TENDER PRICE INDEX DEVELOPMENT: A CRITICAL LITERATURE REVIEW OF MODELS FOR PREDICTION

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Abstract
Tender price determination for every construction project remains a critical variables for a successful project delivery. For project participants it is the fundamental concept for which prices for project are appraised. Proper analysis of how much clients investment can afford within appreciable cost is hinged on the Tender Price Index (TPI), which gives and forecasts the average movement in building prices within a certain time frame and much treasured at design stage for effective cost planning The need for cognizant effort by quantity surveyors in giving a realistic price for project remains crucial due to the extent that clients are willing to spend within their budget peripheral. In the domain of accurate tender price index prediction researchers over the years have conjectured divergent views due to variances of statistical method adopted and their interpretations. This paper reviews various models adopted for prediction of TPI as a way of establishing need for further studies that will ensure more accurate prediction. The findings indicate that a combination of two statistical tools give more accurate prediction. In addition, variables used varies from one model to another which was compounded with a common statistical problem of non-stationary. This suggest that variables for tender price index prediction continues to vary from one geographical location to another, this is due to dynamism in economic indicators. Consequently, the need for development of a robust model cannot be shelved in any developing countries due to the fact that these countries have unstable market conditions.

Keywords: Tender Price Index (TPI), Model, Prediction, Review

1 Introduction

Pioneers modeling discussion describe a model as a technique developed to reflect, by means of derived processes, adequately acceptable output and establish series input data (Seeley, 1996). Shafique and Mahmood (2004) posit that a model is an abstraction or a framework for analysis of a system. It assists researchers in unfolding more accurately to reality; it also aids them to describe, predict, test or understand complex systems or events. Thus, models often provide a framework for the conduct of research and might consist of actual objects or abstract forms, such as sketches, mathematical formulas, or diagrams. It involves simplified representations of real-world phenomena (Powell and Connaway, 2004). Consequently, in Tender Price Index (TPI) development, there have been a number of models that have been developed by previous studies. The need for more unbiased methods, and the benefits of quantitative predictive price models in general has been recognised in the construction industry (Li and Love, 1999; Ng *et al.*, 2000:2004) however, the search for more concretive model remains debatable among researchers as new statistical and econometric methods keep on revolving. As a result, diversity of cost models of varying complexities have been devised by researchers. Statistical methods have been widely applied in TPI prediction, with Regression Analysis (RA) and Time Series (TS) being the most popular approaches. Vector Error Correction (VEC), Fuzzy Sets (Chang et al., 1997), Structural Equation (Akintoye and Skitmore, 1999) and Artificial Neural Network approaches (Williams, 1994). It must be noted that all these methods were adopted as a medium of exploring statistical or econometric methods that will give the best prediction accuracy. In addition, the adoption of any method for the development of any model is founded on availability of the said variables and the conditions existing within geographical context. Hence, the motivation of this study is to critically review the various model for the forecasting TPI.

2 Extant of Tender Price Index Model Development

2.1 Regression Method

Regression are 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 of TPI and remains the most popular techniques in modelling of TPI (Bowley and Corlett, 1970; Ng *et al.*, 2004). McCaffer *et al*. (1983) developed a regression model in United Kingdom which was purposefully done to measure the disparity between the input and output price of building contractor. This produced more accurate predictions of tender price movements than the subjective approach (judgmental) current at that time. This model predicted the TPI of buildings during the early design stage. They provided estimates using a library of data containing rate, quantity and date for the constituent elements of previously constructed buildings, inflation indexes and statistical models. However, this model was predicting a set of data covering a period of 9 years, although the statistical result applies that their data straddling 6-6.5 years. On the other hand, Chau (1988) found out that, there was downward trend of TPI to Building Cost Index (BCI) ratio over a period of 16 years in Hong Kong. This shows that a downturn is expected in the output growth of the industry. In using the data from Florida Department of Transportation, Herbsman (1983), developed composite cost index, which was similar to McCffer's (1983) prediction in terms of the exploratory variables used in the measuring of the industry's output. Runeson (1988) proposed a multiple regression model for forecasting building price movements. The dependent variables were market condition index, whereas the predictor variables included the level of building approvals (a measure of demand), the fixed capital formation of building (a measure of current capacity or output of the industry) and the level of unemployment (a measure of capital utilization). It was found that, the R2 was very satisfactory (0.8556) and the average absolute error stood at 3.67%. However, a multiple regression model was not stable over time and its forecasting accuracy diminished. The Building Cost Information Service (BCIS) produced a 2-year forecast of TPI also based on a linear regression model. The input variables consisted of the building cost index, the amount of construction output as well as the amount of construction new orders. The resulting forecasts were then adjusted by using experts' judgment. A major problem in forecasting TPIs is the contractors' unpredictable reactions to changes in construction demand (Akintoye and Skitmore, 1994). Fitzgerald and Akintoye (1995) found that the TPI forecasts produced by BCIS have been generally over-optimistic, leading to systematic forecast error. The mean absolute percentage error (MAPE) of the forecast indices varied from 3.60% at the first quarter forecast horizon to 12.23% at the eight-quarter forecast horizon. By using an optimal linear correction to remove biases and regression proportions of forecast errors, the MAPE of the forecast value was reduced to 2.20% at the first-quarter forecast horizon and 10.52% at the eight quarter forecast horizon. Regression models provide 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 cedi remains unstable. Several studies have also shown that the weakness of current models are due to changing economic situations, thus 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 predicting (Ng *et al.,* 2000). Consequently, Wisnowski *et al.* (2001) argued that, the candid causal relationships between the TPI and the associated variables cannot be revealed in the regression analysis (Yu, 2014).

2.2 Time Series

Time series analysis involves the identification of the nature of phenomenon represented by sequence of observation and forecasting. Box-Jenkins approach (Box and Jenkins, 1970) is the most common used because it offers a more structured way of choosing the specification of the model and estimating the parameters. This technique determines future trends based on past values and corresponding errors. Since a time series method only requires the historical data of forecast variable itself, it is widely used to develop predictive models. The time series method has been used to forecast Taiwan's construction cost indices (Wang and Mei 1998), building costs (Taylor and Bowen 1987), price index (Fellows, 1991; Goh and Teo, 1993; Goh and Teo, 2000; Goh 2005), cost index (Hwang, 2011) and tender price index (Fellows 1991; Ng *et al.,* 2000). In the study of Engineering News Record (ENR) of Construction Cost Index (CCI) by Williams (1994), time series method was compared with linear regression and neural network models with respect to predictability. Taylor and Bowen (1987), however, modelled the tender price index in South Africa which reflected movements in price that contractors charged their clients. Current statistical methods, such as univariate time series models, do not have expounding capability and suitability for short-term predicting (Goh and Teo 2000; Wong and Ng 2010). However, the univariate time series modelling assumes that recent trends to remain relatively steady, it might produce high forecasting errors when the trend discontinues within the projected timeframe (Tong and Lim, 1980). Besides, the limited structure in the time series approach makes them only suitable for short-term forecasting (Wong et al., 2010). This further suggest time series models are not robust enough to endure economic pressure and such it predictive ability is questionable, thus unsuitable when explanation or reasoning is critical (Goh and Teo, 2000; Wong *et al.,* 2010).

2.3 Multivariate Discriminant Analysis

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, in an attempt 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 by utilizing eight leading economic indicators. These indicators comprised the best lending rate, building cost index, composite consumer price index, gross domestic product (construction), implicit gross domestic product deflator, and money supply and unemployment rate. Two discriminant functions were derived in order to distinguish between 'upward', 'constant' and 'downward' index trends. However, under closer examination the study was uncertain on many fronts. Firstly, the definition of the "constant movement" category of tender price movement change over time. Thus there was constant movement as when the value of the tender price index is the same as the previous quarter (Yu, 2014). In addition, rationalization of the discriminant model by the holdout sample is contentious. 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. Given the clear long term upward trend of the tender price index, the fair benchmark predictions of the direction change would be always upward, which would be correct in 65% of the cases, better than the 59.7% by the model.

2.4 Vector Correction Error

Econometric models were developed for predicting various economic and financial variables, little has been done in the construction industry especially in forecasting the tender price using the VEC modeling approach. Vector Error Correction (VEC) models are readily comprehensible and commonly used to empirically analyse the dynamic behaviour of macroeconomic variables (Price, 1998). This method is also preferred because of its dynamic nature and sensitivity to a variety of factors affecting the measured variable, while it takes into account the long-run equilibrium relationships among the variables in the system (Lutkepohl, 2004) and allows short-term forecasting errors to be eliminated efficiently (Allen and Morzuch, 2006). The forecasting accuracy of the VEC model was also compared with the Box–Jenkins and regression models using the same data set. The MAPEs of the forecast TPI for one quarter ahead generated by the VEC, Box–Jenkins and regression models were 2.9, 11.4 and 4.2%, respectively. 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. Wong and Ng (2010) in a similarly studies use vector error corrections by integrating the correlation of co-integration non-stationary variables, which gave better results.

2.5 Neural Network

Williams (1994) developed back-propagation neural network models to forecast the changes in the construction cost index for time spans of 1 month and 6 months ahead. Variables selected as inputs to neural network models include the percentage change in the construction cost index, the prime lending rate, the percentage change in the prime lending rate, the number of housing starts, the percentage change in housing starts and the month of the year related to. The output from the neural network models is compared with prediction made by exponential smoothing and simple linear regression. It was found that the exponential smoothing and regression models produced a sum of the squares of errors (SSE) equal to 2.45 and 2.65, respectively, whereas the SSE for the neural network was 5.31. The forecasts produced by the neural network model gave a greater error than either exponential smoothing or linear regression. It was concluded that construction cost indices could not be forecasted accurately by using the back-propagation neural network model. Similarly, Yu (2014) also argued that neutral networks require massive amounts of data, although the difficulty in the explanation of the theory behind makes its disadvantage. However, there is an increasing trend toward the use of neutral networks, this due to the extent that neutral networks allows for more complex variables to be recognized and make it more flexible to use.

2.6 Structural Equation Model

Akintoye and Skitmore (1994) derived a structural equation model for forecasting TPI. The demand equation comprises the number claiming unemployment-related benefit, the manufacturing output price/input cost ratio, the real rate of interest and the quarterly gross national product. The supply equation comprises the quarterly TPI, the output per person employed in the construction industry, the quarterly building cost index, the working days lost by workers involved in operation of construction industry due to industrial disputes, the number of registered private contractors and the dummy variable to reflect the general increase in prices(see Table 1 at appendix). 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 Skimore (1994) model showed that some values of some coefficients differ and some variables are less significant statistically.

2.7 Integrated Approach

Ng et al. (2004) in further attempt to improve the accuracy, developed a building tender price index (TPI) forecasting model by combining the multivariate regression model with univariate ARIMA mode. This postulation agrees with Granger's (2001) study which suggested that the integration of techniques might further enhance the predictive ability. It was found that the forecasting accuracy between the regression model and time-series model appeared similar when used in a one-quarter TPI forecast. However, the forecasts were improved when the integrated model was adopted. For a two-quarter TPI forecast, the regression model was found to be the most accurate, whereas the time-series model was the worst. The integrated model improved the forecasting accuracy. However, the multivariate regression model still remains doubtful. The model was built on the levels rather than the growth rates of the TPI and other economic indicators, and many of them, including TPI, display strong upward trend, it is very feasible that the correlation is inaccurate (Yu, 2014). This due to the fact that no unit roots test or co-integration test was carried out.

2.8 Further Studies on TPI Modelling Forecasting

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. They proposed that the TPI was the power function of the ratio of demand over capacity of the industry, which represented the industry's economic condition. The model is represented by TPI= α (Demand/Capacity) $^{\beta:}$ *β = should be greater than 1 in order to give a slower reaction TPI to a lower ratio and a faster reaction to a higher ratio of demand over capacity; and α = acts as a multiplier to generate the TPI as the desired index value*. Actual quarterly demand in 2002 and 2003 and estimated capacities were used to forecast quarterly TPIs for those two years that were then compared to TPIs generated using completed project expenditures and expert opinions. It was found that the differences between actual and forecast TPIs ranged from 0.9 to 5%. However, Li et al. (2006) does not explain how the experts' views are formed or obtained. The description of the demand measures in their model is also brief, stating only that the "s-curve method was applied" to "workload data". Therefore, it is not possible to either replicate the demand measures or apply it to other countries. Furthermore, Ho (2013) in an attempt 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. However, in the construction industry, incomplete works do not give actual cost implication hence, using such data cannot be assumed to give accurate results. The forecasting power of this model depends on the identification of appropriate leading variables. However, the proven leading variables of tender price indices are not known. Moreover, the temporal relations of variables are ignored in this models.

3 Conclusion and Further Research

Tender Price index prediction is still evolving, however, as current economy condition remain very vague with anticipated difficulties, clients are searching for professionals who can give them value for their intend investment. For researchers, the search for appropriate tool for the improvement of the predictive power remains the ultimate agenda. From the review the following conclusion were drawn, that included:

- It is difficult to generalize the use of any of the models that were reviewed due to the fact that there are different economic factors or indicators that were used and data span adopted for the various 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 were hinged on time series and other techniques, have major a problem of stationary. This further indicates an inadequate level of knowledge in statistics on the part of some of the researchers; and
- Furthermore, the use of integrated approach have so far been used by Ng et al. (2004).It thus, shows the robustness of combining two methods, however, there were some weakness (Yu, 2014).

Hence, this suggest that further studies should be carried out on using the integration approach by dwelling on Granger (2001) study which suggested that the integration of techniques enhances the predictive ability of a TPI model. This can be done by improving Ng et al, (2004) work or building a new statistical model based on the combination of two different tools.

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Appendix 1

Table 11. Summary of Review Models

Author	Method	Purpose	Weakness	Conclusion
McCffar et al., (1983)	**Regression**			Can be used when price level are steady constantly upwards or downward. Not suitable for unstable market conditions. Relationship of between TPI and the associate variables cannot be reveal. Non-stationary of variables.
	$\frac{TPI_t}{BCI_t} = a + b + o_{t-4}$ a and b are estimated of the regression coefficients, O = building Cost Index	Measuring disparity between the input and output price of building contractors	Short run supply was basis for curve in terms forecasting, indicating upward trend only. Prediction covered 9 years instead of 6 to 6.5 (Yu,2014)	
Chau(1998)	$\frac{LMI_t}{TPI_t} = 0.8553+0.00912t$ where t is the time in quarters	Relation of Labour and Material and Index (LMI) to TPI	Long run supply was basis for curve in term forecasting thus, long run indicates downwards trend only	
Ng et al (2000)	**Multivariate Discriminant Analysis**			
	$Z = -1.079 + 0.264BCI_{t-2} - 0.007BLR_{t-2} + 0.028CPI_{t-2} - 0.012GDP_{t-2} - 0.024GDPC_{t-3} + 0.0251GDPD_{t-2} - 0.080M3_{t-2} - 0.034UR_{t-2}$ **BCI**= Building Cost Index, **BLR**= Best Lending Rate, **CPI** = Composite Consumer Price Index, **GDP** = Gross Domestic Product, **GDPC** = Gross Value of Investment in Building, Construction, Plant, Developers, Margin and Transfer Costs of Land and Buildings, **IGDPD** = Implicit Gross Domestic Product Deflator, **M3**= Money Supply Definition 3, **UR**= Rate of Unemployment.	Predicting changes of a TPI of new buildings in Hong Kong	Handout sample was not held out from the model. Prediction power of the model show only upward trend. Under constant movement there was change over time, that was change in TPI	It can be use where there are more than one variables from different units or sources
Ng et al, 2004	**Integrated Approach**			

(Time series and Regression)	F= 0.512Ra + 0.488ARIMA= period one forecast F= 0.647RA + 0.353ARIMA = period two forecast Régression Analysis $TPI = 66.6274 + 1.6115BLRT_{t-3} + 0.4746BCI_{t-1} -- 0.3117CPI_t – 2.7375UR_t + 0.0932M3_t – 0.00215HSIVA_{t-1}$ ARIMA $TPI_t - TPI_{t-1} = e_t + 0.7312e_{t-1} + 0.47_{t-2}$ **BCI** = Building Cost Index, **BLR** = Best Lending Rate, **CPI** = Composite Consumer Index, **M3** = Money Supply Definition 3, **UR** = Rate of Unemployment, and **HSIAV** = Hang Seng Index 100 days Moving Average	Forecasting TPI	No root or co-integrated test was carried out. Model was built on level rather than the growth rate of TPI and other economic indicators. Handout sample was not held out from the model. Prediction power of the model show only upward trend.	The need to introduce a variable for validation was not done. Differencing test was also not done to bring variables to stationary (Box-Jenkin, 1970).
Taylor and Bowen (1987)	**TIME SERIES,** P_t =Price index at time t, *d*= is difference operation, *In*= natural logarithm operator $dlnP_t$= is an approximation of the grow rate of the price P over the time t			Suitable for short term forecasting. Errors are forecast when the estimated trend discontinues within the projected timeframe.
	ARIMA (0, 1,2) $P_t = 1.2864P_{t-1} – 0.3115P_{t-2} + 0.76506e_{t-1} + e_t$	Tender Price Index based on information return from QS firms	The variables were non-stationary meaning that either mean or variance of the variables are not constant over time.	
Fellow 1999:1988	ARIMA (0, 1,2)-BCIS $dP_t = 1.161 + 1.33dP_{t-1} — 0.473dP_{t-2} + e_t$ ARIMA (0, 1,1) : PSA $dP_t = 0.673 + 0.8891dP_{t-1} + e_t$ ARIMA (0, 1,3) $dP_t = 1.254 + 1.4425dP_{t-1} – 0.7963dP_{t-2} + 0.2063dP_{t-3} + e_t$	BCIS : All-in tender price index PSA : tender price index Davis, Belfield and Everest Tender Price Index		

Goh and Teo 1993	ARIMA (0, 1,1) $dP_t = -0.38399dP_{t-1} + e_t$	Public industrial buildings tender price index	The indices over time display upward trends indicating that at least means of these indices are not constant	
Goh and Teo,2000	ARIMA (0, 1,1) $dP_t = -0.3864dP_{t-1} + e_t$	Public industrial buildings tender price index		
Goh,2005	ARIMA (0, 1,1) $dP_t = -0.08251dP_{t-1} + e_t$	Building and Construction Authority (BCA)		
Wong and Ng, 2010	**Vector Error Correction**			
	Δ[illegible] = 0.0034 − 0.0737 (l[illegible]g[illegible]) +0.39Δ[illegible]−1 + 0.05Δ[illegible]−2 + 0.04Δ[illegible]−3 −0.06Δ[illegible]−4 + 0.32Δ[illegible]−1 0.11Δ[illegible]−2 + 0.21Δ[illegible]−3 +0.12Δ[illegible]−4 −0.10Δ[illegible]−1 −0.08Δg[illegible]−2 −0.12Δg[illegible]−3 −0.14Δg[illegible]−4 +0.04Δg[illegible]−1 + 0.04Δg[illegible]−2 +0.17Δg[illegible]−3 +0.03Δg[illegible]−4 where *tpit* is log of quarterly tender price index of building industry in Hong Kong at time t; *bcit* is log of quarterly building cost index at time t; *gdpt* is log of quarterly gross domestic product at time t; *gdpct* is log of the quarterly construction component in gross domestic product at time t; *Δ* is the first difference operator such that Δ*tpit* = tpi_t - tpi_{t-1} for *long run relationship* in their preferred model is as follows: =[illegible]−1 +1.81[illegible]−1 +1.88g[illegible]−1 −0.03g[illegible]−1 That is for long run co-integrating equation as follows [illegible]−1 =−1.81[illegible]−1 −1.88g[illegible]−1 +0.03g[illegible]−1 +[illegible]−1 Where e_{t-1} is a white noise random variable with a constant variance and zero mean.	For predicting TPI in Hong Kong first quarter of 1983 and first quarter of 2006	The used of negative coefficient of bid was not explained. From the equation the higher the building cost index the lower the TPI. Which is not normal, but the author did not explain what might have cause for such occurrence.	It is use to correct the ARIMA error of stationary

Akintoye and Skitmore,1994	**Structural Equation**			
	$TPI_t = -3.615 + 0.807InBCI_t + 0.009\ In\ STR_{t-4} - 0.296InPRO_{t-2} - 0.258In\ FRM_{t-5} + 0.003RIR_{t-3} + 0.542In\ MAN_{t-7} - 0.136InEMP_{t-2} + 0.606In\ GNP_t + 0.061OIL_{t-1}$ **SUPPLY** $\ln QS_t = 1.049 + 0.970 \ln TPI_t + 0.628 \ln PRO_{t-4} - 0.695 \ln BCI_{t-2} - 0.019 \ln STR_{t-3} + 0.239 \ln FRM_{t-8} - 0.093\ OIL_{t-1}$ **DEMAND** $\ln QD_t = -14.051 - 0.766 \ln TPI_{t-3} + 1.632 \ln GNP_t - 0.011\ RIR_{t-1} - 0.249 \ln EMP_{t-4} + 1.764 \ln MAN_{t-4}$ **EQUILIBRIUM** $\ln QS\ t = 3.281 + 0.197 \ln QD\ t + 0.158 \ln QD_{t-1} + 0.106 \ln QD_{t-2} + 0.055 \ln QD_{t-3} + 0.02 \ln QD_{t-4} + 0.016 \ln QD_{t-5} + 0.058 \ln QD_{t-6}$ **TPI:**BCIS quarterly tender price index deflated by retail price index, **BCI:** BCIS building cost index deflated by retail price index, **STR:** number of strikes or stoppages, **PRO**: labour productivity, **FRM**: number of construction firms, **RIR:** real interest rate, **MAN:** profit margin in manufacturing sector ,**EMP**: level of unemployment, **GNP**: Gross National Product deflated by retail price index ,**Oil:** Oil crisis dummy	Forecasting price index based on demand and supply curves	Changes in the coefficients of the structural demand and supply equations will change the coefficients of that equation making it inaccurate for forecasting. Variables were not tested for stationarity, e.g. The TPI and GNP for the supply equation	