Quantifying the Relationship between Construction Cost Index (CCI) and Macroeconomic Factors in the United States

Baabak Ashuri
Georgia Institute of Technology
Country: USA

Seyed Mohsen Shahandashti
Org: Georgia Institute of Technology
Country: USA

Significant changes in Construction Cost Index (CCI) are problematic for cost estimation, bid preparation, and investment planning of capital projects in the United States. Quantifying the relationship between CCI and macroeconomic factors helps to have a better understanding about construction cost changes within the US economy. The research objective of this research is to quantify the relationship between eight macroeconomic factors and CCI using two statistical tests: Pearson correlation test and Granger causality test. The dataset under study includes Engineering News-Record (ENR) CCI, consumer price index, federal funds rate, unemployment rate, prime loan rate, money supply, producer price index, GDP, and GDP-implicit price deflator. The results of Pearson correlation tests show that all the eight macroeconomic factors are highly correlated with CCI within 1% significance level. Granger causality test is used to study the lead-lag relationship between the eight macroeconomic factors and CCI. The results of Granger causality tests show that consumer price index, producer price index, GDP, and money supply lead CCI and are useful to predict CCI.

Key Words: ENR Construction Cost Index, Macroeconomic Factors, Pearson Correlation Analysis, Granger Causality Test

Introduction

Engineering News-Record (ENR), which is a professional magazine providing news, data, and analysis regarding the construction industry in the United States, defines CCI as the weighted aggregate of average prices of constant quantities of common labour, standard structural steel, Portland cement and lumber in 20 cities in the US (ENR, 2011). Since historical costs are used in the course of cost estimation, it is important to consider the price level changes over time (Hendrickson, 1998). It is possible to take into account these changes by forecasting future cost indices and correcting the original cost estimates accordingly. CCI is subject to significant variations that are problematic for cost estimators and investment planners. Quantifying the relationship between CCI and macroeconomic factors helps to have a better understanding about construction cost changes within the US economy.

The main research objective of this research is to quantify the relationship between eight macroeconomic factors and CCI using two statistical tests: Pearson correlation test and Granger causality test. In the rest of this section, research background is reviewed and the macroeconomic factors under study are explained. The Research Method Section introduces statistical tests to quantify the relationship between the eight macroeconomic factors and CCI. The

Empirical Results and Discussions Section presents the results of the tests and presents the major findings and their implications. Conclusions are presented in the last section.

Currently, there is no method to formally explain CCI changes using explanatory factors in the United States. Cost engineers and investment planners can use CCI forecasts provided by ENR for cost estimating and construction project planning. These forecasts do not provide formal explanations of CCI trends. Moreover, these forecasts are limited to the following year December's CCI and are subject to considerable errors (Ashuri and Lu, 2010). As an alternative approach, predictive models are created to forecast CCI. For example, Ashuri and Lu (2010) create univariate time series models to forecast CCI. The Univariate time series models do not have explanatory capability and they are just suitable for short-term forecasting (Goh and Teo, 2000). In a rare study regarding the application of explanatory factors to predict CCI changes, Williams (1994) uses the trends in CCI, prime lending rate, housing starts, and the months of the year as the inputs of back-propagation network models to predict changes in CCI. Williams (1994) concludes that CCI prediction is a complex problem and CCI cannot be accurately predicted by the neural network models. Williams (1994) points out that additional research is needed to identify explanatory variables for the development of predictive models for CCI.

Although, much research has been devoted to quantify the relationship between building price indices such as Tender Price Index (TPI) and various explanatory factors (Taylor and Bowen (1987), Runeson (1988), Fellows (1988), Akintoye et al. (1998), Ng et al. (2000), Wong and NG (2010)), the research regarding the quantification of the relationship between CCI and macroeconomic factors is rare. Tender Price Index (TPI), which is an output index, represents the average price that clients and/or owners need to pay to build a facility (Ng et al., 2000 and Wong and Ng, 2010). TPI has been published in the United Kingdom, Hong Kong, and Singapore and is used by clients as an indication of construction cost level (Rowlinson and Walker, 1994). In the rest of this section, the literature regarding the relationship of different factors and TPI is reviewed.

Taylor and Bowen (1987) analyse the Index of Building Cost provided by BER (Bureau of Economic Research). Although this index is called Index of Building Cost, it is a tender price index (Taylor and Bowen, 1987). Taylor and Bowen (1987) emphasize the importance of demand-based factors for formulating future building price indices. They conclude that construction supply capability has a long-term effect on the price movements. Skitmore (1987) finds a positive relationship between the new orders representing the construction demand and price level.

Runeson (1988) identifies that movements in building prices are the product of changes in input prices and changes in prices driven by market conditions. Runeson (1988) represents market conditions as a function of three independent variables: building approvals, fixed capital formation in buildings, and unemployment rate. The movements in price level are further quantified using an Ordinary Least Squares (OLS) multiple regression model. Since the independent variables show small lag periods, the forecasting capability of the proposed model is limited. Fellows (1988) uses correlation analysis and regression modelling to study the explanatory variables of construction price in the United Kingdom. Fellows (1988) concludes that interest rates, investment intentions, architect's new commissions, production drawings, enquiries, orders, expected volume of work, and building cost be the explanatory variables of the construction price in the U.K.

Akintoye et al. (1998) summarize unemployment level, construction output, industrial production, and the ratio of price to cost indices in manufacturing as the consistent explanatory variables of TPI. They find out these variables using two experimental methods: (a) the relationship of turning points of basic indicators and construction price; and (b) the predictive power of lags of the basic indicators.

Ng et al. (2000) use the pattern of changes in eight explanatory variables (Best lending rate, building cost index, consumer price index, gross domestic product, gross domestic product of construction industry, implicit gross domestic product deflation, money supply, and employment rate) for predicting the direction of changes in the Hong Kong TPI. In a recent study, Wong and NG (2010) conduct a comprehensive literature review and choose eight potential indicators (bank interest rate, building cost index, composite consumer price index, gross domestic product, gross domestic product in construction, implicit gross domestic product deflator, money supply, and unemployment rate) for identifying explanatory variables of Tender Price Index. They conclude that building cost index, Gross Domestic Product, and Gross Domestic Product in construction have explanatory value for predicting TPI. Much research has been devoted to quantify the relationship between building price indices such as Tender

Price Index (TPI) and different potential explanatory factors (Taylor and Bowen (1987), Runeson (1988), Fellows (1988), Akintoye et al. (1998), Ng et al. (2000), Wong and NG (2010)); however, there is very limited research on the quantification of the relationship between Construction Cost Index and macroeconomic factors in the United States.

The relationship of eight macroeconomic factors and CCI are quantified in this research. The ENR CCI data from January 1975 to December 2010 is used as CCI time series data in the empirical study. The macroeconomic factors are selected based on the literature and availability. These macroeconomic factors are prime loan rate, unemployment rate, consumer price index, producer price index, gross domestic product, GDP-implicit price deflator, money supply, federal funds rate. These factors are briefly described here:

Prime Loan Rate is a rate applied by top-25 major U.S. insured commercial banks to price short-term business loans (FRB).
Unemployment Rate is the percent of the U.S. labor force that is unemployed (BLS).
Consumer Price Index is measure of the price level of a representative basket of goods and services purchased by urban consumers. It is one of the widely used measures of inflation (BLS).
Producer Price Index is "the averages change over time in the selling prices received by domestic producers for their output" (BLS).
Gross Domestic Product is a measure of the total value of goods and services that are produced in a country in a given period. It represents the economic health of a country (BEA).
Gross Domestic Product-Implicit Price Deflator is a measure of the level of prices of all goods and services that are produced in a country in a given period. This measure is the ratio of nominal GDP and real GDP. Nominal and real GDP are current-dollar and constant-dollar GDP. This measure accounts for inflation (BEA).
Money Supply is a type of measure that represents the amount of money in the nation's economy. In the United States, at least two types of money supply's measures are tracked: M1 and M2. M1 consists of currency in the public banks, institutions and the U.S treasury, traveller's checks, demand deposits, and other checkable deposits. M2 consists of M1 as well as savings deposits, time deposits less than $100, and balances in retail money market mutual funds. M2, which is a broader measure, is used in this research (FRB).
Federal Funds Rate is the interest rate at which banks and other depository institutions charge each other for loans (FRB).

Table 1 summarizes the eight macroeconomic factors, the corresponding IDs that are used in the tables of this research to refer to them, and the corresponding sources from which the data are retrieved.

Table 1

Eight macroeconomic factors, respective IDs, and data sources

Economic factors	**ID**	**Source**
Consumer Price Index	CPI	U.S. Bureau of Labor Statistics
Federal Funds Rate	FFR	Board of Governors of the Federal Reserve Systems
Unemployment Rate	UR	U.S. Bureau of Labor Statistics
Prime Loan Rate	PLR	Board of Governors of the Federal Reserve Systems
Money Supply	MS	Board of Governors of the Federal Reserve Systems
Producer Price Index	PPI	U.S. Bureau of Labor Statistics
Gross Domestic Product	GDP	U.S. Bureau of Economic Analysis
GDP- Implicit Price Deflator	GDPIPD	U.S. Bureau of Economic Analysis

Research method

Pearson Correlation Analysis for Identifying Correlation Coefficients

Pearson correlation analysis is the first statistical analysis tool used to study the relationship between the eight macroeconomic factors and CCI. The test statistic of this test is based on Pearson product-moment correlation coefficient. The null hypothesis of the test for CCI and each macroeconomic factor is that there is no association between CCI and that macroeconomic factor. Researchers use Pearson correlation analysis to study the correlaional relationship between economic and construction factors. For instance, Wong and NG (2010) use Pearson correlation analysis to choose eight potential explanatory factors for TPI (Bank interest rate, building cost index, composite consumer price index, gross domestic product, gross domestic product in construction, implicit gross domestic product deflator, money supply, and unemployment rate).

Unit Root Test for Stationarity

Time series tests, such as Granger causality test, are usually preceded by another test for identifying the integrated order of the variables. Augmented Dickey-Fuller (ADF) test proposed by Dickey and Fuller (1979) and extended by Said and Dickey (1984) is used for the identification of the order of integration of the macroeconomic factors as well as CCI. The null hypothesis is that the time series under study (A macroeconomic factor or CCI) is not stationary and the alternative hypothesis is that the time series is stationary. A time series is stationary if its statistical properties do not change after being time-shifted (Brockwell and Davis, 2002). Critical values recommended by Banerjee et al. (1993) are used for the unit root test. The results of this test depend on the lag length. Akaike Information Criterion (AIC) is used to identify the lag lengths (Akaike, 1974).

If the results of the unit root tests show that the variable under consideration is not stationary, the time series data should be differenced and the unit root test should be repeated for the differenced terms. Differencing should be repeated until the results show that the variable is transformed to stationary time series. The number of times that a variable must be differenced until stationary time series data are created is the order of integration for the variable. This test is utilized because the Granger causality test can only be used for the stationary time series.

Granger Causality Test for Identifying Lead-Lag Relationships

Granger causality test is a statistical hypothesis test to identify whether the information in time series data of one variable is useful to predict the value of another variable (Granger 1969). Granger causality test can be used to identify the lead-lag relationship among variables. If $Y(t)$ is Granger caused by $X(t)$, $X(t)$ leads $Y(t)$. If $Y(t)$ is Granger caused by $X(t)$, the forecasting of $Y(t)$ can be improved by additional information existing in past values of $X(t)$. (X Granger causes Y) means that past values of X are useful to predict Y. The null hypothesis of the test is that the past p values of X do not help the predictability of Y. The rejection of null hypothesis means that the past p values of X can be helpful to predict the values of Y. The results of Granger Causality test depend on the chosen lag lengths (p).

Researchers use Granger causality test to study the lead-lag relationship between economic and construction variables. For instance, the Granger causality test is used to examine the effects of fluctuations in the money supply on the fluctuations in construction activity flows in Hong Kong (TSE and Raftery, 2001). It is used to evaluate the causal relationship between construction and other economic sectors in Singapore (Lean, 2001). It is applied to study the effects of shocks in construction outputs on major economic indicators in Singapore (Chan, 2002). It is utilized to analyze the causality relationships between the growth in macro-economy in Ghana and Ghana's Gross Domestic Product (Anaman and Osei-Amponsah, 2007). Wong et al. (2008) use the Granger causality test to show how construction outputs (measured by gross value of construction works) drive the economic growth (measured by Gross Domestic Product) in Hong Kong. Wong and Ng (2010) use the Granger causality test to identify the explanatory variables of tender price index in Hong Kong (2010). The Granger causality test is not applied for quantifying the relationship between macroeconomic factors and CCI in the United States.

In this research, the Granger causality test is applied to examine the lead-lag relationship of CCI and the macroeconocmic factors. Since the Granger causality test is sensitive to the number of lags, it is applied for 6, 12, 18, and 24 lag lengths to examine the lead-lag relationship between macroeconomic factors and CCI. These lag lengths represent a 2-year time horizon. Next section provide the empirical results of the methods proposed in this section. R is used as the programming language for statistical analysis in this study.

Empirical Results and Discussions

Results of Pearson Correlation Analysis

Table 2 summarizes the results of the correlation tests. Based on the correlation results and test statistics, consumer price index (+0.99), federal funds rate (-0.66), unemployment rate (-0.27), prime loan rate (-0.58), money supply (+0.98), producer price index (+0.99), GDP (+0.99), and GDP-implicit price deflator (+0.99) are correlated with CCI at 1% significance level. More specifically, there is a strong positive linear relationship between CCI and consumer price index, money supply, producer price index, GDP and GDP-implicit price deflator. There is a moderate negative linear relationship between CCI and federal funds rate and prime loan rate. The negative linear relationship between CCI and unemployment rate is weak.

Table 2

Results of Pearson correlation tests between CCI and the eight macroeconomic factors

Variables	Corr.	Test Statistic	Variables	Corr.	Test Statistic
CCI,CPI	+0.99	148.1**	CCI,MS	+0.98	119.5**
CCI,FFR	-0.66	-18.4**	CCI,PPI	+0.99	131.9**
CCI,UR	-0.27	-5.8**	CCI,GDP	+0.99	79.9**
CCI,PLR	-0.58	-14.6**	CCI,GDPIPD	+0.99	79.8**

Notes: ** Rejection of the null hypothesis at the 1% significance level. In other words, it denotes that the correlation is significant at 1% level.

Results of Unit Root Tests

The integrated orders of the eight macroeconomic factors and CCI are determined using ADF unit root tests. The results of ADF unit root tests are presented in Table 3 for the eight macroeconomic factors and CCI. Table 3 shows that all variables are not stationary at the level (i.e. they are not stationary before they are differenced). In the other words, before the variables are differenced, the statistical properties of all variables change by time-shifting. All variables except GDP-implicit price deflator become stationary by applying the differencing operator once. The null hypothesis of non-stationarity is rejected at 1% significance level for all the differenced variables except GDP-implicit price deflator. In the other words, after the variables are differenced, the statistical properties of variables under study, except GDP-implicit price deflator, do not depend on time-shifting. Therefore, all variables except GDP-implicit price deflator are first-order stationary (integrated of order 1). Based on these results, Granger causality test is applied to examine whether the first difference of the macroeconomic factors (except GDP-implicit price deflator) Granger cause the first difference of CCI.

Differencing must be applied twice on GDP-implicit price deflator in order to make it stationary. Since CCI and GDP-implicit price deflator are integrated of different orders, the Granger causality is not applied for them.

Table 3

Results of ADF unit root tests for CCI and the eight macroeconomic factors

Variable	**ADF t-statistic**	**Variable**	**ADF t-statistic**
CCI	0.34[6]	ΔCCI	-12.25**[1]
CPI	-1.9[6]	ΔCPI	-5.33**[10]
FFR	-3.11[10]	ΔFFR	-6.68**[10]
UR	-2.87[7]	ΔUR	-4.87**[5]
PLR	-3.18[9]	ΔPLR	-5.84**[10]
MS	0.61[10]	ΔMS	-4.32**[9]
PPI	-1.86[8]	ΔPPI	-6.50**[7]
GDP	-1.84[10]	ΔGDP	-5.09**[10]
GDPIPD	-3.44*[1]	ΔGDPIPD	-3.06[10]
		Δ_2GDPIPD	-8.89**[10]

Notes: Δ is the first difference operator; Δ_2 is the second difference operator; * Rejection of the null hypothesis at the 5% significance level; ** Rejection of the null hypothesis at the 1% significance level; [.] denotes the lag order that is selected based on the AIC criterion; The critical values that are proposed by Banerjee et al. (1993) are used for the rejection of the null hypothesis.

Results of Granger Causality Tests

Based on the unit root tests, the first difference of all the macroeconomic factors except GDP-implicit price deflator are stationary. Bivariate regression models are used to test the Granger causality relationship between the macroeconomic factors (except GDP-implicit price deflator) and CCI. Table 4 and 5 summarize the results of Granger causality tests between CCI and the macroeconomic factors. The results summarized in Table 4 show how consumer price index and producer price index consistently Granger cause CCI at all specified lag lengths. Money supply and GDP Granger cause CCI in the higher lag lengths (lag 18 and 24). Therefore, past values of consumer price index, producer price index, money supply and GDP are useful to predict CCI and these variables are macroeconomic leading indicators of CCI. Federal funds rate, unemployment rate and prime loan rate do not Granger Cause CCI. In the other words, past values of federal funds rate, unemployment rate, and prime loan rate are not useful to predict CCI. Hence, federal funds rate, unemployment rate, and prime loan rate do not lead CCI.

Table 4

Results of Granger causality test to identify whether the eight macroeconomic factors lead CCI

Null hypothesis	**F Statistics**			
	Lag 6	**Lag 12**	**Lag 18**	**Lag 24**
ΔCPI does not Granger cause ΔCCI	5.71**	3.47**	2.79**	2.63**
ΔFFR does not Granger cause ΔCCI	0.98	1.20	0.99	1.03
ΔUR does not Granger cause ΔCCI	1.98	1.26	1.01	0.89
ΔPLR does not Granger cause ΔCCI	1.10	1.16	1.03	1.04
ΔMS does not Granger cause ΔCCI	0.77	1.14	2.15**	2.61**
ΔPPI does not Granger cause ΔCCI	3.64**	2.75**	2.47**	1.99**
ΔGDP does not Granger cause ΔCCI	1.75	1.71	1.69*	1.54*

Note: Δ is the first difference operator; * Rejection of the null hypothesis at the 5% significance level; ** Rejection of the null hypothesis at the 1% significance level;

The results summarized in Table 5 show how CCI Granger causes consumer price index, and producer price index and money supply consistently at all specified lag lengths. CCI Granger causes GDP in the higher lag lengths (lag 12, 18 and 24). CCI does not Granger cause federal funds rate, unemployment rate and prime loan rate. In the other words, CCI does not lead federal funds rate, unemployment rate, and prime loan rate. According to the results shown in Tables 4 and 5, there is a feedback relationship between CCI and consumer price index, money supply, producer price index and GDP.

Table 5

Results of Granger causality test to identify whether CCI leads the eight macroeconomic factors

Null hypothesis	**F Statistics**			
	Lag 6	**Lag 12**	**Lag 18**	**Lag 24**
ΔCCI does not Granger cause ΔCPI	3.87**	2.44**	2.00**	1.56*
ΔCCI does not Granger cause ΔFFR	0.34	1.01	0.86	0.83
ΔCCI does not Granger cause ΔUR	1.01	0.92	0.92	0.88
ΔCCI does not Granger cause ΔPLR	0.36	0.48	0.74	0.72
ΔCCI does not Granger cause ΔMS	3.52**	2.48**	2.50**	2.22**
ΔCCI does not Granger cause ΔPPI	2.94**	2.23*	1.92*	2.26**
ΔCCI does not Granger cause ΔGDP	1.92	1.94*	1.89*	1.83*

Note: Δ is the first difference operator; * Rejection of the null hypothesis at the 5% significance level; ** Rejection of the null hypothesis at the 1% significance level;

Conclusions

The relationship between Construction Cost Index and eight macroeconomic factors are studied using two statistical tests: Pearson correlation test and Granger causality test. These macroeconomic factors are prime loan rate, unemployment rate, consumer price index, producer price index, gross domestic product, GDP-implicit price deflator, money supply, federal funds rate. Based on the correlation results and test statistics, consumer price index, federal funds rate, unemployment rate, prime loan rate, money supply, producer price index, GDP, and GDP-implicit price deflator are significantly correlated with CCI at 1% significance level.

Granger causality tests are conducted to quantify the lead-lag relationship between CCI and the eight macroeconomic factors in the US. The findings of Granger causality analysis show that past values of a series of factors representing macroeconomic conditions (consumer price index, producer price index, money supply and GDP) contain information that is useful for predicting CCI. In the other words, these macroeconomic factors lead CCI. Moreover, Feedback relationships between CCI and consumer price index, money supply, producer price index and GDP are found. Furthermore, there is no Granger causality relationship between CCI and federal funds rate, unemployment rate, and prime loan rate. Hence, these factors are not useful to predict CCI and do not explain the changes in CCI.

The macroeconomic factors that have relationship with CCI (i.e. consumer price index, money supply, producer price index and GDP) can be used to explain CCI changes. It is expected that consumer price index, money supply, producer price index and GDP can be used to create multivariate econometric models in order to predict CCI accurately.

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