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Identification of Price Leading Indicators for Construction Resources

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Abstract **-** Resources prices fluctuation in many countries is an influential factor in construction projects' characterization of schedule slippages and cost overrun. Each country's market may be defined by its influential materials. In Egypt, Cement, and steel bars have major contribution to most of the construction activities. Changes in the material prices, especially drastic ones, are major threats to any contractor's plans as well as owners' budgets. Hence, timely forecasting of these changes can be a major advantage to contractors or owners. Prior to forecasting the fluctuations, identification of the leading indicators and investigation of the best time lag between these indicators and the predicted prices shall be conducted. Many researchers utilized statistical tests to identify leading indicators of cost indices, however, each resource might have its own leading indicator and unique lag time. This research aims at identifying the leading indicators of Egypt's main material prices through utilizing statistical tests such as Granger causality test. Egypt's macroeconomic indicators GDP, money supply, external debt, lending rate, stock market index, and U.S. dollar to Egyptian pound exchange rate were found to be the leading indicators of steel price. Lending rate, unemployment rate, and foreign reserves were found to be cement prices leading indicators.

Keywords**:** Leading indicators, Forecasting prices, Construction cost management, Economic indicators

1. Introduction

Construction projects are often notorious for schedule slippages, cost overrun, and many contractual disputes between the involved parties [1]. Cost overrun is defined as the difference between the estimated budget for the project and the actual cost incurred, which is often accompanied by failure to meet the contractual deadline of the project. These phenomena are often excessive in projects that span over number of years which entails inaccurate estimations of the budget and timeline for the project. Involved parties in a construction project include contractors, owners, consultants, and subcontractors. These parties often face huge challenge in controlling the project's budget and schedule. External risks are the ones which the parties have no little control over their impacts, including effects of inflation, market conditions, and unforeseen events. On the other hand, internal risks include scope changes, faulty execution, and contract documents conflicts [2]. Several risk factors, specifically external risks, often affect the project during its life cycle, and responsibility for each risk's impact often leads to contractual disputes between parties and the project is then hit with delays and extra costs incurred. Additionally, economic and political instabilities are challenging to predict their probabilities and impacts on the construction prices [3]. To overcome such complexities, many governments, private institutions, as well as researchers have attempted to quantify prices movements and market conditions through developing construction costs and prices indices as well as prediction models to predict them. Construction Cost Index (CCI) and Building Cost Index (BCI) developed by Engineering News-Record magazine as well as the National Highway Construction Cost Index (NHCCI) in the United states, United Kingdom's Tender Price Index [4], Ghana's Tender Price Index [5], Taiwan's Tender Price Index [6], Hong Kong's Construction Cost Index [7], and Egypt 1 Cost Index [8] are examples of indices that try to capture the construction market prices movements. Such indices have intrigued researchers to develop models that aim at timely predict such market movements enough time ahead to aid practitioners mitigate the impact of external risks facing their project. An essential step to develop prediction models is to identify the leading indicators of the predicted variable [9]. However, the process of developing these indices entails many assumptions regarding the weight of contribution of the components in each index. For instance, Engineering News-Record CCI combines 20-city average of common labor, standard structural steel shapes, Portland cement, and lumber prices in one index. Egypt 1 index developed by [8] follows a similar approach to ENR's approach while adjusting the components of the index to fit the Egyptian market. Hence, in Egypt 1, components are steel, Portland cement, bricks, common labor, and skilled labor. While having one index to capture the prices makes it easier for practitioners, the leading indicators for each component in these indices are not necessarily the same, which leads to misleading results. This research aims at identification of the leading indicators of the predominant resources in the Egyptian construction market, namely steel and Portland cement individually.

2. Literature Review

Some previous studies have relied on the potential indicators relevance to the predicted variable as provided in literature [10], [11], while others have investigated such relevance through statistical tests such as Granger causality test, Phillips-Peron test, and Johansen cointegration test [9], [12]–[16]. Engineering News-Record Construction Cost Index (CCI) have been thoroughly investigated in previous studies. Researchers have attempted to produce models that reliably identify the leading indicators of CCI and reach a satisfactory prediction performance accordingly. Prediction models range from regression, time series, and artificial intelligence models. Such models either rely on the past lagged values of the predicted variable as the explanatory variables, such as univariate time series models, or multiple explanatory variables including or excluding the past lagged values of the predicted variable, such as multivariate time series models and artificial neural networks. Using historical values ranging from 1960 to 2006, Hwang [10] has investigated number of housing starts, consume price index, and prime rate as well as past values of CCI as inputs to a dynamic regression model for CCI prediction. Using the same raw data but utilizing time series techniques rather than regression, the author has concluded that univariate time series produced more promising results than multivariate ones [11]. Alternatively, another study has found that multivariate techniques produce more accurate results of CCI predictions [9]. The differences between the above-mentioned studies lie in the study period, prediction method, and leading indicators identification process. Rather than sole reliance on relevance identified in literature, Shahndashti and Ashuri [9] used augmented Dickey-Fuller (ADF) test for unit root, Granger causality test for short term correlation, and Johansen cointegration test for long-term correlation. Using study period covering monthly data from January 1975 to December 2008, the authors found that lagged values building permits, crude oil prices, producer price index, and consumer price index are promising inputs for Vector Error Correction (VEC) models for CCI prediction and were found to have strong correlation with CCI using the above-mentioned statistical tests.

Xu and Moon [13] proposed a Vector Auto Regression (VAR) model to predict Engineering News Record Construction Cost Index (CCI). Using monthly data from January 1975 to June 2010, the authors used only Consumer Price Index (CPI) as an independent variable to predict the (CCI). They identified CPI as a potential indicator for general price level in a country, but no other indicators were tested as potential independent variables. Developing a VAR model requires first testing datasets for stationarity: This paper used Phillips-Peron test. Similar to ADF test, the null hypothesis of the Phillips-Peron test is that data is nonstationary and unit root exists. In that case, CCI and CPI datasets were nonstationary, and first order differencing was required to make both stationary to use them in developing VAR model. The authors also utilized Hannan-Quinn information criterion (HQIC) to find the best lag length for CCI prediction and three months ahead was found as the lag that minimized HQIC. Moreover, the paper found that long-run stable relationship exists between CCI and CPI using Johansen cointegration test. The paper tested their model's adequacy against Holt-Winters exponential smoothing: the cointegrated VAR model proposed by the paper recorder more accurate results than existing Holt-Winters exponential smoothing methods. The authors finally concluded that although the model results are promising, forecasting models for individual resources rather than cost indices might be more useful for practitioners. Faghih et. al [15] followed similar methodology: identification of explanatory variables using causality and cointegration tests, developing time series models Vector Error Correction (VEC), and finally testing the performance of the proposed models against existing techniques. However, drifting from other researchers' paths, the authors developed their approach for individual resources prices rather than a single index. The paper focused on developing VEC models to forecast asphalt, steel, and cement prices in the United States construction market context. The authors investigated several indicators as potential predictors for resources prices, including CPI, number of housing starts, construction spending, GDP, personal income, and employment rate. Using monthly data from January 1997 to December 2016, VEC models were developed individually for each resource of asphalt, steel, and cement. VEC model of 8-months lagged values of CPI, West Texas Intermediate (WTI), and past values of asphalt was defined as the best model for prediction of new values of asphalt prices. For steel, VEC model of 3-months lagged values of Iron ore prices and past values of steel. Finally, VEC model of 3-months lagged values of GDP, number of housing starts, construction spending, and past values of cement was defined as the most promising model. The paper, however, finally concluded that although the proposed approach produced promising results in prediction of individual resources' prices, this approach would not be able to predict fluctuations in prices due to economic shocks.

This paper aims to follow other researchers work in aiding construction industry practitioners in timely and accurate prediction of main resources prices movements. As highlighted by previous studies' conclusions, proper identification of leading indicators improves the prediction models' accuracy and provides insight into what affects the prices movements in each country's market. However, as concluded by [15], existence of models that accurately predict price movements in economically unstable conditions is a gap in the literature. This research concentrates on the Egyptian construction market and its main resources steel and Portland cement. Studying the leading indicators of resources prices in a developing country's market that has been recently characterized by economic shocks and political instabilities aims to fill this literature gap in an integral step to develop accurate prediction models of construction prices.

3. Methodology

This paper follows similar methodology to that of [9], [14], [15], and [17]. Identification of leading indicators entails investigation of both short term and long-term correlations. Many research efforts have tackled the relationship between economic conditions and construction prices in order to propose prediction models that would provide an insight into the impact of such relationship. [14] suggested the following statistical process to identify leading indicators and develop a time series model: Factor identification and initial assessment, leading indicator identification, model creation, and finally model diagnosis and validation. This research follows this process in order to identify the leading indicators for both steel and cement prices in the context of Egyptian construction market. The detailed methodology is summarized in Figure 1.

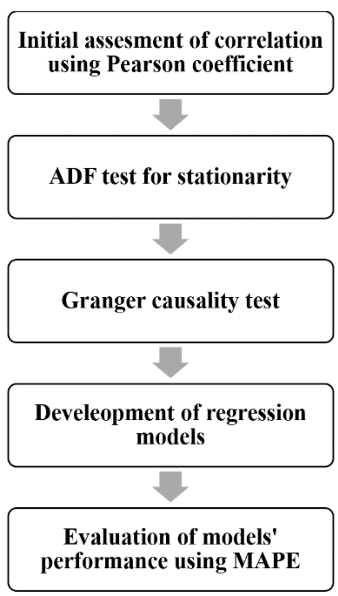

Figure 1- Indicators identification methodology

3.1 Data collection and Initial assessment

Initially, the aim is to select a study period that contains economic shocks and multiple variations in prices as a result. Hence, a study period from May 2008 to April 2019 is selected: two political events in January 2011 and July 2013 as well as one devaluation of the Egyptian pound in November 2016 period can be classified as shocks that caused drastic fluctuations in prices. For the above-mentioned study period, monthly prices of steel and Portland cement were collected from Egypt's Central Agency of Public Mobilization and Statistics (CAPMAS). Eleven macroeconomic indicators were selected for investigation in this paper as potential explanatory variables for steel prices, cement prices, or both: consumer price index (CPI), external debt (ED), Egypt stock market index (EGX30), exports, foreign reserves (FR), gross domestic product (GDP), lending rate (LR), money supply (M2), producer price index (PPI), unemployment rate (UR), and U.S dollar to Egyptian pound exchange rate (USEGY). Statistical correlation coefficients can preliminarily evaluate whether linear correlation exits between variables. Pearson correlation coefficient has been extensively used by previous studies in the context of construction prices [4]–[7], [14]. Hence, Pearson correlation test will be utilized to evaluate the linear correlation between each of the eleven indicators and each of the steel and cement prices. This test will only provide an initial assessment not a conclusive insight into whether these indicators are potential predictors for the predicted variables.

3.2 Checking for stationarity

Prior to checking for correlation, augmented Dickey-Fuller (ADF) test for checking the stationarity, existence of unit root, and identify the order of integration of data series. Stationary time series have constant mean and variance, while nonstationary time series have unit root. Granger test can only be applied to stationary series. Equation 1, as highlighted in [15], clarifies ADF test:

$$\Delta X_t = \delta t + \beta + \alpha X_{t-1} + \sum_{i=1}^{p} \alpha_i \, \Delta X_{t-i} + \varepsilon_t \tag{1}$$

where X is variable is question whether the construction prices series or economic indicators, ΔX_t is the differenced variable, δt is the deterministic temporal trend, β is the non-zero drift, i is the lagged term, ΔX_{t-i} is the ith lagged term of the variable, and ε_t is the residual series [15]. δ, β, and α are the model parameters to be estimated. This equation contains terms for non-zero drift and a deterministic trend. The null hypothesis of ADF test is that unit root exists, or in other words data series is non-stationary. Granger test is only applied for stationary series, hence, in case of non-stationary data, the series is differenced and the ADF test is repeated till there is enough evidence against the null hypothesis. The number of times the data is differenced is called the order of integration [9]. ADF test is conducted here using R software for statistics.

3.3 Granger causality test

After passing the ADF test and proving to be stationary, Granger test for causality is applied for the potential explanatory variables. The Granger test examines whether past lagged values of an explanatory variable are useful to predict values of another variable [9], [15], [16]. The null hypothesis of Granger test is that past values of the explanatory variable are not useful to predict the explained variable. Existence of enough evidence against this null hypothesis would indicate that this incorporation of past lagged values of the explanatory variable would improve accuracy of the explained variable prediction model. Granger test only examines short term relationship between variables [17].

3.4 Autoregression models

Several researchers have utilized time series models to predict construction prices. Such efforts range from Holt-Winters exponential smoothing, vector auto regression (VAR), vector auto correction (VEC), auto regressive moving average (ARMA), autoregressive integrated moving average (ARIMA), and seasonally adjusted auto regressive integrated moving average (S-ARIMA) [18]. These methods are either univariate or multivariate techniques. Univariate techniques would only rely on past lagged values of the target variable as predictors, while multivariate techniques would incorporate past lagged values of other potential predictors in addition. However, other researchers have utilized dynamic auto regression to predict construction prices [7], [10]. The distinctive nature of autoregression models is that they utilize past lagged values of the explained variable as explanatory variable in addition to other leading indicators. This nature would complement the Granger test structure; hence this prediction model is used to confirm Granger test conclusion. Using R software for statistics, this paper utilizes auto regressive model to predict each of the steel and cement prices using the potential explanatory variables that prove to have relationship with the steel and cement prices using Granger test. In this research, short term prediction is targeted, hence lags of 1 month, 3 months, 6 months, and 9 months are investigated.

3.5 Evaluation of model performance

Prediction accuracy may be evaluated through mean absolute percentage error (MAPE) and mean squared error (MSE). Several past studies have associated accepted or accurate predictions with MAPE less than 10% [15], [19], [20]. This paper aims to evaluate whether the potential explanatory variables are useful in prediction of the construction prices through developing these time series prediction models. For each of the explained variables, steel and cement, four prediction models are developed and evaluated. The conclusion this paper targets is identification of which indicators are useful to explain the future trends in steel and cement prices at different lag lengths in the short term.

4. Results & interpretation

4.1 Initial assessment: Pearson correlation test

Pearson correlation test is conducted to initially estimate whether linear correlation exists between explanatory and explained variables. A Pearson correlation coefficient between 0.5 and 1 or -0.5 and -1 would indicate that linear correlation exists between variables [21]. Table 1 record the Pearson correlation test results. For steel prices prediction, CPI, ED, EGX30, GDP, LR, M2, PPI, and USEGY have a high correlation coefficient, very close to 1, which would indicate that there is not enough evidence against the null hypothesis that no correlation exists. Hence, these variables would be investigated further using Granger test. Regarding Exports and UR, correlation coefficient is closer to zero which would indicate no correlation with steel prices, hence Exports and UR are eliminated from further assessment. For FR, correlation coefficient is 0.554, so no conclusive decision on whether adding FR as a leading indicator would affect steel prices prediction. Hence, FR would also be investigated using Granger test.

For cement prediction, Exports has 0.082 correlation coefficient, respectively, hence there is not enough evidence against the null hypothesis that no correlation exists. CPI, ED, EGX30, GDP, LR, M2, PPI, and USEGY have high correlation coefficients, higher than 0.5 and closer to 1, so they will be investigated using Granger test as leading indicators of cement prices.

Table 1- Results of Pearson correlation test

Tested correlation	Pearson correlation coefficient	Pearson test statistic	Tested correlation	Pearson correlation coefficient	Pearson test statistic
Steel, CPI	0.916	26.029	Cement, CPI	0.939	31.153
Steel, ED	0.938	30.965	Cement, ED	-0.920	26.766
Steel, Exports	0.122	1.403	Cement, Exports	-0.082	-0.94
Steel, EGX30	0.920	26.811	Cement, EGX30	0.875	20.673
Steel, GDP	0.940	30.99	Cement, GDP	0.886	21.882
Steel, FR	0.554	7.65	Cement, FR	0.712	15.241
Steel, LR	0.942	32.116	Cement, LR	0.832	17.125
Steel, M2	0.925	27.933	Cement, M2	0.943	32.376
Steel, PPI	0.950	34.681	Cement, PPI	0.895	23.003
Steel, UR	-0.121	-1.388	Cement, UR	0.623	8.11
Steel, USEGY	0.946	33.279	Cement, USEGY	0.878	21.005

4.2 Checking for stationarity: Unit root test

Since Granger test is only applied to stationary time series, ADF test is applied to steel and cement as well as all the potential leading indicators. The null hypothesis is that unit root exists, and data series is nonstationary. Table 2 contains results of ADF tests for all data series examined. If the absolute value of test statistic is less than the absolute value of test statistic critical value of 3.99, there would not be enough evidence against the null hypothesis that unit root exists. Table 2 shows that all the potential leading indicators as well as both steel and cement are nonstationary without differencing. Hence, at least first order differencing is required. After first order differencing, absolute value of ADF test statistic for steel, cement, and all potential leading indicators is higher than the critical value of 3.99. So, no more differencing is required, and Granger test can be applied for these data.

Table 2- Results of ADF test

Variable	ADF test statistic	Variable	ADF test statistic
Steel	-2.571	ΔSteel	-7.136[a]
Cement	-2.767	ΔCement	-11.511[a]
CPI	-0.629	ΔCPI	-7.55[a]
PPI	-0.855	ΔPPI	-8.074[a]
UR	-0.158	ΔUR	-7.423[a]
GDP	-2.099	ΔGDP	-5.207[a]
FR	-0.193	ΔFR	-5.217[a]
USEGY	-1.932	ΔUSEGY	-7.820[a]
LR	-1.726	ΔLR	-6.913[a]
M2	-0.323	ΔM2	-7.806[a]
Exports	-3.585	ΔExports	-12.163[a]
ED	-0.616	ΔED	-5.441[a]
EGX30	-2.920	ΔEGX30	-7.457[a]

[a] Rejection of the null hypothesis that unit root exists at 1% level

Note: Δ denotes first order differencing

4.3 Granger causality test

For short time prediction investigation, Granger test is applied for each of the steel and cement prices to identify the leading indicators for each. Tables 3 and 4 demonstrate the results of Granger test for steel and cement, respectively. The null hypothesis is that the leading indicators do not cause the target variables. Results show that leading indicators for steel prices are different from those for cement prices. Moreover, leading indicators are not constant for steel as well as cement with changes in the lag length. For steel prices with indicators lagged 1 month, the null hypothesis can be rejected for only EGX30, GDP, and M2. For 3 months lag, it can be rejected for ED, EGX30, GDP, LR, M2, and USEGY. For 6 months lag as well as 9 months, null hypothesis can be rejected for GDP, LR, M2, and USEGY. These results indicate the following regarding steel prices:

1. For prediction of steel prices 1 month, 3 months, 6 months, or 9 months ahead, incorporation of GDP, and M2 would improve the prediction accuracy.
2. For prediction of steel prices 3 months, 6 months, or 9 months ahead: incorporation of LR and USEGY would improve the prediction accuracy.
3. For prediction of steel prices 1 month, and 3 months ahead: incorporation of EGX30 would improve the prediction accuracy.
4. For prediction of steel prices 3 months ahead: incorporation of ED would improve the prediction accuracy.

Regarding cement and its leading indicators, Table 4 summarizes the results and the following can be indicated:

1. For prediction of cement prices 1 month ahead, incorporation of only LR would improve the prediction accuracy.
2. For prediction of cement prices 3 months ahead, incorporation of none of the potential indicators would improve the prediction accuracy. Hence, univariate time series might be preferred.
3. For prediction of cement prices 1 month ahead, incorporation of only UR would improve the prediction accuracy.
4. For prediction of cement prices 1 month ahead, incorporation of only FR would improve the prediction accuracy.

To confirm that results of the Granger test can be conclusive, multivariate time series models are developed. Having prediction models that conform with the Granger test results would identify which are the leading indicators for each of the steel and cement prices in the context of the Egyptian construction market.

Table 3- Results of Granger test for steel prices

Null hypothesis	**1-month lag**		**3 months lag**		**6 months lag**		**9 months lag**	
	F-statistics	**p-value**	**F-statistics**	**p-value**	**F-statistics**	**p-value**	**F-statistics**	**p-value**
ΔCPI does not Granger cause ΔSteel	1.095	0.2984	0.568	0.6396	1.087	0.3746	1.161	0.3275
ΔED does not Granger cause ΔSteel	0.906	0.343	3.49	0.017*	1.227	0.296	0.642	0.758
ΔEGX30 does not Granger cause ΔSteel	5.750	0.017*	2.82	0.041*	1.102	0.365	0.807	0.616
ΔExports does not Granger cause ΔSteel	2.99	0.086	0.78	0.50	1.08	0.3782	1.015	0.4366
ΔFR does not Granger cause ΔSteel	2.99	0.086	1.26	0.286	1.032	0.4084	0.855	0.567
ΔGDP does not Granger cause ΔSteel	4.096	0.045*	5.41	0.001*	6.98	0.000002*	4.519	0.00005*
ΔLR does not Granger cause ΔSteel	3.206	0.075	5.10	0.002*	4.366	0.0005*	3.168	0.002*
ΔM2 does not Granger cause ΔSteel	3.95	0.049*	5.51	0.0013*	5.65	0.00003*	4.414	0.00006*
ΔPPI does not Granger cause ΔSteel	1.184	0.278	0.46	0.706	1.235	0.294	1.06	0.395
ΔUR does not Granger cause ΔSteel	1.244	0.266	1.40	0.245	0.786	0.582	0.6357	0.764
Δ USEGY does not Granger cause ΔSteel	1.166	0.282	5.37	0.0016*	6.216	0.00001*	5.855	0.000001*

* Rejection of the null hypothesis that at 5% level

Table 4- Results of Granger test for cement prices

Null hypothesis	**1-month lag**		**3 months lag**		**6 months lag**		**9 months lag**	
	F-statistics	**p-value**	**F-statistics**	**p-value**	**F-statistics**	**p-value**	**F-statistics**	**p-value**
ΔCPI does not Granger cause ΔCement	0.062	0.807	0.4375	0.7266	0.482	0.82	1.105	0.366
ΔED does not Granger cause Δ Cement	0.025	0.873	0.1159	0.950	0.235	0.963	0.48	0.88
ΔEGX30 does not Granger cause Δ Cement	1.406	0.2379	0.822	0.484	0.628	0.707	1.46	0.171
ΔExports does not Granger cause Δ Cement	0.345	0.557	0.294	0.829	0.9011	0.469	0.67	0.73
ΔFR does not Granger cause Δ Cement	2.137	0.1462	2.339	0.078	1.502	0.1837	2.71	0.007*

ΔGDP does not Granger cause Δ Cement	0.057	0.8221	0.215	0.886	0.215	0.9713	0.46	0.898
ΔLR does not Granger cause Δ Cement	5.28	0.023*	1.84	0.1435	1.297	0.264	1.60	0.120
ΔM2 does not Granger cause Δ Cement	1.236	0.268	0.885	0.4509	0.618	0.7149	0.87	0.55
ΔPPI does not Granger cause Δ Cement	0.078	0.784	0.127	0.943	0.46	0.834	1.85	0.06
ΔUR does not Granger cause Δ Cement	0.161	0.688	2.14	0.098	2.78	0.014*	1.54	0.144
ΔUSEGY does not Granger cause ΔCement	1.244	0.2688	0.623	0.601	0.444	0.847	0.633	0.7655

* Rejection of the null hypothesis at 5% level

4.4 Evaluation of prediction accuracy

Tables 5 and 6 show the results of developing autoregression models that use the identified leading indicators from Granger test as the predictors for steel and cement prices, respectively. For both steel and cement predictions at lag lengths of 1, 3, 6, and 9 months, all mean absolute percentage errors are below the above-mentioned 10%. For instance, prediction of cement prices using past 9-months-lagged values of cement and foreign reserves (FR) yielded a 1.08% MAPE. Hence, foreign reserves (FR), when lagged 9 months, can be identified as leading indicators for cement prices in Egypt. These identified leading indicators at the different lag lengths can be used as inputs for other and more advanced prediction techniques such as artificial neural networks and time series. The limitation of this research is the assumption of existence of only a linear relationship between explanatory and explained variables, which may not be the case.

Table 5- Results of prediction model for steel prices

Model	Lag length	MAPE
Steel, EGX30, GDP, M2	1 month	3.4%
Steel, ED, EGX30, GDP, LR, M2, USEGY	3 months	4.67%
Steel, GDP, LR, M2, USEGY	6 months	2.8%
Steel, GDP, LR, M2, USEGY	9 months	5.1%

Table 6- Results of prediction model for cement prices

Model	Lag length	MAPE
Cement, LR	1 month	1.8%
Cement	3 months	0.5%
Cement, UR	6 months	1.23%
Cement, FR	9 months	1.08%

5. Conclusion

In conclusion, this paper aims to aid construction industry parties by providing an essential step in prediction of construction resources prices. This step is the identification of each resource leading indicator and the corresponding lag length between the indicator and resource price. This research concentrates on the Egyptian construction market's resources as the study domain. For the main resources in Egypt, steel and cement, the leading indicators for each were identified through Pearson correlation test and Granger test as well as being validated through autoregression models. Results indicate that in the short term prediction, up to 9 months ahead, incorporation of past lagged values of gross domestic product, money supply, U.S. dollar to Egyptian pound exchange rate, external debt, lending rate, and Egypt's stock market index would improve prediction accuracy of steel prices. On the other hand, incorporation of only lending rate, unemployment rate, and foreign reserves would improve prediction accuracy of cement prices. Having different leading indicators for each of steel and cement would further assure that an identification of leading indicators of a combined index of main resources would not provide a conclusive insight into prices movements. This research paves the way for future research efforts in development of prediction models that utilize the identified leading indicators as inputs to prediction models using time series or artificial intelligence techniques. Mitigation of cost overrun, schedule slippages, and adversarial relationships between parties can only be through accurate and timely prediction of construction prices drastic movements.

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