{\beta}, \hat{\emptyset}$ are estimated coefficients, error (ε), exogenous variables (x) and time (t)

Before proceeding with the estimation of ARIMAX model, stationary analysis of the time series data was carried out using Augmented Dickey Fuller Test. Thus, after second attempt difference level of data (due to non-stationary of the actual data and first difference level of data), the *p-value* was 0.02, beckoning that residuals are stationary hence no further transformation data and deemed fit for further analysis (see Table 1).

Table 1 Root Test (ADF)

Variable	P-value	Null hypothesis	Decision
Actual data	0.99	Not stationary	**Fail to reject H0**
First differenced data	0.32	Not stationary	**Fail to reject H0**
Second differenced data	0.02	Not stationary	**Reject H0**

Furthermore, in selecting a suitable model for the data, an ARIMAX model with different order ARIMA was compared. Following this, ARIMA with the order (0,2,1) was selected based on its least value of Akaike Information Criterion (AIC), (see Table 3). To establish the relevancy of each independent variable to TPI prediction, granger test was performed (**see Table 2**). The results suggest that TPI has a strong significance relationship with Producer Price Index (PPI) and Composite Consumer Price Index (CCPI). Hence, this indicates some economic indicators have relationships with TPI and identified economic indicators (see Table 2).

Table 2 Granger Test

Independent variable	F statistic	DF	P-values
CCPI	**5.201**	**3**	**0.009**
GDP	0.852	3	0.484
ER	0.853	3	0.483
PPI	**3.406**	**3**	**0.040**
IR	0.803	3	0.509

Following this, further analysis was carried out using the PPI and CCPI to develop the ARIMAX model using both ARIMA model based on the order (0,2,1). From the Table 3 ARIMA model was then subjected to ARIMAX model building by adding up each economic indicator (PPI and CCPI). Each variable was analysed and then later the combined effect of the two variables was carried out. Based on the Akaike Information Criterion the best

Table 3 Selection of the Model

Arima 1	(x = t.dat, order = c (0, 2, 1))		
Coefficients:			
	MA1		
	-0.8428		
S.E.	0.1067		
sigma^2 estimated as 20.62: log likelihood = -82.72, AIC = 167.44			
Arimax Model 1	**(x = t.dat, order = c (0, 2, 1), xreg = exo [CCPI])**		
Coefficients:			
	MA1		CCPI
	-0.8492		0.0097
S.E.	0.1022		0.0144
sigma^2 estimated as 20.26: log likelihood = -82.49, **AIC = 168.98**			
Arimax Model 2	**(x = t.dat, order = c (0, 2, 1), xreg = exo [PPI])**		
Coefficients:			
	MA1		PPI
	-0.8467		-0.0076
S.E.	0.1047		0.0118
sigma^2 estimated as 20.3: log likelihood = -82.51, **AIC = 169.02**			
Arimax Model 3	**(x = t.dat, order = c (0, 2, 1), xreg = exo)**		
Coefficients:			
	MA1	CCPI	PP1
	-0.8488	0.0064	-0.0032
S. E	0.1030	0.0267	0.0218
sigma^2 estimated as 20.25: log likelihood = -82.48, **AIC = 170.96**			

ARIMAX model was selected in terms of the model with least AIC. Thus, ARIMAX model 1 was selected based on the AIC value of 168.98 where CCPI was the exogenous variable.

EVALUATION OF THE MODELS

In the evaluation of the models in Table 3, the following tests were carried out. The results indicate the null hypothesis should not be rejected; rather it should be accepted. From the analysis in Table 4, Shapiro-Wilk normality test has a t-statistics value and p-value within the acceptable, hence the models fail to reject the null hypothesis of normality of the model residual. In addition, One Sample t-test has a t-statistics and *P*-value within the acceptable, hence the models fail to reject the null hypothesis indicating that true mean is not equal to zero (See Figure 2 at Appendix). These confirm that the residuals from the fitted model ARIMAX (0, 2, 1) – ***TPI*** are independent and normally distributed. In addition, Box-Ljung test fails to reject the null hypothesis of independence, thus, the data was significant.

Table 4 Parameter for evaluation of the models Residuals

Parameter for evaluation of the models				
Box-Ljung test	**X-squared**	**p-value**	**Null hypothesis**	**Decision**
	8.4609	0.7482	Independent	**Fail to reject**
	8.5162	0.7436	Independent	**Fail to reject**
	8.6825	0.7298	Independent	**Fail to reject**
	8.6183	0.7351	Independent	**Fail to reject**
One Sample t-test	**t-statistics**	**p-value**	**Null hypothesis**	**Decision**
	0.93909	0.3554	Zero mean	**Fail to reject**
	0.99693	0.3270	Zero mean	**Fail to reject**
	0.95820	0.3459	Zero mean	**Fail to reject**
	0.98542	0.3326	Zero mean	**Fail to reject**
Shapiro-Wilk normality test	**W**	**p-value**	**Null hypothesis**	**Decision**
	0.97270	0.6152	Normality	**Fail to reject**
	0.97412	0.6568	Normality	**Fail to reject**
	0.97095	0.5655	Normality	**Fail to reject**
	0.97325	0.6315	Normality	**Fail to reject**

GOODNESS OF FIT OF THE MODELS

The goodness of fits analysis was done alongside with benchmark model of the three main ARIMAX models (0, 2, 1) in Table 3. The model comparison was done based on in-sample and out-sample data. The in-sample data consist of the actual data used in fitting the models (30 quarters) whiles the out-sample data consist of the remaining data (three and four of 2016). The in-sample performance of models were evaluated using, mean absolute percentage error (MAPE), Theil's inequality Coefficient U, mean absolute error (MAE), mean square error (MSE) and root mean square error (RMSE) in Table 5. However, in similar studies by Ng and Wong (2010), Goh and Teo (2000) and Oshodi, et al. (2017) mean absolute percentage error (MAPE) and the Theil's inequality coefficient *U* were used to assess the predictive precision of the model. According to Oshodi, et al. (2017) and Crone, et al. (2011) a good model would yield reliable result across several metrics. It further argued that for a prediction to be dependable and tolerable, the value of MAPE should be less than 10% and Theil's inequality coefficient *U* should be close to zero (Fan, et al., 2010; Goh and Teo, 2000). From the in-sample analysis of the models based on the performance metrics, model 3 recorded least values performance of Theil's inequality coefficient *U*, mean square error and root mean square error indicating a strong predicting ability. However, the model 1 recorded a least in Mean Absolute percentage error and mean absolute error indicating that it has a strong performance indicating can be used to predict TPI.

Table 5 MAPE, U, MAE, MSE and RMSE was calculated for the models (in-sample)

Parameters	MAPE	Coefficient U	MAE	MSE	RMSE
ARIMA	2.05940	0.01349991	3.324159	19.24695	4.387135
ARIMAX 1	**2.035043**	0.0133834	**3.284110**	18.9128	4.348885
ARIMAX 2	2.037611	0.0133947	3.286254	18.94655	4.352763
ARIMAX 3	2.038525	**0.01337857**	3.288228	**18.89961**	**4.347368**

The out-sample data performance of the models was evaluated using the time-order handout using the data that was left behind (2016Q3 to 2016Q4). Table 6 contains the observed TPI, predicted values using the various models and the performance metrics each of the mode (MAPE, Theil's inequality coefficient *U* and MAE). From the performance metrics ARIMAX model 1 with composite consumer price index recorded the least values as compared to other models in Table 6, indicating that it can give better predictive values. In buttressing this, its predicted values were closer to the observed values as compared to the other models. In addition, the ARIMAX model 3 with exogenous variables composite consumer price index will give second better predictive values while the ARIMAX model 2 with producer price index will give worst possible values in terms of prediction.

Table 6 Out sample forecast comparison

Parameter	2016Q3	2016Q4	MAPE	Coefficient U	MAE
Observed Value	237.41	241.52			
ARIMA	241.3	247.9	2.139892	0.01092576	5.1348
ARIMAX 1	**241.2**	**247.8**	**2.102853**	**0.01073732**	**5.0459**
ARIMAX 2	241.3	248.0	2.166210	0.01106462	5.19805
ARIMAX 3	241.2	247.9	2.125691	0.01085559	5.10075

Discussion

The outcome of the findings revealed that in the building industry tender price levels can be affected by several economic indicators. In the Ghanaian building environment, the analysis showed that composite consumer price index and producer price index have significant relationships with Tender price index. This suggest these variables have the tendency to influence price levels in the building industry. From an economic theory, composite consumer price index and producer price both measure price variations for goods and services, however, they vary in the composition of their target sets of goods and services and in the type of price collected for those different goods and services.

Generally, in every economic setting CCPI remains a leading economic indicator which reflect the changes in price of package of consumer goods and service in a period, it was therefore not surprising that CCPI was significant in terms of its relationship with tender price index. In addition, in selecting best models based on Akaike Information Criterion to the in-sample analysis and predictive ability of the (out–sample analysis) model 2 was chosen as best model for future analysis of Tender Price Indices. Thus, in this model CCPI act an exogenous variable, suggesting a change in CCPI will affect TPI figures. It further shows that any change in the variable will affect tender price and consequently effects on TPI. The past value of the indicator of tender price movement has shown that it can be useful for predicting TPI.

Furthermore, the occurrence of CCPI as strong economic indicator that can influence TPI is in line with other similar studies by Ng, et al. (2004) and Wong and Ng (2010) that economic indicators such CCPI have the tendency to influence TPI predictions. It is worth to note that, CCPI and inflation have a strong relation as a decrease in the CCPI tends to increase inflation, which will automatically cause a change in the pricing of goods and services in the building industry. CCPI therefore has a strong interdependence with other economic variables such as inflation and by extension exchange rate and interest rate. CCPI seeks to measure the effects of the price disparities on prices of the household item which construction industry remain a subset of the household consumptions.

Conclusion

To achieve the general aspiration of project participants' keen attention must be given to factors that have the propensity to cause financial distress in the project execution process. Thus, the ability to determine the economic indicators that influence TPI and modelling remains imperative to the development of pricing factors. However, the focus of many researchers is the ability to used statistical or econometric techniques to accurately predict the movement of prices. Therefore, there has been much research in this perspective providing a firm basis for further studies (on single statistical approach), notwithstanding, Granger (2001) propagation for the use of the integrated approach. In line with this Ng, et al. (2004) adopted the use of integrated of regression and time series for the prediction TPI in Hong Kong which yields satisfactory results. Hence, the current study adopted the use of autoregressive integrated moving average with exogenous variables which yielded a better prediction ability when compared with the single approach. This further affirms the need to continue the use of the integrated approach due to its ability to give powerful results. This further shows that researchers should adopt a more rigorous approach in the prediction of TPI. Notwithstanding the contribution this current study makes to the body of construction management literature, the study is limited in the number of data sets that was used in the out-sample analysis. Hence, further study is encouraged to use more data sets. Finally, the model will help professionals in forecasting tender price movement.

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APPENDIX 1 DATA SET

No	Year	Index
Base Year	**2008**	**100**
1	2009 Q1	111.29
2	2009 Q2	113.41
3	2009 Q3	119.11
4	2009 Q4	122.13
5	2010 Q1	125.37
6	2010 Q2	128.17
7	2010 Q3	129.75
8	2010 Q4	131.05
9	2011 Q1	134.67
10	2011 Q2	137.14
11	2011 Q3	145.58
12	2011 Q4	141.25
13	2012 Q1	148.73
14	2012 Q2	147.46
15	2012 Q3	146.71
16	2012 Q4	155.71
17	2013 Q1	156.91
18	2013 Q2	157.56
19	2013 Q3	151.55
20	2013 Q4	162.45
21	2014 Q1	173.12
22	2014 Q2	176.93
23	2014 Q3	185.79
24	2014 Q4	194.98
25	2015 Q1	201.65
26	2015 Q2	202.98
27	2015 Q3	208.91
28	2015 Q4	213.75
29	2016 Q1	222.6
30	2016 Q2	234.63
31	2016 Q3	237.41
32	2016 Q4	241.52