2016

Analysis and Management of the Price Volatility in the Construction Industry

Alireza Joukar
Louisiana State University and Agricultural and Mechanical College

ANALYSIS AND MANAGEMENT OF THE PRICE VOLATILITY IN THE CONSTRUCTION INDUSTRY

A Dissertation

Submitted to Graduate Faculty of the
Louisiana State University and
Agricultural and Mechanical College
in partial fulfillment of the
requirement for the degree of
Doctor of Philosophy

in

The Department of Engineering Science

by
Alireza Joukar
B.S., University of Isfahan, 2007
M.S., Louisiana State University, 2013
May 2016

ACKNOWLEDGMENTS

This dissertation would not have been possible without the support of many people. I would like to express my gratitude to my major professor, Dr. Isabelina Nahmens. I have been very fortunate to have a great advisor who gave me the freedom to explore and at the same time guidance on the right track. She gave me courage and taught me to become an independent researcher. I am also grateful for the assistance and knowledge provided by the supervisory committee members Dr. Marwa Hassan, Dr. Craig M. Harvey, and Dr. R. Kelley Pace. I am also thankful to Mr. Charles Nickel from the Louisiana Department of Transportation and Development for his valuable assistance.

None of this would have been possible without the love of my family. My father who wanted, most of all, a good education for his children, and my mother who defined sacrifice for me by example.

I would like to express my gratitude to my uncle, Ali Fini and his family for their continuous support, love, and inspiration during this journey. Also I want to extend my gratitude to my good friends: Joshua Fini, Benjamin North, Hooman Movafagh for their continuous support and encouragement throughout this journey.

Lastly and most importantly, I wish to express my deep gratefulness to my love, Sara, my wife and my best friend. As a PhD student herself, Sara with her love, continuous support and encouragement helped me to get through this unique period of time in the best way.

TABLE OF CONTENTS

ABSTRACT

The problem of price volatility as it pertains to material and labor is a major source of risk and financial distress for all the participants in the construction industry. The overarching goal of this dissertation is to address this problem from both viewpoints of risk analysis and risk management. This dissertation offers three independent papers addressing this goal.

In the first paper using the Engineering News Record Construction Cost Index (ENR CCI), a predictive model is developed. The model uses General Autoregressive Conditional Heteroscedastic (GARCH) approach which facilitates both forecasting of the future values of the CCI, and capturing and quantifying its volatilities as a separate measure of risk through the passage of time. GARCH (1,1) was recognized as the best model. The maximum volatility was observed in October 2008 and results showed persistent volatility of the CCI in the case of external economic shocks.

In the second paper using the same cost index (ENR CCI), the methodology of the first paper is integrated with Value at Risk concept to cautiously estimate the escalation factor in both short and long-term construction projects for avoiding cost overrun due to price volatilities and inflation. Proposed methodology was also applied to two construction projects in which the estimated escalation factors revealed satisfactory performances in terms of accuracy and reliability.

Finally, the third paper addresses the price volatility from the view of risk management. It entails two objectives of identifying and ranking of potential management strategies. The former is achieved via in-depth literature review and questionnaire interviews with industry experts. The latter is done using Analytic Hierarchy Process (AHP). Quantitative risk management methods, alike those offered in foregoing papers are considered as one of the candidates in dealing with the

price volatility risk. Cost, risk allocation and duration were perceived as the most significant criteria (project indicators) in construction projects. Also, Integrated Project Delivery (IPD) with respect to project duration; quantitative risk management methods with respect to the cost; and Price Adjustment Clauses (PAC) with respect to the risk allocation, were recognized as the top strategies to manage the risk of price volatilities.

CHAPTER ONE: INTRODUCTION

1.1 INTRODUCTION

Risk is defined as the likelihood of occurrence of an undesirable event (Zou et al., 2009). With no doubt, one of the scientific achievements of the modern world is the way that businesses are dealing with risk. Transforming the attitude of risk control from guts and sixth sense or will of God to scientific measurements and an independent area of study, risk management. In the construction industry, there is a new trend of using risk analysis tools and techniques to devise new strategies in order to measure, control and mitigate risk of construction projects. Historically, the practice of risk management in construction projects, started with the use of insurance. The primary function of the insurance policies in the construction industry is to transfer certain risks from contracting parties of the construction projects to insurers (Chapman, 2001). However, development of sophisticated mathematical and statistical methods along with dramatic improvements in computational software programs have enabled risk managers to take huge leaps toward quantifying risk. The construction industry due to its nature is fraught with uncertainties. Nevertheless, cost risk, schedule risk, and quality risk are indeed three major areas of concern in any type of construction project for all the contracting parties (Galway, 2004; Mehdizadeh, 2012; Zou et al., 2009). This dissertation intends to shed light on the topic of cost risk in construction projects. Specifically, scrutinizing the cost fluctuations of construction projects due to price volatilities in materials and labor, from both perspectives, risk analysis and risk management. Risk analysis refers to the process of measuring risk; whereas risk management uses the results of risk analysis to identify and implement management strategies to mitigate risk.

All construction projects, to some extent, experienced price fluctuations in material and labor costs. Sometimes these fluctuations are insignificant enough that can be absorbed by contractors. However, nowadays there is an increased tendency of prolonged price volatilities in material and labor costs that pose a significant risk to all contracting parties in the construction industry. The average number of construction companies that filed for bankruptcy due to price volatilities have risen over the past decade in the U.S. (Mehdizadeh, 2012), and it seems that dealing with these price volatility has become one of the priorities of each contracting party.

1.2 PROBLEM STATEMENT

Material and labor costs are two major components of the overall construction project cost (Ashouri et al., 2010). Recently unprecedented price volatility was reported for essential construction materials such as steel, Portland cement, and diesel (Rowse, 2009). The world economy has been experiencing dramatic changes, potentially due to rising of new economic powers like India and China, ever-increasing technological changes, and globalization. Even if it can be assumed that the construction material market has stable supply and demand, still dynamics from other markets may impact the cost of materials. For example, the costs of shipments of materials cause volatility in the construction market due to volatility within the fuel market. In addition to price volatility in the construction material market, price fluctuations in the labor market also contribute to overall cost volatilities of construction projects. In a recent survey conducted by the Construction Financial Management Association, about 70% of contractors' major concern is fluctuation in construction cost (CFMA 2012).

The existence of price volatility in construction projects puts forward substantial risk for all parties involved. Over the past decade, this risk has amplified. Recently, these issues have drawn attention

of researchers in the field of quantitative methods. Researchers have tried to address these issues via econometric and mathematical techniques; mainly by forecasting construction cost indices like Construction Cost Index (CCI) or Construction Building Index (CBI). Forecasting construction cost indices like the Engineering News Record (ENR) CCI is one of the few practical methods available commonly used by industry. However, current forecasting methods do not account for price volatilities in the material and labor market. In other words, they do not incorporate volatility into the modeling process. Therefore, these models treat all the data points through passage of time equally, whereas integration of time-varying volatility would allow estimators to distinguish riskier periods with high price volatility from more tranquil periods with relatively stable price movements. Moreover, current forecasting models do not provide cost estimators and risk managers with quantified risk measures. The proposed method in this dissertation provide numerical indicators for measuring uncertainty through passage of time which could be enormous help in the process of risk management (Paper 1).

Furthermore, one application of integrating price volatilities with construction cost forecasting models could be in estimation of the escalation rates (escalation factors). Escalation factor is applied to baseline cost estimate of construction projects. It is intended to account for material and labor price volatilities, as well as the general inflation in the construction sector. Price movements in the construction sector usually differ significantly from general price movements in the state of economy (Wilmot and Cheng 2003). Therefore, employing popular construction cost indices (e.g. CCI) together with incorporating the risk of price volatilities will result in more accurate and reliable estimations of escalation factors. Moreover, review of the existing literature reveals that there is lack of systematic methodologies in estimation of escalation factors (Ashuri et al. 2012;

Dawood and Bates 2002; Guan and Liao 2014; Shane et al. 2009; Touran and Lopez 2006) (Paper 2).

On the other hand, in terms of price volatility there are various strategies that different contracting parties use to manage the risk of construction price volatilities. These methods usually depend on parties involved, type of contracts, existing market condition, estimation of the project duration, and even type of the construction. However, parties involved in a construction project usually lack comprehensive knowledge over all the strategies available and their attributes. Specifically following questions have not yet been answered by the previous studies: What are all the strategies which directly, or indirectly deal with price volatility, how effective are these different methods with respect to various project criteria? What are the general advantages and disadvantages of each method? Are these methods fair to the all parties? and many other questions. Therefore, with an ever increasing price volatility issue, it is imperative for the construction industry to have access to information regarding existing and potential strategies and their attributes, as well as a decision making guideline which could help practitioners to systematically evaluate potential projects (paper 3).

1.3 RESEARCH OBJECTIVES

The overarching goal of this dissertation is to develop a new method and decision-making guidelines to help cost estimators, as well as risk managers to effectively address price volatility. This dissertation comprises of three journal papers (chapters) directed toward managing construction cost volatilities in construction projects. Although these chapters are independent, each chapter contributes to the predominant goal.

The major purpose of the first paper is to develop a predictive model that accounts for price volatilities in the material and labor market. The main objective of the second paper is to provide a practical application for the method proposed in the first paper in the estimation of the escalation factor in construction projects. Finally, the third paper's major objective is to deliver a standard decision making guidelines for all the contracting parties involved in a construction project in order to systematically evaluate potential projects and guide strategy selection for dealing with price volatilities.

The first paper has two objectives:

<u>Objective 1:</u> develop a predictive model for the Engineering News Record (ENR) Construction Cost Index (CCI) that accounts for price volatility in the construction material and labor market.

<u>Objective 2:</u> provide a quantified volatility measurement like standard deviation that can be used in cost estimation and risk analysis.

The second paper has two objectives:

<u>Objective 1:</u> estimate and forecast the escalation factor in both long-term and short-term construction projects.

<u>Objective 2:</u> integrate price volatility into the estimation process of the escalation factor as an application of the method introduced in the previous paper.

The third paper has five objectives:

<u>Objective 1:</u> identify the most important risk management strategies as it relates to price volatilities. These strategies will be collected from the literature, and interview with panel of experts (including general contractor, subcontractor, supplier, and owner).

Objective 2: identify the most important project criteria in selecting a risk management strategy for the purpose of dealing with price volatility in construction projects. These criteria will be collected from the literature and interview with panel of experts (including general contractor, subcontractor, supplier, and owner).

Objective 3: develop a decision making guideline to help various contracting parities in construction projects to make consistent, logical decisions for mitigating the risk of material price volatility.

1.4 RESEARCH APPROACH

In order to achieve aforementioned objectives, the research methodology in this dissertation is divided into three phases: 1- Using General AutoRegressive Heteroscadastic Conditional (GARCH) methodology for the purpose of developing a predictive model that accounts for volatility. 2- Using Value at Risk (VaR) methodology to provide a practical application of the developed model in the previous phase. 3- Using semi-structured interviews, extensive literature reviews, and the Analytic Hierarchy Process (AHP) to develop a decision-making framework. In this section a brief summary of each paper, and its approach are presented.

Paper 1: Volatility Forecast of the Construction Cost Index (CCI) Using General Autoregressive Conditional Heteroskedastic (GARCH) Method

Engineering News Record (ENR) publishes the Construction Cost Index (CCI) monthly, which is a composite index of 20-city average price of construction activities in the U.S. The CCI has been used widely for calculating and modeling escalation factors, contingency amount in the fixed price contracts, and price fluctuation in prices for highway and infrastructure projects. Aggregate type

construction cost indices such as the CCI reflect the changes in prices more clearly, produce more accurate results in terms of forecast; and at the same time provide cost estimators with good background knowledge for individual contracts and improve budgeting decisions. Therefore, Forecasting the CCI benefits both contractors and owners in the sense of cost management throughout the project. Using both univariate and multivariate methods, previous studies have attempted to forecast the future values of the CCI. Homogeneity of variance is the assumption of these models, however the CCI shows periods of substantial volatility. In these cases, questions are about volatility and the standard tools to address this problem, have become Auto Regressive Conditional Heteroskedasticity (ARCH) and Generalized Auto Regressive Conditional Heteroskedasticity (GARCH) models. In this study, a seasonal historical data set from ENR Construction Cost Index is analyzed, using Eviews 8 software, to forecast volatilities of CCI in a short-term period. Findings from this paper will be used to propose a procedure and implementation guidelines to manage risk better in construction projects as it relates to material cost fluctuations.

Paper 2: Short and Long-Term Forecast of the Escalation Factor in Construction Projects Using Value at Risk

Over the past decade, a majority of the large and heavy construction projects, particularly those with longer durations have experienced cost overruns (Bhargava et al., 2010; Koushki et al., 2005; Shane et al., 2009; Touran and Lopez, 2006).

After a baseline estimation of the construction project cost, estimators commonly apply a deterministic escalation rate or so-called “escalation factor” in order to account for the escalation due to the material and labor price volatility and general inflation in the state of the economy. However, this method has been considered arbitrary (Cioffi and Khamooshi, 2009). On the other

hand, for the sake of accuracy and reliability, cost estimators should somehow integrate periods with higher risk into their escalation factor calculations to distinguish between periods with higher risk and lower risk.

Therefore, using Value at Risk (VaR) as an underlying methodology in this paper, the two approaches of Historical Method (HM), and Variance-Covariance Method (VCM) are built upon it to estimate the escalation factor in long-term and short-term construction projects respectively. HM is based on the assumption that past will repeat itself. It present simple, but reliable way to forecast and cross validate the escalation factor estimation of long-term construction projects. VCM on the other hand, is based on statistical assumptions and utilizes GARCH methodology proposed in paper 1. It allows estimators to integrate short-term price volatilities into their forecasts of the escalation factor. Volatility in this context is defined as the standard deviation of the escalation factor, which is the best measure of uncertainty.

<u>Paper 3: An AHP-Based Selection Model for Ranking Potential Strategies for managing the Construction Cost Volatilities</u>

In recent years, the construction industry has experienced unprecedented price volatilities, which has severely impacted the industry (e.g. Construction companies' bankruptcies, disputes, cost and time overruns, etc.). Depending on the parties involved in construction projects, type of contracts and state of the market, various strategies are practiced by contracting parties to manage project risks related to price volatility.

First, using a semi structured interview with a panel of experts, as well as comprehensive review of the literature is intended to identify current strategies and criteria used by contractors and owners

to manage price volatility and provide a clear overview regarding them and their role in dealing with construction price volatilities.

On the other hand, there may be various strategies that the construction industry uses to deal with these issues; however, still the priority of various strategies with respect to various project criteria, is not clear for different parties involved in the construction contract. In other words, it is imperative for the industry to have access to a guideline that will allow for decision-making at a broader level. A comprehensive decision making support system should allow inclusion of the alternative risk management strategies and their relevant project criteria. Therefore, in this study a selection model based on Analytic Hierarchy Process (AHP) is used aiming to consider both solutions and criteria concurrently for different parties involved in the construction project. The model essentially uses objective mathematical model in order to formalize the knowledge of an expert panel of experienced practitioners. Then, guidelines are proposed to help various parties to systematically evaluate potential projects and guide strategy selection for dealing with price volatilities. Results from this paper will further enhance the implementation guidelines developed in the first paper as one of the potential alternatives that the construction industry can rely on to deal with price volatility.

1.5 OUTLINE OF THE DISSERTATION

This dissertation follows the paper style, and entails an introduction, literature review, three journal papers, and conclusion and discussion section. Paper one focuses on the development of a process for forecasting volatilities of the CCI. This paper has been published in the journal of Construction Engineering and Management (ASCE). The second paper provides an application of the method introduced in the first paper in estimation and forecast of the escalation factors in construction

projects. This paper has been submitted to the journal of Construction Management and Economics (Taylor & Francis). The third paper for the first time identifies and collects current alternatives and project criteria used or noted by both academicians and practitioners for dealing with construction price volatility. Next, it develops a decision making guideline for dealing with price volatility. This paper has been submitted to the journal of Management in Engineering (ASCE).

1.6 REFERENCES

Ashouri , B., and Lu, J. (2010). "Time Series Analysis of ENR Construction Cost Index." *Journal of Construction Engineering and Management*, 136, 1227-1337.

Ashuri, B., Shahandashti, S. M., and Lu, J. (2012). "Empirical tests for identifying leading indicators of ENR Construction Cost Index." *Construction Management and Economics*, 30(11), 917-927.

Bhargava, A., Anastasopoulos, P. C., Labi, S., Sinha, K. C., and Mannering, F. L. (2010). "Three-stage least-squares analysis of time and cost overruns in construction contracts." *Journal of construction engineering and management*, 136(11), 1207-1218.

CFMA(2012)."BuildingProfits." (http://www.cfmabponline.net/cfmabp/20070708?pg=62#pg62).

Chapman, R. J. (2001). "The controlling influences on effective risk identification and assessment for construction design management." *International Journal of Project Management*, 19(3), 147-160.

Dawood, N. N., and Bates, W. (2002). "A decision support system specification for cost escalation in heavy engineering industry." *Computer‐Aided Civil and Infrastructure Engineering*, 17(5), 342-357.

Cioffi, D. F., and Khamooshi, H. (2009). "A practical method of determining project risk contingency budgets." *Journal of the Operational Research Society*, 60(4), 565-571.

Galway, I. (2004). "Quantitative Risk Analysis for Project Management." RAND, RAND publication, 7.

Guan, Y., and Liao, H. (2014). "Studying the Reasons for Delay and Cost Escalation in Construction Projects: The Case of Iran Abstract ID."

Koushki, P., Al-Rashid, K., and Kartam, N. (2005). "Delays and cost increases in the construction of private residential projects in Kuwait." *Construction Management and Economics*, 23(3), 285-294.

Mehdizadeh, R. (2012). "Dynamic and multi-perspective risk management of construction projects using tailor-made Risk Breakdown Structures." Université Paris-Est Marne la Vallée.

Rowse, B. (2009). "Construction Material Costs: Recent Years and Beyond." Cost Engineering, 15(1), 17.

Shane, J. S., Molenaar, K. R., Stuart Anderson, and Schexnayder, C. (2009). "Constructin Project Cost Escalation Factors." *Journal of Management in Engineering*, 25.

Touran, A., and Lopez, R. (2006). "Modeling Cost Escalation in Large Infrastructure Projects." Journal of Construction Engineering and Management, 853-860.

Wilmot, C. G., and Cheng, G. (2003). "Estimating Future Highway Construction Cost." *Journal of Construction Engineering and Management.*

Zou, P. X., Chen, Y., and Chan, T.-Y. (2009). "Understanding and improving your risk management capability: assessment model for construction organizations." *Journal of Construction Engineering and Management*, 136(8), 854-863.

CHAPTER TWO: LITERATURE REVIEW

2.1 BACKGROUND

This section presents an overview of the history and previous literature in four major areas pertaining to this dissertation and stated objectives in the first chapter. The first area is construction cost forecasting and quantitative methods in construction risk management. The second area is escalation factor estimation in construction projects. The third area is primary strategies and attributes considered in previous studies in the sense of dealing with construction price volatilities. Finally, the fourth area relates to Analytical Hierarchy Process (AHP), its benefits and concerns and application of this decision-making method in the construction industry.

2.2 QUANTITATIVE RISK MANAGEMENR METHODS

Numerous factors affect the cost of the construction project like scope change, under or over estimation of the project cost, change orders, time overrun, and length of design process period (Touran and Lopez 2006). However, one of the major contributor to fluctuations in cost of construction projects, over the past decade has been unprecedented price volatilities of construction resources, namely materials and labors (Hwang et al. 2012; Smith et al. 2011; Weidman et al. 2011; Xu and Moon 2013). By increasing price volatilities of construction resources, researchers have started to think of ways to analyze, estimate and possibly forecast these fluctuations. Previous literature in regard to construction cost forecasting could be divided into three chief categories. The first category are those studies that try to use traditional multiple regression analysis in order to identify the most significant variables with highly explanatory power of the dependent variables (Ashuri et al. 2012; Hwang 2009; Lowe et al. 2006; Olatunji

2010; Shane et al. 2009; Trost and Oberlender 2003). Dependent variable is either cost of projects or one kind of construction cost indices. The second category includes studies in which time series methods are applied (Ashouri and Lu 2010; Hwang 2009; Hwang et al. 2012; Xu and Moon 2013). Time series analysis embraces a variety of techniques for a variety of series; however, the core idea typically is using previous values of a variable as the primary variable of interest. The third category embraces broader range of methods, such as neural networks, subjective methods and probabilistic simulations like Monte Carlo (Cheung and Skitmore 2006; Chou et al. 2009; Kim et al. 2004; Wilmot and Mei 2005).

2.2.1 Traditional multiple regression

Researchers have been using regression analysis for forecasting future cost of construction projects for a long time. As it was briefly discussed earlier, researchers using traditional multiple regression methods, first aim to identify the most relevant explanatory variables. In the second step specify the most suitable functional form for the regression equation (e.g. linear, nonlinear, quadratic, exponential, etc.). In the construction industry, linear additive functional form is the most widely used form of function that has been applied for forecasting construction cost indices. However, multiplicative functional form has been employed as well (Wilmot and Cheng 2003). Review of studies using multiple regression reveals that the primary concern of these studies is selecting the most relevant and significant independent variables.

Akintoye et al. (1998) investigated factors explaining fluctuating construction prices in U.K. The study showed there is a strong relationship between unemployment levels, construction output and industrial production exist. Similar studies have been done in the U.S. Hwang proposed a multiple regression equation in order for forecasting future values of CCI (2009). The study introduces prime interest rate, housing starts and consumer price index as predictive variables of the CCI.

Similarly, another study performed a comprehensive evaluation on ENR Construction Cost Index (CCI) (Ashuri et al. 2012). Ashouri et al. attempted to identify the most leading indicators of this index using Granger causality test i.e. a statistical hypothesis test to increase the accuracy of the CCI forecast relative to previous similar studies. They concluded that producer price index, GDP, employment levels in construction, number of building permits, number of housing starts and money supply are the most important variables that explain the CCI. The study however, points out that CCI has been subject to significant variations in recent years.

Besides developing predictive model for the CCI, similar studies have been done on highway construction costs as well. Wilmot and Cheng (2003) developed a tailor-made cost index for highway construction projects in state of Louisiana. Moreover, using a multiplicative regression equation they tried to predict the future trend of highway construction projects costs. Shane et al. (2009) point out that in terms of cost forecasting, highway construction projects should be assessed in a separate group due to the nature of public funded projects, funded as part of a pool of projects. As a result, any variation in cost of one project affects other projects as well. Then the study highlights the importance of highway construction projects from the political perspective. Therefore, the study came to the conclusion that the case of public construction projects are more sensitive and should be examined in details. The study eventually found eighteen variables that should be considered before developing any predictive model.

The main downside of multiple regression in terms of forecasting is that a researcher or estimator should come up with future values of all independent variables that have been detected to be influential on a cost index or on a cost of a particular project, in order to be able to forecast the future value of dependent variable itself. A model with more independent variables most likely has higher error rate. Moreover, finding all the explanatory variables that explain the cost dynamics

of a project or a certain construction cost index can be a tedious job. Nevertheless, construction industry and practitioners very often employ multiple regression methods for modeling and forecasting cost of construction projects mostly for simplicity and applicability of such methods.

2.2.2 Time series methods

Time series is a sequence of values or date points, equally ordered with respect to a time space (Enders 2008). While multiple regression analysis is used to test various hypothesis or find the relationships between various variables (i.e. dependent variable with series of independent variables); time series analysis relies on the fact that data points collected throughout the time may carry internal statistical information and structures. Therefore, all the time series methods attempt to gain statistical inferences and even forecast the future data points of a series based on analyzing previous data points. For this reason, time series analysis frequently are referred to as univariate methods in contrast with multivariate methods. When dealing with one variable, this trait has been considered as one of the advantages of time series analysis (Hill et al. 2008). On the other hand, a researcher typically needs to have access to historical data set to attain reliable inferences. It may not always possible, which can be considered a downside of time series application. In particular, in construction industry where having access to historical series are not quite common.

Compared to multiple regression, time series analysis is much younger. This category includes a broad family of time series analysis methods such as Auto-Regressive (AR), Moving Average (MA), Auto-Regressive Integrated Moving Average (ARIMA), different seasonal adjustment methods (additive, multiplicative, census method, seasonal dummy variables), smoothing and detrending techniques (Holt-Winters, Hodrick-Prescott filter) Vector Error Correction Method (VECM). In just recent years, these methods have drawn attention of researchers in the construction industry. In particular, for analyzing and forecasting conventional construction cost

indices that are widely used in the construction industry, such as CCI or Building Construction Index (BCI). These indices are commonly used for calculating and forecasting price adjustment amounts, cost escalation amounts and calculating contingency fees in fixed price contracts (Ashouri and Lu 2010; Pierce et al. 2012; and Xu and Moon 2013).

In a major study, Ashouri and Lu (2010) compared different common time series methods (e.g. AR, MA, ARIMA, Holt ES, Seasonal ARIMA) to identify the best method for in-sample and out-of-sample forecast of the CCI with respect to the accuracy, application and implementation. They proposed seasonal ARIMA (0, 1, 0) (0, 12, 1) as the best predictive model for constructing in-sample forecast of CCI and Holt-winters exponential smoothing as a better model for out-of-sample forecast of CCI. Xu and Moon (2013) using a different approach (Cointegrated Vector Autoregression Model) attempted to forecast the CCI with higher accuracy comparative to Ashouri and Lu (2010) study. Integrating with time series enable researchers to add more variables into the analysis. The study concluded integrating a few more variables into the analysis will decrease the error of forecast. The integration approach could be found in another study prior to Xu and Moon (2013) as well. Hwang (2009) also used two dynamic models in order to forecast CCI. However, instead of using pure time series modeling, the study used a combination of traditional and dynamic techniques. The study used interest rate, housing starts and Consumer Price Index (CPI), which is an inflation factor, as leading variables in the prediction of CCI. In addition, three lags of CCI (CCIt-1, CCIt-2 and CCIt-3) were used as the dynamic components of the model. Hwang et al. (2012) point out that price forecasting for a large number of construction materials using time series methods requires a simplified and automatic procedure. Therefore, they developed an automated time-series material cost forecasting based on ARIMA models to simplify the process

for the practitioners with respect to compatibility with current estimation software, and simplicity in analysis procedures.

2.2.3 Other methods

In addition to traditional and modern forecasting techniques, Neural Networks (NN) and subjective methods (qualitative) are other approaches used by previous studies to forecast future values of construction cost indices or assess the risk and uncertainty associated with their original cost estimate. An NN is an information processing system. Its working process is quite similar to biological nervous system. An NN is composed of a large number of interconnected assembly of nodes and directed links, analogous to the human brain (Srivastava et al. 2000).

The NN is a viable alternative for predicting construction costs because this method eliminates the need to variables that explain the cost of construction projects; on the other hand, the process of knowledge acquisition process is very time-consuming.

The applications of NN methods have not been seen in cost estimation literature as much as multiple regression analysis or time series techniques. For the first time Williams (1994) applied the NN to the construction cost context. Williams used neural networks to forecast changes in the construction cost index (CCI) by comparing three different methods; neural networks, exponential smoothing and multiple regression. Results revealed that neural networks generate the least accurate results. Similarly, Kim et al. (2004) employed the NN in cost estimation of construction projects. Like Wiliam's study, Kim et al. (2004) compared the NN to multiple regression method and Case Based Reasoning (CBR) method. The data set used in Kim et al. (2004) study was composed of costs of 530 projects of residential buildings that were built by general contractors between 1997 and 2000 in Seoul, Korea. Contrary to expectations, Kim et al. (2004) concluded that "although the best NN estimating model gave more accurate estimating results than either the

MRA or the CBR estimating models, the CBR estimating model performed better than the NN estimating model with respect to long-term use, available information from result, and time versus accuracy tradeoffs." Wilmot et al. (2005) also used neural networks to predict the escalation of highway construction costs over time in the state of Louisiana. While they did not compare their results with other conventional methods, the study reported that neural networks results were reasonably acceptable (2005). Their study has been one of the latest studies that used NN in construction cost forecasting.

On the other hand, qualitative methods are beneficial mostly for longer term forecasts; where statistical methods are subject to higher error bounds for long-term forecasts (Touran et al. 2006). Two of the most known methods under this category are Case Based Reasoning (CBR) and surveys of expectations. CBR is carried out upon experience and expert technical opinion (Aamodt and Plaza 1994). CBR developed recently for various fields of construction (i.e. architecture, structural design, cost estimation, safety systems and decision making) (Kim et al. 2004; Maher and Balachandran 1994; Morcous et al. 2002; Tah et al. 1999). Kim et al. (2004) compared three cost estimation methods (multiple regression analysis, neural networks, and case-based reasoning) based on 530 historical costs. The study found that the CBR estimating model performed better than the neural networks estimating model with respect to long-term predictions. Surveys of expectation are another economical method of forecasting escalation factor or future trend of construction cost (Touran and Lopez 2006). ENR Construction Industry Confidence Index (CICI) and Associated Builders and Contractors Confidence Index (ABC CI) are two instances of familiar surveys to which cost managers refer, in order to gain the sense of the current and future state of the risk in the construction industry.

2.3 ESCALATION FACTOR

One application of the forecasting cost indices in the construction industry is to estimate the escalation factor (escalation rate) for construction projects. Escalation factors in the form of percentage are usually applied to the baseline cost estimate in order to account for the price changes in the material and labor markets. Existing methods practiced until now suggest that there are not sufficient systematic cost escalation methodologies to achieve an appropriate cost analysis at the planning phase of a construction project. Also, construction projects in some cases have long lead times between planning and construction which could exacerbate the problem of the cost escalation (Shane et al. 2009). There are relatively few studies in the specific area of escalation factor estimation. Studies in this area could be classified into three categories.

The first category suggests forecasting construction cost indices can be helpful in assisting cost estimators to determine the escalation rate at the design phase, as well as throughout the project (Ashouri and Lu 2010; Blair et al. 1993; Hwang 2009; Hwang et al. 2012; Kuen and Hoong 1992; Ng et al. 2004; Wang and Mei 1998; Xu and Moon 2013). Relevant studies in this regard were explained in details previously.

The second category suggests using Monte Carlo Simulation Methods as a way to integrate uncertainty into estimation of the escalation factor (Chou et al. 2009; Diekmann 1983; Touran and Lopez 2006). One of the most well-known studies in this category is a study done by Touran and Lopez (2006). They use Building Construction Index (BCI) as a base historical data set to create escalation factor time series; consequently, they use Monte Carlo Simulation as a tool to integrate uncertainty into their estimation. However, they failed to quantify the magnitude of uncertainty for various periods. Therefore, they assumed the fixed amount of risk for all the periods. In a

similar study, Chou et al. (2009) using data from the Texas Department of Transportation developed an approach to help cost estimators to estimate the probabilistic costs of highway bridge replacement projects in the conceptual design phase. Their proposed model utilizes practical simulations, and Cumulative Distribution Functions (CDF).

Finally, studies in the third category, instead of proposing any particular approach for estimation of the escalation rate, are focusing on the decomposition of the underlying factors causing escalation in the construction projects (Anderson et al. 2010; Bhargava et al. 2010; Guan and Liao 2014; Koushki et al. 2005; Nejat et al. 2010; Olatunji 2010). These studies typically use questionnaire interviews with experts as the principal research methodology. For instance, Dawood and Bates (2002) suggested that there is a lack of structured methodologies to deal with cost escalation in the construction projects. They aimed to identify, and quantify the causes of the cost escalations through questionnaire interviews and workshops. Eventually, they reported 1- market variations, 2- unforeseen conditions, and 3- error in estimation which they referred to as "bias" throughout the study. In another study by Koushki et al. (2005) material related issues like material price volatility, and material supply problems were recognized as the major causes of the escalation cost in the construction projects. these results were supported by the Guan and Liao (2014). They also added the "lack of attention to inflation" as another reason for cost escalation in the construction projects.

2.4 CRITERIA AND ALTERNATIVES

With current price volatilities in the construction material and labor markets, still many estimators prepare their estimate like old days and at the end of the estimating job, they add an arbitrary premium amount to their final price to cover for the potential price changes in the future (Burke

2013). On the other hand, owners are not satisfied with this approach. Mainly because they believe that the inflated value not only is not fair, but also given the present state of the world economy, the opposite scenario, the price decline is very likely. Having no plan to manage the risk of price volatilities will lead to price speculations or exaggerated premiums that contractors add to the bid prices to cover their risks. Furthermore, it could also cause material shortages, which will be the source of other problems, like cost escalation, schedule delays and disputes (Skolnik 2011).

This section intends to discuss the most common strategies that are currently used in the construction industry or have been proposed in previous studies as viable options to deal with the problem of price volatilities in the construction industry. Furthermore, advantages and disadvantages of each method along with other essential facts of each method will be presented.

2.4.1 Price Adjustment Clauses (PAC)

Price adjustment clauses (PAC) are usually provided for specific items in construction projects contracts (e.g. fuel price in highway projects contracts, steel price for commercial construction projects, etc.). The specification of the clauses usually varies depending on the amount of material required, total duration of the contract or type of the material. By including PAC in the contract, owner promise an adjustment to or from the contracting parties contingent on the direction of the price change either inclusively or exclusively (Brown and Randolph 2011; Kosmopoulou and Zhou 2014). The inclusive PAC allows for the entire price difference while the exclusive allows only for the partial price adjustment.

All kinds of PAC required a trigger value and Cap value; implying the start and end point of price adjustment clauses. Selection of trigger value amount is crucial. It apparently determines the total amount of adjustment and its frequencies. From one view, including PAC lead to mitigation of the price volatility risk for the contractors and material suppliers. On the other hand, it pushes the

higher portion of the risk toward owners. Adversaries of this strategy claim that these kinds of price adjustments define new extra role of insurer for the owners and provides protection and support to less productive firms (Kosmopoulou and Zhou 2014). They also emphasize on the role of trigger value as a tool in support of owners. Even though this method of dealing with price volatilities over the past 5 years has gained the increasing popularity, there has been a few systematic studies on how motivations and bidding behavior of contracting parties are influenced due to these price adjustment policies or how this strategy has been effective with respect to other important attributes (criterions) like risk mitigation, dispute, accuracy, fairness and so forth. (Brown and Randolph 2011; Kosmopoulou and Zhou 2014; Pierce et al. 2012).

Historically, highway construction sector has been the first sector to notice the importance of minimizing the effects of price volatilities (Pierce et al. 2012). Mainly because of intensive use of fuel in this industry and high volatility of oil prices. However, the requirement for price adjustment clauses in 80s and 90s had been very strict, and it has been limited to specific projects under certain conditions. For instance, contractors were required to provide the history of material costs. This historical trend of material price had to demonstrate the significant, uncontrollable changes from the normal price trends over the longer term (reference the FHWA 1980).

In a very recent study Kosmopoulou and Zhou (2014) using a six-year data set provided by Oklahoma Department of Transportation, attempted to evaluate the price adjustment clauses for the specific fuel based items and highlight its potential effects on bidding behaviors of contractors. The results of the study show that the bidding becomes more competitive after implementation of the PAC policies. Moreover, it also decreases the risk of price uncertainties for contractors mainly because this policy significantly increases the incentives of the risk averse parties to participate in bids. However, the study emphasizes on the trigger value as the most critical factor in the success

of this policy. Similarly, Zhou (2011) notes that in the absence of such clauses most likely contractors inflate their bid prices to the point that it might cost owners even more than the actual cost escalation amount. While the true direction of price changes is not determined, and it pose owners who do not adopt this strategy to an even higher risk.

The results of a study by National Cooperative Highway Research Program indicates that using similar clauses are moderately positive (2012). The report revealed that, while this mechanism could be effective for certain materials (i.e. asphalt and fuel). It cannot provide a reliable way for dealing with price volatilities for other construction materials like steel and concrete; mainly because the large number of such products that are manufactured. Application of aggregate indices like CCI or BCI or multiple price indices could help to manage this problem (Pierce et al. 2012). The report also lists some benefits of PAC including “positive effect on bid prices, number of bidders, market stability and supply chain”. Nevertheless, the study points out that there is not enough evidence showing that contractors tend to withdraw their bids in absence of a PAC. Furthermore, the report recommended the use of PAC for only projects that last longer than six months. Interestingly the study did not recommend the use of trigger value in the use of PAC. Whereas other studies focused on the trigger value as a critical element of such clauses (Pierce et al. 2012; Zhou and Damnjanovic 2011).

Eckert and Eger III (2005) performed a study on five states (including GE, SC, NC, FL, TN, AL) regarding the PAC and its potential benefits and downsides for contractors and owners. The report underlined the fact that surviving price volatilities of asphalt binder in fixed price contracts in highway industry has become more difficult and contractors are using contingent amounts to minimize risk. The study interviewed 48 highway contractors. It highlighted the chance that using PAC provides for smaller contractors to submit their bid. Contractors also noted that using PAC

may reduce legal fees due to litigation arising from severe price changes in a project. Likewise, Eger III and Guo (2008) and Redd and Hibbard (2009) performed survey-based studies in order to capture the general opinions of contractors and owners in highway construction projects pertaining to PAC. They reported that all contracting parties observed advantages and disadvantages in applying PAC. Particularly, with respect to different attributes and criterions PAC demonstrates different rewards and drawbacks.

While the PAC strategy has become more common in administering highway projects. Residential and commercial construction have also started to apply this tool to manage price volatilities. Particularly, after the recent financial crisis in 2007. Number of studies is still very limited. In a very rare studies Weidman et al. (2011) noted that most of the contracts in commercial construction are fixed price. The study revealed that contractors in this sector typically use other methods to deal with risk of extreme price spikes; such as early procurement of materials along with stockpiling materials and good communication. Smith et al. carried out a similar study in Utah residential area (2012). The study interviewed twenty general contractors and material suppliers to grab the general state of practice in Utah residential sector regarding price volatilities. The study reported that the combination of strategies are utilized. However, in contrary Weidman et al. (2011) the study pointed out that the use of PAC has gained in popularity in recent years.

2.4.2 Alternative project delivery methods

There are few common methods of designing and constructing a construction projects: 1) Design-Bid-Build, 2) Design-Build, 3) Construction Management, 4) Fast track, 5) Partnering/alliances, 6) Lean Project Delivery methods (LPD) (Forbes and Ahmed 2010). In regard to project delivery methods with respect to price volatilities, fast track and LPD have been explored in previous studies (Smith et al. 2011; Weidman et al. 2011). These studies separately proposed using LPD

and fast tracking as two alternatives for dealing with price uncertainties in today volatile market. Consequently, both of these studies interviewed commercial and residential contractors in the state of Utah. The results suggest positive attitudes of contractors in regard to use of these methods. However, the majority of participants mentioned LPD is a new concept to the construction industry, and it requires cultural foundations for its successful implementation.

As it was noted LPD is relatively new to the construction industry, it was developed in 2000 from abstract and applied information. LPD encourages all the parties involved in the construction project to behave as a team for the success of the project. In other words, lean project delivery methods involve tactics that construct on the relational principles. Forbes and Ahmed (2010) in their book explain:

> "Relational contracting enables the parties to work together for mutual benefit, gain knowledge, and use it creatively within each project. This enables them to reduce risk instead of shifting it to others, and to achieve a successful outcome beyond their self-interest."

Likewise, the lean construction institute recommends use of Integrated Project Delivery (IPD) which is one type of relational contract for dealing with various risks in projects of long duration, high uncertainty and high complexity (Ballard 2008). IPD is a close partnership of contracting entities in order to maximize the communication, share the risk and eventually optimize the project. It concentrates on fairness and collective risk management of the construction project and introduce the team success and shared responsibility in contrast with individual success.

Previous studies have address different aspects of a construction project on which LPD influence (Ballard and Howell 2003; Khanzode et al. 2005); scheduling and total duration of a project

(Lichtig 2005; Lichtig 2006), numbers of disputes throughout a project (Thomas et al. 2004) logistic and supply chain of a construction project, (Ballard 2008; Lichtig 2006) total cost of a project and Target Value Design (TVD), (Mitropoulos et al. 2005; Nahmens and Ikuma 2009; Nahmens and Mullens 2009) safety and productivity. Although none of these studies addressed the specific case of price volatility and potential impact of LPD. However, the major theme emerged form reviewing the current literature on LPD, which indicates that LPD can act as a promising platform on which other strategies of dealing with price volatilities could be conducted with lower risk and essentially with higher influence.

Project fast tracking is another delivery method that aims to minimize the possibility of price fluctuations by minimizing project duration (Allen and Iano 2013). In fast track, construction of the project starts while the design phase of the project still is in progress. This method can be utilized by factory built type of construction to achieve the ultimate pace (Kasim et al. 2005). Similar to IPD, project fast tracking requires high communication and collaboration of the parties involved in the project for the successful implementation.

2.4.3 E-Commerce, Building Information Modeling (BIM), Geographical Information Systems (GIS)

The use of Information and Communication Technologies in the construction industry is exponentially growing (Forbes and Ahmed 2010). These technologies allow sharing and access of information conveniently, locally, and worldwide (Forbes and Ahmed 2010). This category covers the vast range of tools and techniques. However, this dissertation intends to focus on those aspects of ICT that directly relates to construction cost and price fluctuations of construction projects. E-Commerce, utilizing Building Information Modeling (BIM) and Geographical Information System (GIS) are few ways on which construction industry rely and grow with respect to ICT.

ICT brings material buyers and suppliers close together, eliminate middle men, break the space limits and often reduce the time limit (Li et al. 2003). For example, the integration of BIM with GIS can help BIM with all the necessary spatial information. This issue is critical to the supply chain and logistic processes of the construction industry.

It is expected that transportation costs alone could be between 20 to 25% of total construction costs (Shakantu et al. 2003). These figures are significantly higher in highway construction projects (Pierce et al. 2012). Moreover, according to Construction Industry Research and Information, 10% of materials are wasted on the job site; interestingly however, the study points out that even a 2% saving on materials can push the profit margin up by 15 % (Ng et al. 2004). Therefore, by utilizing ICT tools and eliminating or reducing wastes pertinent to material flow from the beginning which is supplier, to the final destination which is the construction site, or other types of material waste on the job site, contractors could achieve significant savings. This saving is great, considering the high price volatility in fuel market as well as other critical construction materials such as steel and concrete products.

Williamson, Harrison, and Jordan (2004) performed a research on the use of information systems within supply chain management and use of the Internet as a monitoring tool. They noted that in order to improve the effectiveness of supply chain management and remain competitive in the global village, synchronizing "operations of all partners in the supply chain is required."(Williamson et al. 2004) Their study focused on the use of Internet as a platform for information system development and tried to evaluate its use. Their evaluation method was based mostly on previous studies and qualitative approaches and also used to some public data resources to support their argument. For instance, they mentioned that 57.2% of American companies use the Internet to improve relations with their suppliers. Tserng et al. (2006) first noted high

variability of construction environments as one factor that lead to construction cost variations. In order to address this issue throughout a sample case (steel rebar production and supply operations) they established an optimal design, aiming at minimizing the combined inventory cost of the supply chain and then developed a decision support system to create a production and supply plan for a supplier and buyers of steel rebar. (Vaidyanathan and O'Brien 2009) developed an IT model to improve material management and control. Utilizing this model, a list of materials to order will be produced, as well as reporting the status of materials on site, and generate alerts when the material amount on site is less than the defined minimum. Even though the proposed plan would address the significant problems of material management, there is still significant capacity for improvement.

Cheng and Yang (2001) pointed to the possible role of GIS in developing an automated site layout system for construction materials. They developed GIS-based cost estimates, as an approach to identify options and solutions for problems related to materials layout. When GIS layout data is linked with three-dimensional models, the entire material circulation path on site can be real-time simulated. They deployed the concept of “searching by elimination”, to model the process of human decision making to identify possible locations on site for material staging areas. They conclude that GIS is a promising tool for solving construction design problems and thus creating new opportunities for innovation regarding spatial information in construction planning and design.

In another model developed by (Said and El-Rayes 2011), the focus is on ordering and financing cost. They recognize the existing gap in the current literature regarding separate views toward material procurement and storage layout as two separate planning activities without considering their interdependencies. Their model utilizes "genetic algorithms to minimize construction

logistics costs that cover material ordering, financing, stock-out, and layout costs." The results indicate that the material procurement decisions are influenced by the importance of construction activities consuming the material and site space availability, whereas the dynamic site layout decisions are function of the material procurement decisions and material storage space needs and other site layout restrictions.

2.4.4 Price cap contract for material procurement as real option

Typically, contractors buy a certain amount of materials every year. Price cap agreement provide the contractors with the opportunity to place a cap on the price of construction materials (Ng et al. 2004). The price-cap option allows contractors to minimize their inventory cost, as well as the risk of price volatility. Price cap agreement also helps suppliers with a certain share of the market and smooth production schedule (Weidman et al. 2011). Price cap contract for material procurement essentially is similar to "call option" in financial markets. A call option is a financial contract between two parties in which the buyer of the "call option" has the "right but not the obligation to buy an agreed quantity of a particular commodity or financial instrument from the seller. On the other hand, seller is obligated to sell the commodity or financial instrument to the buyer if the buyer decides. The buyer pays the fee for this premium" (O'Sullivan and Sheffrin 2007). Apparently, this option stresses on long run agreements between buyer and seller and relationships become significantly vital (Carr 1982).

Ng et al. (2004) compared the cost of long term contract with a price cap to spot purchases in construction material market. They attempted to quantify the savings that contractors can achieve by entering into a long-term material contract with a price cap rather than making spot purchases. They concluded using this approach while suppliers benefit from steady demand and long term contracts, it secure contractors from the price volatilities and reduce the contingency value of the

contract. Similarly, Weidman et al. (2011) suggested price cap contract as one of the approaches that commercial construction industry can utilize in order for dealing with market price fluctuation. However, the result of the study did not demonstrate the broad adoption of this strategy in commercial construction market. Dong and Chiara (2010) in their study titled "improving economic efficiency of public-private partnerships for infrastructure development by contractual flexibility analysis in a highly uncertain context", highlighted the role of price cap contracts and real options as a risk management device for risk mitigation in infrastructure projects.

In addition to application of price cap contracts in construction industry, various studies have investigated the role of call options in risk mitigation with respect to price volatilities in other fields like oil drilling, real state, budgeting and software sale (Smith and McCardle 1999; Techopitayakul 2004; Van Mieghem 1999).

2.4.5 Contingency

Contingency refers to the category of costs that estimator is uncertain regarding the amount (Jelen 1970). According to the Association of the Advancement of Cost Engineering (AACE, 2010); "contingency is an amount added to an estimate to allow for items, typically estimated using statistical analysis or judgment based on past experience." Contingency in cost estimation entails items such as minor price fluctuations or changes within the scope (Kul B. Uppal PE 2010), and it is generally determined either by expert judgment or stochastic methods. Recently due to increasing of price volatilities, many contractors rely on a contingency plan to deal with volatile prices. Particularly, for contracts without price adjustment clauses (Zhou 2011).

It is discussed that frequently in fixed price contracts, where owners tend to transfer the risk of price fluctuations to the contractors, contractors include large contingencies in their initial estimate in order to cover such changes in prices and hedge against the risk exposures. On the other hand,

it is also argued that if contractors overestimate the contingency amount, the prices of fixed price contracts could go above of those contracts with adjustment clauses (Gallagher and Riggs 2006; Zhou and Damnjanovic 2011). Furthermore, this situation could cause even more loss for owners with high likelihood of price decreases in today market. MacDonald (2007) in his periodic report for Washington State Department of Transportation mentioned that including price adjustment clauses for Hot Mix Asphalt (HMA) and fuel had made the bidding climate more competitive and decreased the risk of price volatilities for both contractors and owners.

Farid and Boyer (1985) introduced Fair and Reasonable Markup (FaRM) pricing model in fixed contracts in particular in commercial projects. FaRM is the smallest fee that fulfill the required rate of return based upon minimum acceptable price for the contract. The method is essentially suitable for cost plus contract format where the FaRM would be determined via the negotiation between owner and contractor. The study noted that the FaRM pricing model could provide contracts with a substitute method for subjective estimation of contingencies as well. However, this approach has not gained in popularity in commercial construction (Smith et al. 2011).

Similar to PAC method, in the contingency method in order to eliminate the subjectivity from the contingency amount, other methods beside the conventional percentage have been proposed. These techniques typically apply quantitative methods like Monte Carlo simulation, regression analysis, time series techniques and artificial neural network. However, in practice, most likely this number is subjective based on past experience; therefore, subject to a significant error and weaknesses, including: 1) rely fully on estimator, 2) double counting risk, in particular in projects with various subcontractors, any of them include contingencies and premiums in their calculation, and 3) percentage method do not provide any confidence interval for the results (Chapman 2001; Smith et al. 2011; Zou et al. 2009). Overall, it seems that previous studies tend to consider PAC as a

better approach toward risk mitigation of price volatilities in construction projects compared to contingency amount or other types of risk premiums.

2.4.6 Other practices

In addition to strategies to deal with price volatilities mentioned so far, there are a few other simple, yet effective alternatives that can be found in previous studies. Pierce et al. (2012) highlights the fact that many highway agencies break the projects into smaller pieces or into smaller phases in order for limiting the time and scope of the project and minimize the risks of price uncertainties and material shortages; in particular, in highway and complex projects this project. Another strategy documented in the literature, with regard to price volatilities strategies, is considering alternative designs with respect to material prices and availability for minimizing the effects of price spikes (Administration 2010; Skolnik 2011).

Early material procurement method is another way of dealing with price volatilities. It is the advance purchase of materials or at least those materials that are more susceptible to price fluctuations. In this scenario contractors attempt to either separate the material with volatile price from the rest of the estimate job or they place the order within the hour of signing the contract (Koushki et al. 2005; Moore 2008). The major downfall concerning this approach is rise of potential dispute between owner and contractor over the place or warehouse rent payments for stockpiling of materials. However, typically owners are willing to come up with some policies to pay for contractors for stockpiling the materials as a way to manage the risk of price volatilities (Smith et al. 2011). The second issue in regard to this strategy is the risk of theft and overall risk of material management.

2.5 ANALYTIC HIERARCHY PROCESS (AHP)

In many decision-making situations, final decision is dependent on the assessment of a number of alternatives (solutions) with respect to a number of tangible or intangible attributes (criterions). This decision-making problem is referred to as Multi Attribute Decision Making problem (MADM). Selecting the best alternative can be very difficult for the human being in this context. AHP is a method that provides a systematic approach for making the best-informed decision in such complex problems that deal with quantitative and qualitative features. Saaty (1977) originally introduced AHP. Since then AHP has been adopted widely by many researchers in different areas like manufacturing, construction, computer science, data science, engineering, management and etc. (Al-Harbi 2001; An et al. 2007; Anderson et al. 2010; Arbel and Seidmann 1984; Belton and Goodwin 1996; Dey 2010; Frazelle 1985; Hsu and Pan 2009; Li and Zou 2012; Lootsma 1980; Mustafa and Al-Bahar 1991).

The AHP takes advantage of the psychological fact that although making decision for an individual among various alternatives with respect to different attributes could be extremely confusing and overwhelming, an individual is typically good and rational at pairwise comparisons. Therefore, AHP essentially offers a framework in which making simple pairwise comparisons enable decision makers to overcome the entire problem. This is one of the main reason that have made AHP as one of the leading decision-making tools for both academics and practitioners.

2.5.1 Analytic Hierarchy Process in Detail

AHP foundation lies upon three principals: decomposition, comparative judgment and constructing priorities:

1- Decomposition principal refers to the breakdown of the AHP problem into hierarchy levels. Each of these layers can be analyzed independently. The components of the hierarchy could pertain to any feature of the decision problem; tangible or intangible, quantitative or qualitative, conceptual or abstract, in general anything that applies to the under review problem.

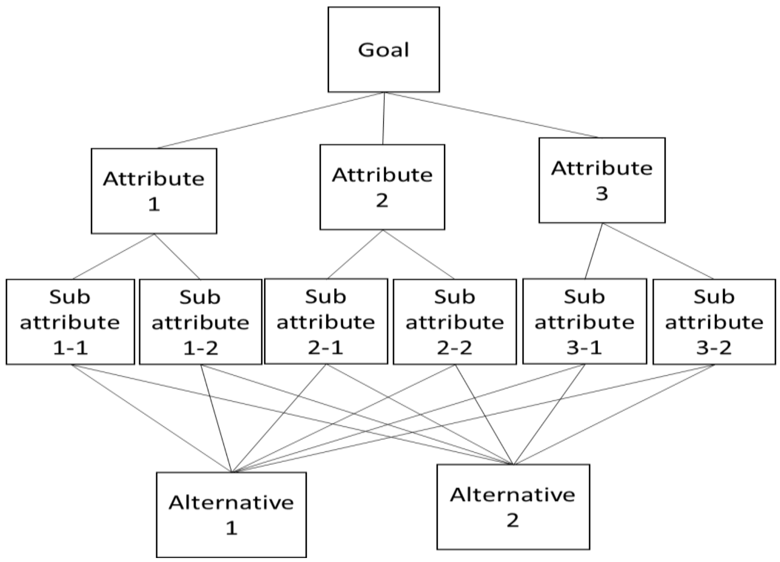

Figure 2.1: AHP Hierarchy with sub-attributes

2- Comparative judgment refers to pairwise comparisons made by either a decision maker or group of experts across the layers of hierarchies with respect to elements above them. At this stage, both quantitative data and qualitative date can be used. However, typically the final decision is made by judgment of the panel of experts (Saaty 2008). The outcome of this step is a matrix called Pairwise Comparison Matrix (PCM).

3- Construction priorities or raking alternatives refers to converting the pairwise comparisons evaluations to numerical values that can be treated and compared over the whole range of the problem.

The values of elements in PCM are assigned by panel of experts according to their experience and knowledge over the problem. Therefore, it is quite possible their answers to be inconsistent. Kou et al. (2012) labels two types of inconsistency (i.e. ordinal and cardinal). The book points out that in real world problems it is impossible to have perfect consistency. Thus, AHP is able to absorb a certain level of inconsistency in PCM. The inconsistency is measured by inconsistency ratio (CR) (Saaty 1980). The Saaty's original study noted that in general having informed panel of experts lead to higher consistency. The AHP methodology measures both micro consistencies for individual comparison and macro consistencies for the whole decision problem.

2.5.2 Benefits and concerns of AHP

AHP has turned to be one of the most successful MADM method due to its simplicities along with strong capabilities. It necessarily simplifies a complex decision-making problem and enable a decision maker to capture and consider all components of the problem. Also, it takes advantage of both quantitative and qualitative approaches which make this tool applicable to use expert knowledge in a systematic way. However, despite these benefits, there are a number of concerns reported in previous literature regarding this method. The most stated concern regarding AHP is the problem of "rank reversal". Belton and Gear (1983) were the first who noticed the potential of rank reversal problem in AHP. This problem arises when adding a new alternative or omitting the old ones could reverse the results, and turn the least preferred alternative to the best alternative.

The next matter found in the literature is the problem of internal inconsistency due to limited interval of pairwise comparisons. For instance, A may score 3 in comparison with B, and B may score 4 compared to C. in this case for having consistent scale we should get score of 12 for pairwise comparison of A and C. However, the range of comparisons in AHP questionnaire is usually bounded between 0 and 9.

Despite these concerns found in previous literature, Saatyfrequently in various studies and various cases reject both of these concerns. He emphasized that occurrence of these situation are natural in business environment and it can be dealt with through well designed and well specified questionnaire (Mustafa and Al-Bahar 1991; Saaty 1981; Saaty 2003; Saaty 2008). Moreover, Vargas and Perez (1991) responded to those concerns in a separate study as well. Their study demonstrated that AHP has a concrete theoretical background and applied basis. Interestingly, Beloton and Goodwin addressed their own concern later in 1996. They revealed ensuring the user's full understanding of the questionnaire is the key to success of the AHP (Belton and Goodwin 1996).

2.5.3 AHP applications in construction

As it was noted, AHP has been adopted widely in a variety of applications and different decision-making scenarios. In this section, it is intended to briefly describe the most leading papers found in previous literature utilizing AHP in process of decision making in the construction industry.

During 1980s researchers started to apply AHP to a variety of decision-making problems mostly in the industrial sector regarding material handling and purchasing in manufacturing sector (Frazelle 1985; Vargas and Saaty 1981), conflict resolution (Saaty 1981), flexible manufacturing (Arbel and Seidmann 1984), manpower selection and performance (Lootsma 1980), and automation of office system (Seidmann and Arbel 1983). Although few of these cases are replicable for the construction industry as well, not much attention in general turned toward application of AHP in the construction sector.

Mustafa and Al-Bahar (1991) conducted one of the first studies on utilization of AHP in field of construction management. The study underlined the potential benefit of AHP in the construction industry, where presence of various qualitative factors makes it hard for the construction entities

to make systematic and formalized decisions. They proposed using AHP methodology in risk assessment of construction projects. The study offered considering the six most importation attributes that contractors need to consider in the bid stage of the construction projects in order to select among the projects. The study's initial model included management, nature, labor, environment, society and machine as the general factors with which a typical construction project should be assessed. Based upon these general factors the study built the hierarchy layers of attributes (Figure 2).

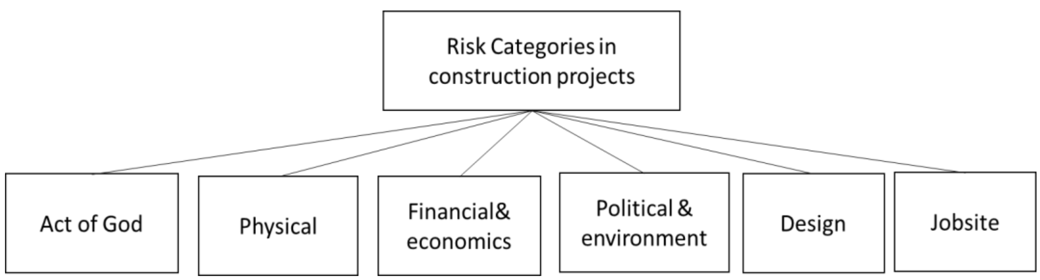

Figure 1.2: The proposed risk classification (Mustafa and Al-Bahar 1991)

In another study Al-Harbi (2001) attempted to address one of the most critical concerns of the owners, problem of selecting the best contractor among bidders. The study suggests AHP as a powerful decision-making tool in this context. In addition to solving the best contractor problem, the study highlights the ability of performing sensitivity analysis within AHP method and how it can help decision makers to see the variation in results by making slight changes in judgment of experts. Shapira and Goldenberg (2005) established an AHP model for construction equipment selection. The study first points out that previous methods in selecting an appropriate construction equipment could not address all influential factors properly due to lack of considering soft factors.

The study suggested that using AHP enable contractors to solve this problem. The study developed a hierarchy layers of attributes and alternatives incorporating both soft and hard elements (attributes) into the model and make the fair assessment of soft benefits of each alternative versus its costs.

An et al. (2007) developed a cost estimating model using Case Based Reasoning model and AHP methodology. While case based reasoning reuses the experience of specialists from prior cases to acquire the cost of new projects, they use AHP along with CBR technique to include experience in all process of cost estimating, particularly in determining the important weights of attributes in the CBR model. The study noted that AHP is a reliable tool for measuring experience. An et al. (2007) compared their results with three different methods and concluded the model using AHP is more accurate, reliable and explanatory than other models. Dey (2010) by integration of AHP and risk map developed a framework for risk management of projects. The study primary goal was to address the risk management of the project at both project level and activity level. The study proposed that in order to fulfill this goal, project stakeholders should take cautions against both operational and business risk. According to this goal, the study developed a hierarchy process for selecting among projects according to both operational and business related attributes.

In a very recent study, Li and Zou (2012) applied fuzzy AHP in a unique case of public private partnership infrastructure projects like motorways, bridges, tunnels and railways for risk identification and assessment with respect to project life cycle. The study first highlights the uniqueness of this projects due to a large amount of investment and long business period and the necessity of a robust and reliable risk assessment system. Then using previous literature, all the risks are identified and consequently classified with respect to projects' life cycles. Resulting in the identified risk factors: 1) feasibility, 2) financing, 3) design, 4) construction, 5) operation and

6) transfer. Each of these factors was broken into sub factors to form layers of hierarchies (figure 3). Lastly, using fuzzy AHP methodology, the assessment process was completed.

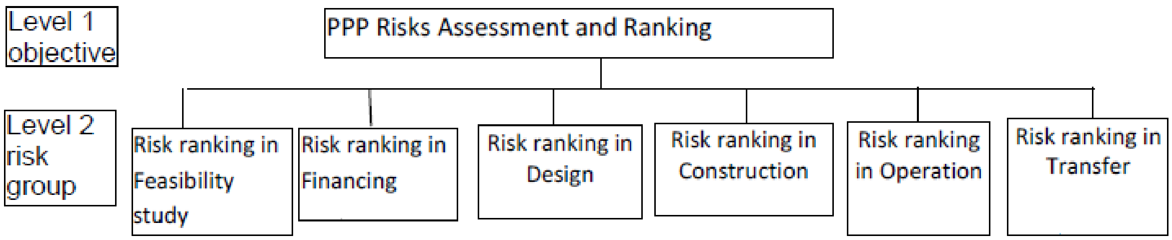

Figure 2. 2: Risk structure in public private partnership construction projects (Li and Zou 2012)

Surprisingly, just during the past two years AHP has drawn increased attention of researchers and practitioners in the construction industry. Aminbakhsh et al. (2013) underlined the fact that AHP can provide robust results in terms of ranking safety risks in construction projects. Consequently, enable contractors and subcontractors to make a logical budget and set realistic objectives without compromising safety. The presented framework in their study was built upon the theory of cost of safety (COS). In similar way, Janackovic et al. (2013) applied fuzzy AHP in order for ranking the indicators of occupational safety throughout a case study in road construction companies and supported the results of Aminbakhsh et al. (2013).

Liu et al. (2011) used a combination of AHP and fuzzy theory in order to create an evaluation system of concrete pavement. In the same vein, Hosseinijou et al. (2014) utilized AHP in material management for construction projects. The study acknowledged the substantial role of construction materials in the final cost of a construction project and attempted to improve the efficiency of material management in construction projects. Zhang-yin and Sheng-hui (2013) used AHP along with entropy method to build a framework for evaluating the effectiveness of

sustainable engineering construction project management. In the same way, Whang and Kim (2014) utilized AHP in the context of sustainable design management. Torfi and Rashidi (2011) points out to the project managers' assessment problem in the construction projects and developed a hierarchy model in order to solve this problem.

Collectively, these studies outline a critical role for AHP in construction management. In particular, in areas in which requires dealing with hard decisions like project risk management. This dissertation is intended to introduce the application of AHP to another critical area in which the construction industry is also struggling- price volatilities, in particular material price.

2.6 REFERENCES

Administration, U. D. F. T. (2010). "Riska and Contingency Review." US DOT Federal Transit Administration, 17.

Akintoye, A., Bown, P., and Hardcastle, C. (1998). "Macro-economic Leading Indicators of Construction Contract Prices." *Construction Management and Economics*, 16, 157-175.

Al-Harbi, K. M. (2001). "Application of the AHP in project management." *International journal of project management*, 19(1), 19-27.

Allen, E., and Iano, J. (2013). *Fundamentals of building construction: materials and methods*, John Wiley & Sons.

Aminbakhsh, S., Gunduz, M., and Sonmez, R. (2013). "Safety risk assessment using analytic hierarchy process (AHP) during planning and budgeting of construction projects." *Journal of safety research*, 46, 99-105.

An, S.-H., Kim, G.-H., and Kang, K.-I. (2007). "A case-based reasoning cost estimating model using experience by analytic hierarchy process." *Building and Environment*, 42(7), 2573-2579.

Anderson, S. D., Damnjanovic, I., and Nejat, A. (2010). "Effects of Project Cost Reduction Methods." *Transportation Research Record: Journal of the Transportation Research Board*, 2151(-1), 28-35.

Arbel, A., and Seidmann, A. (1984). "Performance evaluation of flexible manufacturing systems." *IEEE transactions on systems, man, and cybernetics*, 14(4), 606-617.

Ashouri , B., and Lu, J. (2010). "Time Series Analysis of ENR Construction Cost Index." *Journal of Construction Engineering and Management*, 136, 1227-1337.

Ashuri, B., Shahandashti, S. M., and Lu, J. (2012). "Empirical tests for identifying leading indicators of ENR Construction Cost Index." *Construction Management and Economics*, 30(11), 917-927.

Ballard, G. (2008). "The lean project delivery system: An update." *Lean Construction Journal*, 2008, 1-19.

Ballard, G., and Howell, G. (2003). "Lean project management." *Building Research & Information*, 31(2), 119-133.

Belton, V., and Goodwin, P. (1996). "Remarks on the application of the analytic hierarchy process to judgmental forecasting." *International Journal of Forecasting*, 12(1), 155-161.

Bhargava, A., Anastasopoulos, P. C., Labi, S., Sinha, K. C., and Mannering, F. L. (2010). "Three-stage least-squares analysis of time and cost overruns in construction contracts." *Journal of construction engineering and management*, 136(11), 1207-1218.

Blair, A. N., Lye, L. M., and Campbell, W. J. (1993). "Forecasting construction cost escalation." *Canadian Journal of Civil Engineering*, 20(4), 602-612.

Brown, I., and Randolph, L. (2011). "Evaluation of Price Adjustment Clauses for Construction Materials."

Burke, R. (2013). *Project management: planning and control techniques*.

Carr, R. I. (1982). "General bidding model." *Journal of the Construction Division*, 108(4), 639-650.

Chapman, R. J. (2001). "The controlling influences on effective risk identification and assessment for construction design management." *International Journal of Project Management*, 19(3), 147-160.

Cheung, F. K. T., and Skitmore, M. (2006). "Application of cross validation techniques for modelling construction costs during the very early design stage." *Building and Environment*, 41(12), 1973-1990.

Chou, J.-S., Yang, I. T., and Chong, W. K. (2009). "Probabilistic simulation for developing likelihood distribution of engineering project cost." *Automation in Construction*, 18(5), 570-577.

Dawood, N. N., and Bates, W. (2002). "A decision support system specification for cost escalation in heavy engineering industry." *Computer-Aided Civil and Infrastructure Engineering*, 17(5), 342-357.

Dey, P. K. (2010). "Managing project risk using combined analytic hierarchy process and risk map." *Applied Soft Computing*, 10(4), 990-1000.

Diekmann, J. E. (1983). "Probabilistic estimating: mathematics and applications." *Journal of Construction Engineering and Management*, 109(3), 297-308.

Dong, F., and Chiara, N. (2010). "Improving economic efficiency of public-private partnerships for infrastructure development by contractual flexibility analysis in a highly uncertain context." *The Journal of Structured Finance*, 16(1), 87-99.

Eckert, C., and Eger III, R. J. (2005). "Study of liquid asphalt price indices applications to Georgia contracting."

Eger III, R. J., and Guo, H. (2008). "Financing Infrastructure: Fixed price vs. Price Index Contract." *Journal of Public Procurement*, 8(3).

Enders, W. (2008). *Applied econometric time series*, John Wiley & Sons.

Engle, R. F., and Ng, V. K. (1993). "Measuring and testing the impact of news on volatility." *The journal of finance*, 48(5), 1749-1778.

Forbes, L. H., and Ahmed, S. M. (2010). *Modern construction: lean project delivery and integrated practices*, CRC Press.

Frazelle, E. (1985). "Suggested techniques enable multi-criteria evaluation of material handling alternatives." *Industrial Engineering*, 17(2), 42-48.

Gallagher, J., and Riggs, F. (2006). "Construction Briefings."

Guan, Y., and Liao, H. (2014). "Studying the Reasons for Delay and Cost Escalation in Construction Projects: The Case of Iran Abstract ID."

Hill, R. C., Griffiths, W. E., and Lim, G. C. (2008). *Principles of econometrics*, Wiley Hoboken, NJ.

Hosseinijou, S. A., Mansour, S., and Shirazi, M. A. (2014). "Social life cycle assessment for material selection: a case study of building materials." *The International Journal of Life Cycle Assessment*, 19(3), 620-645.

Hsu, T.-H., and Pan, F. F. C. (2009). "Application of Monte Carlo AHP in ranking dental quality attributes." *Expert Systems with Applications*, 36(2), 2310-2316.

Hwang, S. (2009). "Dynamic regression models for prediction of construction costs." *Journal of Construction Engineering and Management*, 135(5), 360-367.

Hwang, S., Park, M., Lee, H.-S., and Kim, H. (2012). "Automated Time-Series Cost Forecasting System for Construction Materials." *Journal of Construction Engineering and Management*, 138(11), 1259-1269.

Janackovic, G. L., Savic, S. M., and Stankovic, M. S. (2013). "Selection and ranking of occupational safety indicators based on fuzzy AHP: A case study in road construction companies." *South African Journal of Industrial Engineering*, 24(3), 175-189.

Jelen, F. C. (1970). "Cost and optimization engineering."

Kasim, N., Anumba, C., and Dainty, A. "Improving materials management practices on fast-track construction projects." *Proc., Proceedings Twenty First Annual Association of Researchers in Construction Management (ARCOM) Conference, Khosrowshahi*, 793-802.

Khanzode, A., Fischer, M., and Reed, D. "Case study of the implementation of the lean project delivery system (LPDS) using virtual building technologies on a large healthcare project." *Proc., 13th International Group for Lean Construction Conference: Proceedings*, International Group on Lean Construction, 153.

Kim, G.-H., An, S.-H., and Kang, K.-I. (2004). "Comparison of construction cost estimating models based on regression analysis, neural networks, and case-based reasoning." *Building and environment*, 39(10), 1235-1242.

Kosmopoulou, G., and Zhou, X. (2014). "Price Adjustment Policies in Procurement Contracting: An Analysis of Bidding Behavior." *The Journal of Industrial Economics*, 62(1), 77-112.

Kou, G., Ergu, D., Peng, Y., and Shi, Y. (2012). *Data Processing for the AHP/ANP*, Springer.

Koushki, P., Al-Rashid, K., and Kartam, N. (2005). "Delays and cost increases in the construction of private residential projects in Kuwait." *Construction Management and Economics*, 23(3), 285-294.

Kul B. Uppal PE, E., , (2010). "Contingency." *AACE International*AACE International.

Kuen, T., and Hoong, T. (1992). "Forecasting volatility in the Singapore stock market." *Asia Pacific Journal of Management*, 9(1), 1-13.

Li, H., Kong, C., Pang, Y., Shi, W., and Yu, L. (2003). "Internet-based geographical information systems system for E-commerce application in construction material procurement." *Journal of Construction Engineering and Management*, 129(6), 689-697.

Li, J., and Zou, P. (2012). "Risk identification and assessment in PPP infrastructure projects using fuzzy Analytical Hierarchy Process and life-cycle methodology." *Australasian Journal of Construction Economics and Building*, 8(1), 34-48.

Lichtig, W. A. (2005). "Sutter health: Developing a contracting model to support lean project delivery." *Lean Construction Journal*, 2(1), 105-112.

Lichtig, W. A. (2006). "Integrated Agreement for Lean Project Delivery, The." *Constr. Law.*, 26, 25.

Liu, Z. B., Fei, W. S., Wu, P. G., and Chen, F. (2011). "The research on building up the hierarchy process and fuzzy evaluation model and evaluation system about the cement concrete pavement on the basis of the fuzzy mathematics theory." *Advanced Materials Research*, 255, 3228-3233.

Lootsma, F. (1980). "Saaty's priority theory and the nomination of a senior professor in operations research." *European Journal of Operational Research*, 4(6), 380-388.

Lowe, D., Emsley, M., and Harding, A. (2006). "Predicting Construction Cost Using Multiple Regression Techniques." *Journal of Construction Engineering and Management*, 132(7), 750-758.

MacDonald, D. B. (2007). "Measures, Markers and Mileposts." *The Gray Notebook for the Quarter Ending December 31*.

Mitropoulos, P., Abdelhamid, T. S., and Howell, G. A. (2005). "Systems model of construction accident causation." *Journal of Construction Engineering and Management*, 131(7), 816-825.

Moore, M. A. (2008). "Build local, Price global." McGraw Hill Construction, ENR

Mustafa, M. A., and Al-Bahar, J. F. (1991). "Project risk assessment using the analytic hierarchy process." *Engineering Management, IEEE Transactions on*, 38(1), 46-52.

Nejat, A., Anderson, S. D., and Damnjanovic, I. (2010). "Effects of Project Cost Reduction Methods." *Transportation Research Record: Journal of the Transportation Research Board*, 2151(-1), 28-35.

Nahmens, I., and Ikuma, L. H. (2009). "An empirical examination of the relationship between lean construction and safety in the industrialized housing industry." *Lean Construction Journal*, 2009, 1-12.

Nahmens, I., and Mullens, M. (2009). "The impact of product choice on lean homebuilding." *Construction Innovation: Information, Process, Management*, 9(1), 84-100.

Ng, F. P., Björnsson, H. C., and Chiu, S. S. (2004). "Valuing a price cap contract for material procurement as a real option." *Construction management and economics*, 22(2), 141-150.

Ng, S. T., Cheung, S. O., Skitmore, M., and Wong, T. C. (2004). "An integrated regression analysis and time series model for construction tender price index forecasting." *Construction Management and Economics*, 22(5), 483-493.

Olatunji, O. A. (2010). "The impact of oil price regimes on construction cost in Nigeria." *Construction Management and Economics*, 28(7), 747-759.

O'Sullivan, A., and Sheffrin, S. M. (2007). *Economics: Principles in action*, Boston, Mass.: Pearson/Prentice Hall.

Olatunji, O. A. (2010). "The impact of oil price regimes on construction cost in Nigeria." *Construction Management and Economics*, 28(7), 747-759.

Pierce, C., Huynh, N., and Guimaraes, P. (2012). "Cost Indexing and Unit Price Adjustments for Construction Materials."

Redd, L., and Hibbard, T. (2009). "Asphalt Risk Management at the Wyoming Department of Transportation."WYDOT.

Saaty, T. L. (1981). *Decision Making for Leaders: The Analytical Hierarchy Process for Decisions in a Complex Work*, Lifetime Learning Publications.

Saaty, T. L. (2003). "Theory of the analytic hierarchy process. Part 2.1." *Системні дослідження та інформаційні технології*.

Saaty, T. L. (2008). "Relative measurement and its generalization in decision making why pairwise comparisons are central in mathematics for the measurement of intangible factors the analytic hierarchy/network process." *RACSAM-Revista de la Real Academia de Ciencias Exactas, Fisicas y Naturales. Serie A. Matematicas*, 102(2), 251-318.

Seidmann, A., and Arbel, A. (1983). "An analytic approach for planning computerized office systems." *Omega*, 11(6), 607-617.

Shakantu, W., Tookey, D. J. E., and Bowen, P. P. A. (2003). "ThE Hidden Cost Of Transportation Of Construction Materials " *Journal of engineering managment and design*

Shane, J. S., Molenaar, K. R., Stuart Anderson, and Schexnayder, C. (2009). "Constructin Project Cost Escalation Factors." *Journal of Management in Engineering*, 25.

Shapira, A., and Goldenberg, M. (2005). "AHP-based equipment selection model for construction projects." *Journal of Construction Engineering and Management*, 131(12), 1263-1273.

Skolnik, J. (2011). *Price Indexing in Transportation Construction Contracts*, Jack Faucett Associates.

Smith, J. E., and McCardle, K. F. (1999). "Options in the real world: Lessons learned in evaluating oil and gas investments." *Operations Research*, 47(1), 1-15.

Smith, J. P., Miller, K., Christofferson, J., and Hutchings, M. (2011). "Best Practices for Dealing with Price Volatility in Utah's Residential Construction Market." *International Journal of Construction Education and Research*, 7(3), 210-225.

Srivastava, J., Cooley, R., Deshpande, M., and Tan, P.-N. (2000). "Web usage mining: Discovery and applications of usage patterns from web data." *ACM SIGKDD Explorations Newsletter*, 1(2), 12-23.

Techopitayakul, D. (2004). "ASP-based software delivery: economics, pricing and contract structuring using real options."

Thomas, H. R., Horman, M. J., de Souza, U. E. L., and Završki, I. (2004). "Closure to “Reducing Variability to Improve Performance as a Lean Construction Principle” by H. Randolph Thomas, Michael J. Horman, Ubiraci Espinelli Lemes de Souza, and Ivica Zavrski." *Journal of Construction Engineering and Management*, 130(2), 300-301.

Torfi, F., and Rashidi, A. (2011). "Selection of project managers in construction Firms using analytic hierarchy process (AHP) and fuzzy Topsis: a case study." *Journal of Construction in Developing Countries*, 16(1), 69-89.

Touran, A., and Lopez, R. (2006). "Modeling Cost Escalation in Large Infrastructure Projects." *Journal of Construction Engineering and Management*, 853-860.

Trost, S., and Oberlender, G. (2003). "Predicting Accuracy of Early Cost Estimates Using Factor Analysis and Multivariate Regression." *Journal of Construction Engineering and Management*, 129(2), 198-204.

Van Mieghem, J. A. (1999). "Coordinating investment, production, and subcontracting." *Management Science*, 45(7), 954-971.

Vargas, L. G., and Saaty, T. L. (1981). "Financial and intangible factors in fleet lease or buy decision." *Industrial Marketing Management*, 10(1), 1-10.

Wang, C.-H., and Mei, Y.-H. (1998). "Model for forecasting construction cost indices in Taiwan." *Construction Management & Economics*, 16(2), 147-157.

weidman, J. E., Miller, K. R., Christoffersen, J. p., and Newitt, J. S. (2011). "Best Practices for Dealing with Price Volatility in Commercial Construction." *International Journal of Construction Education and Research*, 7(4), 17.

Whang, S.-W., and Kim, S. (2014). "Determining sustainable design management using passive design elements for a zero emission house during the schematic design." *Energy and Buildings*, 77, 304-312.

Williams, T. P. (1994). "Predicting changes in construction cost indexes using neural networks." *Journal of Construction Engineering and Management*, 120(2), 306-320.

Wilmot, C. G., and Cheng, G. (2003). "Estimating Future Highway Construction Cost." *Journal of Construction Engineering and Management*.

Wilmot, C. G., and Mei, B. (2005). "Neural network modeling of highway construction costs." *Journal of construction engineering and management*, 131(7), 765-771.

Xu, J.-w., and Moon, S. (2013). "Stochastic Forecast of Construction Cost Index Using a Cointegrated Vector Autoregression Model." *Journal of Management in Engineering*, 29(1), 10-18.

Zhang-yin, L., and Sheng-hui, J. (2013). "Evaluation Method on Effectiveness of Sustainable Engineering Construction Project Management." *International Journal of Applied Environmental Sciences*, 8(9).

Zhou, X. (2011). "Managing commodity risks in highway contracts: Quantifying premiums, accounting for correlations among risk factors, and designing optimal price-adjustment contracts." Texas A&M University.

Zhou, X., and Damnjanovic, I. D. (2011). "Optimal Hedging of Commodity Price Risks in Highway Contracts." *Transportation Research Record: Journal of the Transportation Research Board*, 2228(1), 19-25.

Zou, P. X., Chen, Y., and Chan, T.-Y. (2009). "Understanding and improving your risk management capability: assessment model for construction organizations." *Journal of Construction Engineering and Management*, 136(8), 854-863.

CHAPTER THREE: VOLATILITY FORECAST OF THE COSNSTRUCTION COST INDEX USING GENERAL AUTOREGRESSIVE CONDITIONAL HETEROSCEDASTIC (GARCH) METHOD (PAPER 1)

3.1 INTRODUCTION

When estimating a construction project, cost estimators need a broad range of information and inputs, including price of materials, condition of the project, price volatilities on labor and material, site condition, and current state of the economy, before or throughout the project (Blair et al. 1993; Shane et al. 2009; Touran and Lopez 2006). Price fluctuations in labor and material during the course of a given construction project is unavoidable. Sometimes these fluctuations are insignificant enough that minor changes can be absorbed. However, very often industry experienced fluctuations in prices, either in positive or negative directions that last for longer periods and have a severe impact on various entities involved in the construction project. These price fluctuations or so-called “volatilities” on construction cost poses a significant risk to the contracting parties (e.g. contractors, owners and suppliers). Although a decline in prices does not directly cause any financial trouble for owners, they may raise the question whether they are being treated fairly. 2007-2008 financial crises and its following economic downturn, which leaded to 10% decrease in construction cost in the state of New York, is an example of such circumstances (Fung 2009). According to Webster dictionary, the term “volatility” means “the property of being likely to change in a sudden and extreme way” (Webster 2011). In the context of cost analysis, volatility is a trait of price fluctuations, typically in terms of labor and material. Also, it should be noted that volatility measures do not show the direction of price fluctuations; but the magnitude of change. Therefore, volatility can be associated with project risk. Periods with higher volatility are considered riskier than tranquil periods in terms of budgeting the project.

The Construction Financial Management Association in a recent study has reported approximately 70% of general contractors have mentioned fluctuations in construction costs as the main project risk (2012). In addition, the number of heavy construction projects suffering from over budgeting has increased substantially over the past decade (Touran and Lopez, 2006). The industry has turned to quantitative risk analysis as an approach to overcome or manage volatility, in particular for complex construction projects (e.g. Federal Transit Administration, Washington State Department of Transportation, and Department of Defense). Therefore, modeling escalation factor (i.e. the rate of change in construction cost index such as the CCI) in construction projects, forecasting construction cost indices (i.e. Construction Cost Index, Construction Building Index or Federal Highway Administration Construction Bid Price Index) and probabilistic risk assessment of cost in construction projects (i.e. Monte Carlo simulation) have drawn attention of researchers.

Most recently, different studies have endeavored to address this issue via multivariate and univariate methods of econometrics (Multiple Regression Analysis and Time Series such as ARMA (p, q), ARIMA (p, I, q), VAR (p) models) (Ashouri & Lu, 2010; Olatunji, 2010; Touran & Lopez, 2006; and Xu & Moon, 2013). Typically, these methods make the assumption that the variance of a series as a measure of uncertainty is constant through time (i.e. homogeneity of variance). Homogeneity of variance has been the underlying assumption on previous studies related to modeling and forecasting construction cost to date. While, real data sets reject this assumption in many cases. The construction cost indices show periods of large volatilities alongside with stable periods (Figure 1). In these situations, the assumption of constant variance is inappropriate since the series shows time-varying volatility.

Another point is that the contractor normally would be interested in the prediction of the CCI over the contract period or specific period of time. In such cases, the unconditional variance, which is

assumed constant, would be unimportant. Figure 1 shows high variability of the CCI over the period 1978 to 1985. In the 1990s the CCI changes seem tranquil alongside with a few significant increases and decreases. Most dramatic are monthly changes in the CCI during 2000 to present. According to Enders (2008) such series are called conditionally heteroscedastic in which the unconditional (or long-term) variance may be constant, but still there are periods with relatively high or low variance. Thus, cost estimators should be aware of time-varying volatility in the CCI, because the risk factor in terms of price changes in labor and material is different for all the periods. Therefore, the predictability of projects' construction cost is different for all periods. The standard tools to address this issue have become ARCH (Auto-Regressive Conditional Heteroskedasticity) or its generalized form GARCH (Generalized Auto-Regressive Conditional Heteroskedasticity) methods (Engle, 2003). In this study Engineering News Record's Construction Cost Index time series (ENR CCI) was adopted (January 1987 to July 2014) and analyzed using EViews 8 software. The objective of this study is to extend the ARCH family methodology by developing a predictive model that accounts for volatility of the CCI for the first time. Also, providing and forecasting a concrete volatility measure like standard deviation that can be used in cost estimation, risk analysis, escalation factor and contingency calculations. Furthermore, using ARCH and GARCH methods, this paper intends to determine the persistency of volatilities in the case of external shocks, (e.g. economic shocks or political shocks) detect salient features of the economic series, and capture the stylized characteristics of the data which enable us to answer the question of whether or not volatilities of series has persistent nature in the case of bad or good news in the economy. The results of this study could help construction participants (i.e. owners, contractors and other stakeholders) with their risk assessment, cost engineering, contingency calculations as well as adding to the body of knowledge in regard to the cost forecasting.

3.2 FORECASTING METHODS USING IN THE CONSTRUCTION INDUSTRY

Many factors affect the cost of construction projects like scope change, under or over estimation of the project cost, change orders, time overrun, and length of design process period (Pierce et al 2012; Touran and Lopez 2006). However, one of the major contributors to fluctuations in cost of construction projects, over the past decade has been unprecedented price volatilities of construction resources, namely materials and labors (Hwang et al. 2012; Smith et al. 2011; Weidman et al. 2011; Xu and Moon 2013). Due to the increasing price volatilities of construction resources, researchers have started to think of ways to analyze, estimate and possibly forecast these fluctuations. Previous literature in regard to construction cost forecasting could be divided into three chief categories.

3.2.1 Traditional Econometric Methods (TEM)

In this context TEM refer to those studies that have used multiple regression analysis techniques. In this regard, previous studies have endeavored to discover two essential items: 1) specification of the functional form, 2) leading independent (explanatory) variables. In the construction industry, regarding the former, researchers have used linear additive functional form widely along with Ordinary Least Squares (OLS) technique. Therefore, the primary focus of previous studies on TEM to date has remained on determining the most significant explanatory variables (Ashuri et al. 2012; Chen 2007; Lowe et al. 2006; Martin Skitmore and Thomas Ng 2003). Akintoye et al. (1998) identified unemployment level, construction output, and industrial production as leading indicators of construction prices in U.K. In the same way, Hwang (2009) found prime interest rate, housing starts and consumer price index as predictive variables of the CCI. In a recent study Ashuri et al. (2012) using Granger causality test, identified consumer price index, crude oil price, producer price index, GDP, employment levels in construction, number of building permits, number of

housing starts and money supply as the principal variables in determining historical trend of CCI in the U.S. They also used Johansen's cointegration tests to validate their result in terms of long-term relationships of these variables with CCI. Shane et al. (2009) through in-depth literature review and interviews with 20 state highway agencies, found 18 major factors explaining variations in cost of all types of construction projects in the U.S. Wilmot and Cheng (2003) developed a tailor made cost index for highway construction projects in state of Louisiana and in the next step using a multiplicative regression equation tried to predict the future trend of highway construction projects costs.

The main disadvantage of TEM typed techniques, in terms of forecasting, is that the researcher must identify the extensive lists of explanatory variables and forecast or estimate all future values of these variables to be able to forecast his or her desired variable (dependent variable). In the construction industry, this approach has not gained popularity because there are numerous independent variables affecting construction cost. Moreover, in order to create reliable forecast, the researcher is required to forecast future values of these variables as well. This makes the forecasting tedious and increases the error margin of the final forecast significantly.

3.2.2 Modern Econometric Methods (MEM)

In this study MEM refer to time series analysis. Time series is a sequence of values or date points, equally ordered with respect to a time space (Enders 2008). While multiple regression analysis is used in a way to test various hypothesis or find the relationships between various variables (i.e. dependent variable with series of independent variables); time series analysis rely on the fact that data points collected throughout the time may carry internal statistical information and structures. Therefore, all the time series methods attempt to gain statistical inferences and even forecast the future data points of a series based on analyzing previous data points. This category includes a

broad family of time series analysis methods such as Auto-Regressive (AR), Moving Average (MA), Auto-Regressive Integrated Moving Average (ARIMA), different seasonal adjustment methods (additive, multiplicative, census method, seasonal dummy variables), smoothing and detrending techniques (Holt-Winters, Hodrick-Prescott filter) Vector Error Correction Method (VECM). MEM are usually univariate analysis, meaning previous values of the variable of interest are the only ingredient for forecasting future values of the variable. This characteristic along with relatively easy replication of these practices have contributed to the popularity of these models in recent years (Ashouri and Lu 2010; Blair et al. 1993; Hwang 2009; Ng et al. 2004; Wang and Mei 1998; Xu and Moon 2013). Xu and Moon (2013) used Cointegrated Vector Autoregression Model(C-VAR) to forecast the CCI. In another major study, Ashouri and Lu (2010) compared different common time series methods (e.g. AR, MA, ARIMA, Holt ES, Seasonal ARIMA) to identify the best method for in-sample and out-of-sample forecast of the CCI with respect to the accuracy, application and implementation. They proposed seasonal ARIMA (0, 1, 0) (0, 12, 1) as the best predictive model for constructing in-sample forecast of CCI and Holt-winters exponential smoothing as a better model for out-of-sample forecast of CCI. Hwang (2009) also used two dynamic models in order to forecast CCI. However, instead of using pure time series modeling, Hwang (2009) used integration of traditional and dynamic techniques. The study used interest rate, housing starts and Consumer Price Index (CPI), which is an inflation factor, as leading variables in the prediction of CCI. In addition, three lags of CCI (CCI_{t-1}, CCI_{t-2} and CCI_{t-3}) was used as the dynamic components of the model.

The common assumption underlying both traditional (i.e. multiple regression analysis) and modern techniques (i.e. time series methods) is homogeneity of variance as one of the fundamental assumptions of regression analysis in general. However, the question proposed in this study tries

to verify if this assumption is correct. Variance is the measure of uncertainty. In fact, by assuming constant variance, we are implicitly accepting during different periods of time we are dealing with a fixed amount of uncertainty. In this study, it is intended to relax this assumption in order for further investigation of the CCI variance as a measure of future uncertainty (risk).

3.2.3 Other (None-econometric) forecasting methods used in construction

In addition to traditional and modern forecasting techniques, neural networks and subjective (qualitative) methods are other techniques used by researchers. Neural networks is a computer-based system that simulates the learning procedure of the human brain and built upon mathematical methods (Wilmot and Mei, 2005). In a study in 1990s, Williams used neural networks to forecast changes in construction cost index by comparing three different methods; neural networks, exponential smoothing and multiple regression. Results revealed that neural networks generate the least accurate results (1994). Wilmot also applied neural networks to predict the escalation of highway construction costs over time in the state of Louisiana. While he did not compare his results with other conventional methods, he reported that neural networks results were reasonably acceptable (2005). On the other hand, qualitative methods are beneficial mostly for longer-term forecasts; where statistical methods are subject to higher error bounds or when there is lack of historical data (Kim et al. 2004).

Two of the most known methods under this category are Case Based Reasoning (CBR) and surveys Of expectations.

Table 3.1: Methods of construction cost forecasting

Econometric methods			
Forecasting methods	**Techniques**	**Advantages**	**Barriers**
Traditional	Multiple Regression Analysis (i.e. additive or multiplicative functional forms)	-Easy implementation by practitioners. -good results can be gained with fairly small data set.	-All the independent variables to be identified. -prior to forecast of dependent variable, forecast of each individual independent variable is needed.
Modern	Times series methods (e.g. MA, AR, ARIMA, VAR, VECM, De trending methods)	-typically one variable is needed in order to forecast. -internal structure of the data set is captured. -highly accurate	-Depending on the proposed technique implementation can be difficult for practitioners. -Historical data set is needed.
Non-econometric methods			
Quantitative	Neural Networks	-Less formal statistical training is required. -Ability to address relatively complex non-linear relationships.	-Its black- box nature. -Susceptible to model over fitting and less precision.
Qualitative	-Case-based reasoning -Survey of expectation (e.g. ENR CICI)	-Quick and easy to implement. -Beneficial for longer term period.	-Subject to opinion of experts. -Less accurate compared to quantitative methods.

(Kim et al. 2004; Maher and Balachandran 1994; Morcous et al. 2002; Tah et al. 1999). Kim et al. (2004) compared three cost estimation methods (multiple regression analysis, neural networks, and case-based reasoning) based on 530 historical costs. The study found that the CBR estimating model performed better than the neural networks estimating model with respect to long-term predictions.

Surveys of expectation are another economical method of forecasting escalation factor or future trend of construction cost (Touran and Lopez). ENR Construction Industry Confidence Index (CICI) and Associated Builders and Contractors Confidence Index (ABC CI) are two instances of familiar surveys to which cost managers refer, in order to gain the sense of the current and future

state of the risk in the construction industry. Table 1 summarizes common forecasting methods discussed in this section with their main advantages and barriers for the purpose of the forecast.

3.3 CONSTRUCTION COST INDEX

Since 1913 the Engineering News Record (ENR) has been publishing the Construction Cost Index (CCI) in both forms of the aggregate index and separate for 20 major cities of the U.S. For more information regarding the CCI, readers could refer to the ENR website (www.enr.constructin.com). The CCI helps cost managers to make decisions for costs among a wide variety of materials and projects and always can be used as background information on the cost (Lewis and Grogan 2013). This index has been used widely for calculating and modeling escalation factors, contingency amount in fixed price contracts, and price fluctuations in prices for highway and infrastructure projects.

3.3.1 Data

This study uses monthly CCI for the period of January 1978 to July 2014. This data set is called range data set and includes 439 monthly observations. In this study, the range data set first is divided into two subsets; the first subset covers periods of January 1978 to July 2012 (415 observations) and is used to develop the GARCH model and perform in-sample forecasts. The smaller subset (July 2012 to July 2014) is used for out-of-sample forecast and model performance evaluation.

Prior to any time series modeling, it is a good practice to examine stationary and seasonality status of the series of interest in order to gain reliable results (Enders 2008; Diebold 2006). Conceptually, a time series is called stationary if its statistical properties (mean, variance, and covariance) are independent of time. It is important to notice that if the unconditional variance of a series is not

constant, the series is non-stationary. However, conditional heteroskedasticity is not source of non-stationary (Enders 2008). In time series analysis in addition to visual examination of the series (e.g. presence of trend or presence of seasonality), quite a few famous methods have been developed to check the stationary status of a series of interest statistically (e.g. Augmented Dickey-Fuller unit root test, Philips and Perron test). Fortunately however, in this study there is no need to check upon stationary condition of the CCI, since both Ashouri and Lu (2010), and Xu and Moon (2013) in separate studies have tested CCI time series. Both of these studies concluded that CCI is not a stationary (Enders 2008) process. Moreover, seasonality occurs when a time series repeats constant cyclical patterns over the time (e.g. increase in summer and decrease in winter). Similarly, a few of previous works in the construction industry have approved existence of seasonality in CCI (Kuen and Hoong 1992; Ng et al. 2004; Xu and Moon 2013). Using the first difference of the series of interest instead of the original level of the series is the most common practice by econometricians in order to tackle the non-stationary issue (Hill et al. 2008). This strategy was adopted in this paper as well, and all the calculations were conducted on first-level difference of CCI that is denoted as DCCI (Difference of Construction Cost Index). In this paper, DCCI refers to the differences of successive values of the CCI (CCI_t-CCI_{t-1}). This technique is also called first integration. Furthermore, in order to remove seasonal components of time series, application of seasonal dummy variables are utilized. We will add 12 separate dummy variables for 12 months (M1, M2, M3… M12) to the specified mean equation. These dummy variables extract seasonal impacts of different months on the variable of CCI. However, after fitting the model non-significant dummy variables must be removed from the model. Figure 1 displays step by step the condition of the CCI during the period studied. The first graph on the right side demonstrates presence of evident trend in the current values of CCI. Visually one can sense the statistic

properties of CCI at the current level would be under influence of time. The second graph shows the first-difference of the original series of CCI. As it is observed this technique removes time related properties of the CCI that is critical for obtaining reliable results. The third graph demonstrates monthly incremental change of DCCI. It is evident that in general, average of DCCI values (variations) are higher for months of May to September.

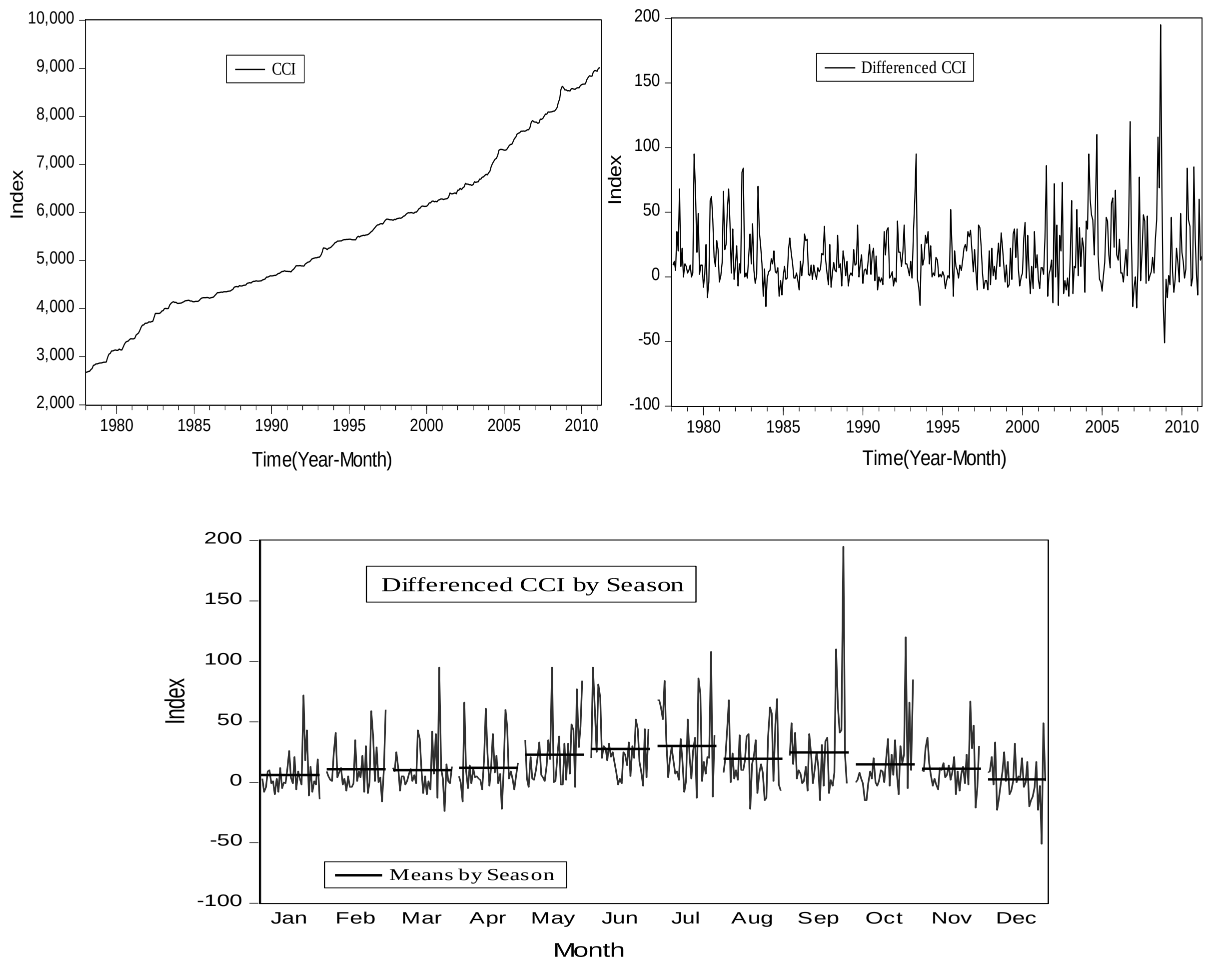

Figure 3.1: The original series of CCI, the first-difference series of CCI (DCCI), and monthly pattern of DCCI

3.4 METHODOLOGY

The main purpose of this study is to develop a predictive model for the CCI that accounts for volatility. This will provide cost managers with a separate tool to assess the cost risk of construction projects with respect to price volatilities, a gauge for current and future volatility of the CCI. Considering the high incidents of budget over run in construction projects and recent prolonged price volatilities in material and labor, this study proposes to develop a better understanding of the dynamics of labor and material cost volatilities and current practices to estimate the CCI. The construction industry will benefit from the outcome of this study with provision of a measurement tool for assessing and forecasting the price volatilities in construction market. It essentially helps cost managers to evaluate the predictability of the CCI. The CCI is the measure of the relative price of materials and labors, if predictability of CCI due to high volatility of prices is low, various contracting parties will predict loss over the course of the project construction. Moreover, the GARCH model used in this study will produce more efficient estimator for forecasting the CCI compared to other methods suggested to date. Figure 2 displays an overview of the methodology proposed in this study, which entails three major steps. The first step entails discovering whether time-varying volatilities in CCI are statistically significant. The second step uses ARCH family methods to capture these volatilities and eventually reassessing the model in terms of remaining volatilities. Once the final model is estimated, and its applicability is tested, upon which in-sample and out-of-sample forecasts for both CCI and CCI volatilities will be constructed, completing the third step.

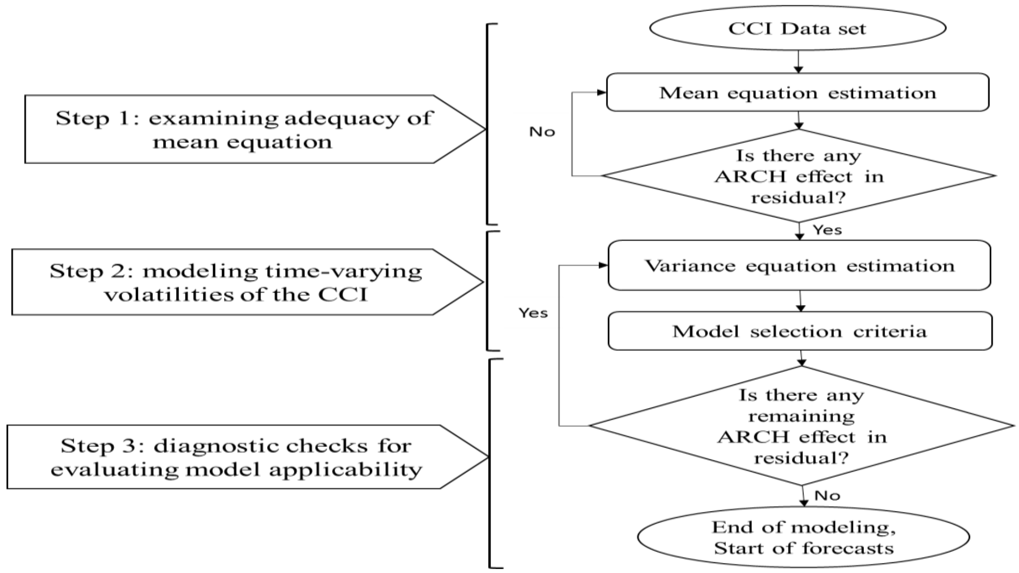

Figure 3.2: Research Design

3.4.1 Autoregressive Conditional Heteroskedastic (ARCH)

The Autoregressive Conditional Heteroskedastic (ARCH) model was born in 1982 by Robert Engle, a Nobel Prize winner economist during his studies on U.K.'s inflation time series. For the first time he noticed that although estimations of U.K. inflation have provided white noise residuals, the squared values of these residuals shows strong signs of autocorrelation (Engle 1982). In 1986, Tim Bollerslev, Engle's student made the first Generalization to the ARCH model and introduced Generalized Autoregressive Conditional Heteroskedastic or GARCH model. In this section, a brief summary of ARCH and GARCH models is presented starting with a simple regression model when homoscedasticity (homogeneity of variance) assumption holds:

$CCI_t = m_t + e_t$ mean equation for the CCI_t (1.a)

$e_t \sim N(0, \sigma_t^2)$ error term, normally distributed with variance of σ_t^2 (1.b)

$\sigma_t^2 = \alpha$ variance of error term is constant, equal to α (1.c)

Equations (1.a) to (1.c), specify standard assumptions of the regression analysis. The equation (1.a) represent a simple regression model for the $CCI_{t;}$ m_t represents the specification of the simplest functional form of the regression model which could follow either traditional or time series methods. e_t is error term (residuals or disturbance term). The equation (1.b) represents the underlying assumption of the regression model indicating normal distribution of residuals with mean of 0 and variance of σ_t^2 and finally, the equation (1.c) shows the variance over time is constant and is equal to α. Engle targeted the third equation and discussed the violation of the third assumption; when the variance of the series is varying over time. Following equations present the new assumptions (i.e. ARCH (1)).

$CCI_t = m_t + e_t$ (2.a)

$e_t \mid I_{t-1} \sim N(0, h_t)$ in this case distribution of the error term is conditionally normal and I_{t-1} represents the information set available at time t-1 (2.b)

$h_t = \alpha_0 + \alpha_1 e^2_{t-1} \quad \alpha_0 > 0, \quad 0 < \alpha_1 < 1$ (2.c)

Equation (2.c) states that variance is a function of the constant term (α_0) and lagged error squared, indicating variance is not constant anymore and is dependent on or "conditional on" lagged effects of residuals. In other words, information sets available at the moment of t (2.b) are used to forecast variance of the series at time t, instead of assuming it is constant. In ARCH and GARCH modeling not only we relax the assumption of constant variance, but also we will specify linear models to explain the variations of variance or so-called volatility as a best measure of risk and uncertainty. Variance itself in a one-time section is allowed to be a function of other variables in general and disturbance terms. As Engle (2003) has noted the ARCH family methods "explicitly recognize the difference between the conditional and unconditional variance." The conditional variance possibly

will depend on other variables, whereas unconditional variance assumes fixed variances over time. Moreover, Estimation of the mean equation simultaneously with variance equation will provide more efficient estimators with less standard error and higher accuracy (Hill 2008). The figure two demonstrates the methodological flow-chart proposed in this study in order to develope a CCI predictive model that accounts for volatilities of the CCI.

3.4.2 Mean Equation Specification: beginning of the step 1

While the strength of the ARCH and GARCH techniques is that the conditional means and variances can be estimated jointly using specified models for economic variables. The weakness of the procedure is that the mean equation (m_t) must be specified very carefully. Otherwise, it will generate biased estimate of variance (Engle 2004). Thus, the mean equation is needed to be specified for the CCI series with the high power of explaining the current data set. The mean equation selected in this study is built upon Ashouri and Lu study (2010). The study introduced Seasonal ARIMA as the best estimate of the mean equation of DCCI for in-sample-forecast. However, in this study for increasing the accuracy of the model another dummy variable is added to the seasonal ARIMA, reflecting 2008 financial crises. Looking at the first-difference series of CCI graph (DCCI); it is apparent that there is an unusual jump in volatilities of the CCI between the short period of August 2008 and November 2008. This pattern seems an exception due to the financial crisis shock. In an attempt to capture this effects in the model, we inserted another dummy variable for this period (D). This variable is a key variable in the model since it captures the unusual volatilities of the CCI and keep the model unbiased. Therefore, the equation three would be the final specification of the mean equation of DCCI.

$$DCCI_t = DCCI_t(-1) + M1 + M2 + M3 + M4 + M5 + M6 + M7 + M8 + M9 + M10 + M11 + M12 + D + e_t \quad (3)$$

DCCI$_t$ *(-1)* is the autoregressive part of the mean equation; it also can be shown as AR (1). *DCCI*$_t$ is the first difference of the CCI that satisfies the integrated part of ARIMA model, and variables M1 to M12 are monthly dummy variables to capture the seasonal components of *DCCI*$_t$. Non-significant dummy variables will be removed from the model after initial estimate of the model. e_t is the error term or residuals of the specified regression equation. Having the mean equation specified, in the next step, test of ARCH effect will be conducted to assess if there is any unexplained volatilities left in the CCI series.

3.5 TEST OF ARCH EFFECT

After fitting the mean equation, in case of model adequacy residuals resulted from the estimation should follow the White Noise process (Hill 2008). However, the squared residuals might not be WN. It is the central point in order to find the existence of ARCH errors. In another word, instead of test of residuals, the squared residuals will be tested for the presence of conditional volatility (ARCH errors). The standard test for this purpose is Lagrange Multiplier (LM). This test will regress squared residuals e_t^2 resulted from the mean equation on the squared residuals lagged e_{t-1}^2. Equation 4 shows the LM test of presence of ARCH (1) error.

$$e_t^2 = \gamma + e_{t-1}^2 + v_t \qquad (4)$$

The null hypothesis (H_0) in this test is "having no conditional volatility or ARCH effect." The EViews software performs this test for pre-determined number of lags and gives the F statistics for the whole test as well as t statistics for the individual lags with corresponding probabilities. The results of LM test show after specification of the mean equation, strong signs of ARCH errors remain in the residuals (F-statistic: 5.347769, Prob. F= 0.0051). Which lead us to specify variance equation in the next section (Appendix A1).

3.6 VARIANCE EQUATION SPECIFICATION: BEGINNING OF THE STEP 2

In this section, the decision would be between ARCH (p) and GARCH (p, q) and determine the appropriate number of lags (p in case of ARCH and p & q in case of GARCH). The ARCH (1) model was introduced in the section 4. The ARCH (q) model with the same idea just brings qth order of lagged effects of residuals into the model. However, the tradeoff would be the degrees of freedom (Hill 2008). The GARCH (p, q) modeling is an efficient way of capturing the long lagged effects of residuals with fewer parameters, (Engle 1982). Therefore, these models have gained popularity over the last decade. In this study both ARCH (q) and GARCH (p, q) are fitted with a different number of lags. Model selection criterions or so-called model diagnosis criterion are deployed to select the best model among the candidates. Equations 4 and 5 show the general specifications of ARCH (q) and GARCH (p, q).

ARCH (q): $h_t = var\ (DCCI_t) = \alpha_0 + \alpha_1 e^2_{t-1} + \alpha_2 e^2_{t-2} + \alpha_3 e^2_{t-3} + ... + \alpha_q e^2_{t-q}$ (5)

GARCH (p, q): $h_t = var\ (DCCI_t) = \alpha_0 + \alpha_1 e^2_{t-1} + \alpha_2 e^2_{t-2} + ... + \alpha_q e^2_{t-p} + \beta_1 h_{t-1} + \beta_2 h_{t-2} + ... + \beta_p h_{t-q}$ (6)

It can be recognized that GARCH (p, q) in fact is a generalized form of ARCH (p) meaning that GARCH (p, 0) is the same as ARCH (p). Positive e_t suggests an unexpected increase in the cost index and negative e_t suggest an unexpected decrease in the cost index. The magnitude of the parameters of α_i and β_i define the short-term dynamic forces of the resulting volatility time series. Large β_i displays that shocks to a conditional variance take a long time to die out, so uncertainty is intended to remain persistent for a longer period, large α_i means that volatility reacts quite strongly to market movement (Alam, Siddikee, & Masukujjaman, 2013). If α_1+β_1 is close to one,

it means that a shock at time t will persist for many future periods, and if it is equal to one it implies that any shock will cause to permanent change in all future values of h_t.

3.6.1 Model selection criteria and determine the lag length

As it was noted, typically the proper number of lags (p or p &q) is determined via model selection criterions, however in case of modeling volatilities, visual properties of the series play an important role as well (Alam et al. 2013). If the series of interest shows clustering effect, the best model to explain the volatilities would be GARCH (1, 1). In this paper, both approaches are utilized to decide on different competing models. Akaike Information Criterion (AIC) and Schwarz Information Criterion (SIC) are two major criterions for choosing between competing models. They both impose penalty for inserting large numbers of independent variables into the model. Therefore, they establish a tradeoff between the “goodness of fit” and its degree of freedom. The lower values of AIC and SIC are preferred in terms of model selection.

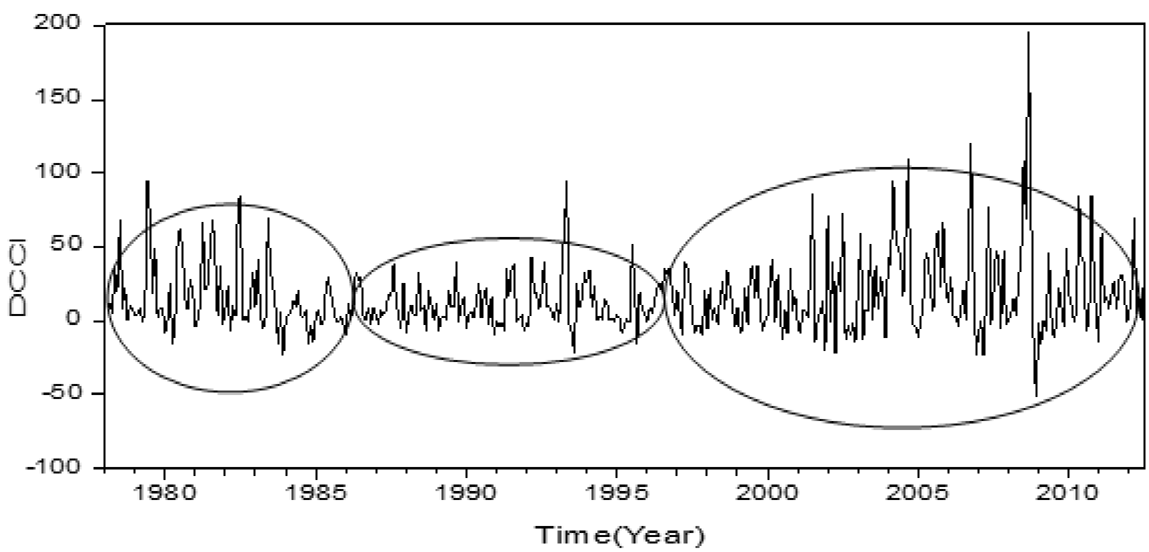

Figure 3.3: Clustering effect of the DCCIt series

The main difference between AIC and SIC criteria are that, AIC criteria impose a harsher penalty for losing degrees of freedom than SIC. Normally the procedure is to estimate maximum combination of p and q, then reduce it to the point to optimize the AIC and SIC. Figure 3 exhibits the first integrated series of CCI (DCCI) for the period of January 1978 to July 2014. From figure 3 it seems evident that there are stretches of times where smaller changes in the CCI are clustered together (1990s), and similarly greater changes in the CCI are followed by greater changes (1980s, 2000s), indicating an apparent clustering effect in the CCI rate of change. As it was noted if the series of interest shows clustering effect, the best model to capture the volatility of the series would be GARCH (1, 1). Nevertheless, various combinations p and q in the GARCH process were computed in order to find the lowest values of BIC and AIC. After fitting quite a few candidates, three models of GARCH (1, 1), GARCH (1, 0) and GARCH (2, 0) with the AIC: 8.932185, 8.932593, and 9.095666 respectively and SIC: 9.030001, 9.030013 and 9.193086 respectively provided the lowest BIC and AIC. Therefore, GARCH (1, 1) was selected as the best model for modeling conditional variance (volatilities) of CCI.

3.7 ESTIMATING THE PARAMETERS:

The mean and variance equation specified in section 5 are estimated simultaneously as a whole system using Maximum Likelihood (ML) method. The standard errors of the estimates of the parameters in the ARIMA equation were reduced by the inclusion of GARCH equations.

This suggests that the estimation of the mean equation model have been improved. In another words, ML estimation of the mean equation with considering GARCH errors gives more efficient estimates.

Table 3.2: Coefficients of fitted mean and variance equation (GARCH (1, 1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C_1	8.94	2.36	3.77	0.00
C_2	16.29	2.17	7.49	0.00
C_3	16.80	2.44	6.87	0.00
C_4	8.00	2.29	3.49	0.00
C_5	5.13	2.48	2.06	0.03
C_6	4.20	0.93	4.51	0.00
C_0	0.15	0.03	4.10	0.00
ω	192.37	79.13	2.43	0.01
α	0.32	0.13	2.44	0.01
β	0.39	0.18	2.15	0.03

Sample: 1978 June-2012 July, 413 observations. Maximum Likelihood method of estimation,
Mean equation: DCCI= C_0 *AR (1) +* C_1*M5+* C_2*M6+* C_3*M7+* C_4*M8+* C_5*M9+* C_6*D*
Variance equation: $h_t = \omega + \alpha e_{t-1}^2 + \beta h_{t-1}$

C_1 to C_5 are seasonal dummy coefficients (May, June, July, August, September) capturing the monthly seasonality of data. The initial model included 12 dummy variables representatives of 12 months of year. However, non-significant dummy variables were removed from the model. C_6 is coefficient of dummy variable capturing the effect of financial crisis. α and β are coefficients of ARCH and GARCH term respectively. All the coefficients are highly significant within 95% confidence intervals. The model implying that volatility changes with lagged shocks (e_{t-1}^2) but there is also momentum in the system working via ht-1 (Hill et al. 2008). α + β = 0.721658 which is above 0.5 high, suggesting that a shock at time t will persist for relatively few future periods. But eventually die out. The magnitude of the parameters of α and β determine the short-run dynamics of the resulting volatility time series. Large β suggests that a shocks to conditional variance take a long time to die out, thus volatility has a persistent nature. If α+β close to one, indicates that a shock at time t persist for long time or series implies long memory (Karmakar 2005).

3.8 DIAGNOSTIC CHECKS FOR EVALUATING MODEL APPLICABILITY: BEGINNING OF THE STEP 3

An estimated model not only should capture all dynamic features of the mean and variance equations, but also the final estimated residuals of the model should follow a White Noise process (Hill 2008). It simply proposes that; 1-residuals should show no serial correlation among themselves (e_t with e_{t-1} and e_t with e_{t-2}, etc.) and 2-should not demonstrate any remaining conditional volatility (ARCH error). Ljung-Box Q test check for both of these conditions. The first condition will be carried out on the original series of residuals (e_t, e_{t-1}, e_{t-2}, e_{t-3}, …etc.), and the latter condition will be performed on the squared series of residuals (e^2_t,e^2_{t-1}, e^2_{t-2}, e^2_{t-3}, …etc.). Additionally, in order to check the remaining conditional variance (ARCH error) one may be willing to use LM test as well (explained in section 6). In the Ljung-Box test, the null hypothesis is "NO Autocorrelation." The Q statistic follows chi-square distribution and corresponding probability values should be all above 0.05 in order for “failing to reject the null hypothesis." The test results are apparent by visual examination of Autocorrelation Function (ACF) and Partial Autocorrelation Function (PCF) as well. The EViews software by default computes autocorrelations of residuals and squared of them up to order 20 th-lag order to ensure there is no serial correlation among residuals. Typically, 20 is considered an appropriate length to determine whether there is any correlation among error terms of fitted model. The graph of ACF and PCF of residuals and squared of residuals can be found in the appendix section of this paper (appendices A2 and A3). The results of the Ljung-Box test, as well as visual examination of graph, strongly reject the hypothesis of the existence of serial autocorrelation in the original series of residuals or any remaining conditional volatility in squared series of residuals.

3.9 COMPARISON OF VARIOUS TIME SERIES MODELS

There are a few traditional statistical error measures to assess the accuracy of predictability of time series models. In this study, for brevity only Mean Absolute Percentage Error (MAPE), and Mean Absolute Error (MAE) are presented in order to measure accuracy of in-sample and out-of-sample forecast of CCI. The conclusion is quantitatively unaffected by not using the rest of accuracy measures. It is worth to mention all performance measurement formulas are constructed based on the calculation of the difference between the actual and forecasted values of the time series of under study.

Table 3: Evaluation of forecast accuracy of three different models (In-sample, Out-of-sample)

Models	**Applicability**	**Implementation**	**MAE**		**MAPE**		**Accuracy** [a]	
			In-sample forecast	Out-of-sample forecast	In-sample forecast	Out-of-sample forecast	In-sample forecast	Out-of-sample forecast
GARCH(1,1)	Yes	Difficult	16.10	21.51	0.29%	0.22%	Highly acceptable	Highly acceptable
Holt-Winters	Yes	Moderately difficult	17.19	21.17	0.31%	0.21%	Acceptable	Highly acceptable
ARIMA (seasonally adjusted)	Yes	Difficult	16.56	21.24	0.30%	0.22%	Highly acceptable	Highly acceptable

[a] The accuracy of all models is acceptable since the MAPE for all models is well below 5%

Due to simultaneous estimating of mean and variance equation in GARCH modeling, we are able to conduct in-sample and out-of-sample forecast for both mean equations which is CCI and variance of CCI, which is a measure of volatility. Although the primary objective of the GARCH modeling, as well as this paper, is providing conditional variance estimation (volatility), in-sample and out-of-sample forecasts of CCI are provided and compared with popular methods of forecasting of CCI. The most recent update on the forecast of CCI have introduced seasonally adjusted ARIMA and exponential smoothing (Hot-Winter without seasonal variation or with

additive or multiplicative seasonal variations) as two relatively accurate and applicable methods for forecasting CCI (Ashouri and Lu 2010). In this section, the results of in-sample and out-of-sample forecasts of the CCI will be compared with both of these methods.

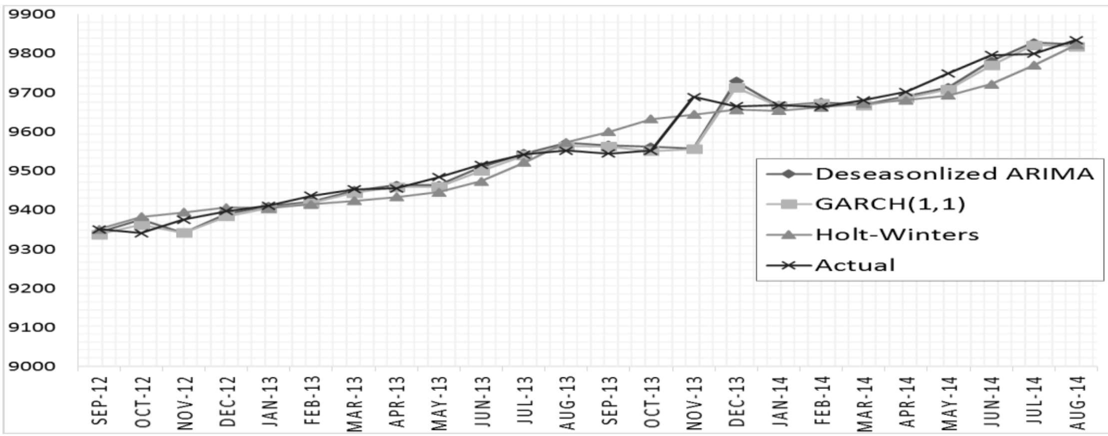

Figure 3.4: Out-of-sample forecast of CCI

Results of the table 2 show that for in-sample data set, GARCH (1, 1) slightly provide more accurate forecasts than exponential smoothing and seasonally adjusted ARIMA models. Furthermore, both seasonally adjusted ARIMA and GARCH (1, 1) shows a good and accurate estimate for out-of-sample data set. Using ARCH (GARCH) technique will reduce the standard error (Std. Error) of estimates parameters considerably. Consequently, it will improve the efficiency of estimators. However, in terms of forecasting, in comparison with ARIMA methods the parameters remain in a similar range. Hence, ignoring the ARCH (GARCH) error may not affect the forecast of CCI significantly. On the other hand, using ARCH (GARCH) techniques provide researchers and policy makers with entirely different tools, measure of volatilities of series.

3.10 IN-SAMPLE AND OUT-OF-SAMPLE FORECAST OF THE CCI VOLATILITY

In this study the GARCH (1, 1) was used to forecast volatilities of the CCI. The basic methodology remains the same similar to forecasting the CCI itself.

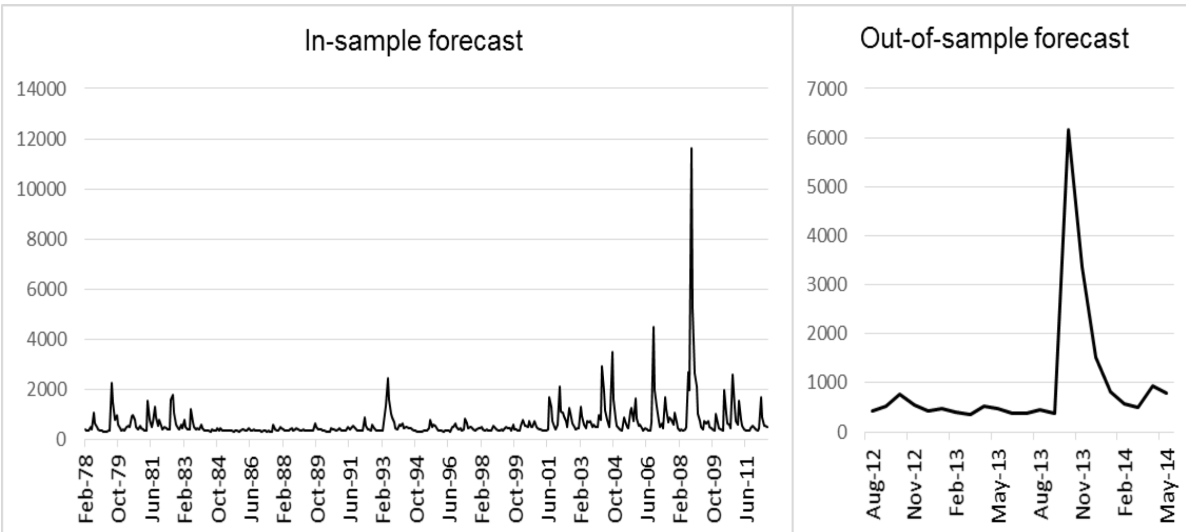

Figure 3.5: Estimate of conditional variance (volatility) of series of CCI

It starts with estimating of the model's parameters using initial data set (1978.January to 2012.July) and extracting in-sample-forecast of volatilities of the CCI, afterward the application of resulted parameters to later data and ultimately forming out-of-sample forecasts. The results suggest the maximum of the CCI variance (volatility) occurred in September 2008, and the minimum occurred in May 1990. The figure 5 shows the five-year interval average of volatility of the CCI. Those periods in which, the CCI has the higher volatility, is harder to predict and consequently cost estimators have to deal with higher risk of over or underestimation. However, the GARCH (1, 1), proposed in this study has addressed this problem. It is apparent that variance begins to rise in

2000 and it continued to its increasing trend until 2010. Since then volatility of the CCI has started to decline.

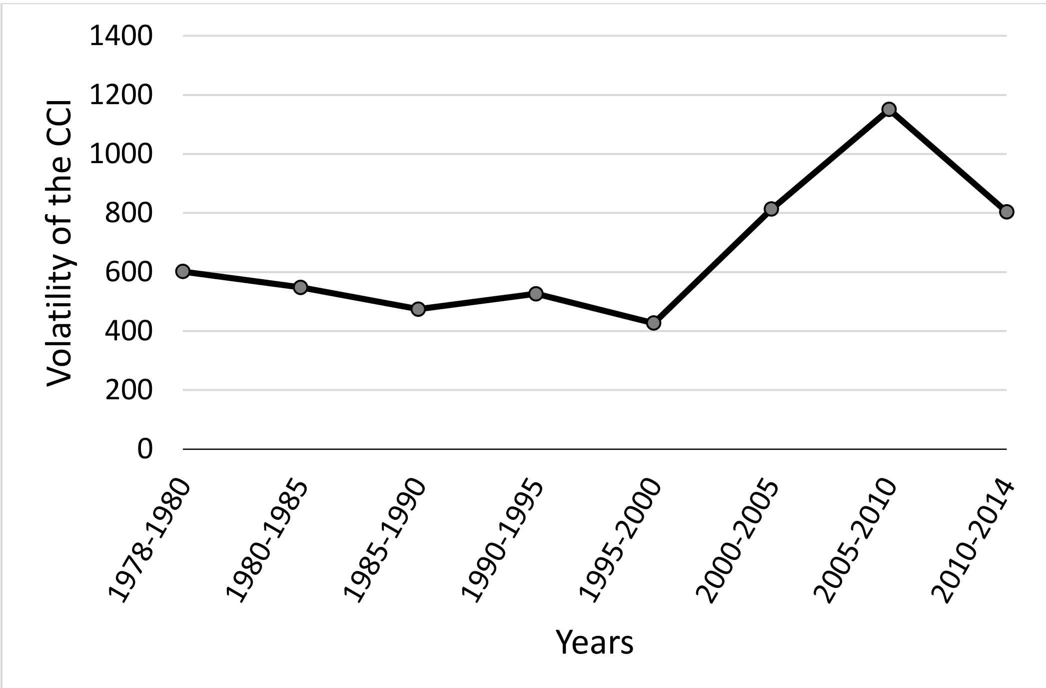

Figure 3. 6: Five-year interval average of the CCI volatility

3.11 PERFORMANCE EVALUATION OF THE FORECAST VOLATILITY

Validation of the GARCH process involves some measure of the latent volatility. Because volatility of a series is calculated after fitting the mean regression line to the series of interest and it is not observable. Therefore, researchers have used a variety of methods to calculate the actual volatility of the series, often called realized volatility as a general benchmark for overall evaluation of the forecast volatility (Balaban 2004; Fair and Shiller 1990). However, it is important to notice that actual volatility or so-called “realized volatility” in this context is different from actual values of the CCI discussed in the previous section. In the CCI forecast, actual CCI is observable and its exact value is determined; as a result, the evaluation process is fairly a straightforward procedure;

while actual volatility of a series is not observable and researchers just try to get the general sense of their estimation.

One method to compute realized volatility is to calculate the square rate of change for a series (Karmakar 2005) (e.g. $[(CCI_t/CCI_{t-1})-1]^2*100$). In the construction cost context, this rate is often referred to as escalation factor (esc_t) (Touran and Lopez 2006). For this reason, one simply could compare the forecast variance with square of the escalation factor in order to monitor the general consonance between these two series.

Another method to evaluate the estimated volatility was offered by Balaban (2004). In this method the consecutive 6-month averages of monthly volatility forecasts ($h_{t)}$ are computed (equation 6), then these averages are compared to realized volatility which is defined as consecutive 6-month intervals of variance values of escalation factors (esc_t) (e.g. [1-6], [7-13], [14-20], etc.) (Equation 7).

$$\widehat{\sigma_t^2} = \frac{1}{6} \sum_{t=1}^{6} h_t \qquad (7)$$

$$\sigma_t^2 = \frac{1}{6} \sum_{t=1}^{6} [esc_t - E(esc)]^2 \qquad (8)$$

After calculation of the realized and forecast volatility we may use the regression-based efficiency test or performance measures like Mean Error (ME) or Mean Absolute Error (MAE) to evaluate the forecast. Here only one model (GARCH (1, 1) is estimated, thus the scope for comparison is limited and regression-based efficiency test should be used. Regression-based efficiency test is a method for examining the informational content of forecasts (Fair and Shiller 1990). This method essentially entails regressing forecast volatility on the realized volatility as shown below:

$$\widehat{\sigma_t^2} = \alpha + \beta \sigma_2^2 + \varepsilon_t \qquad (9)$$

The main idea is that if the forecast volatility covers information about subsequent realized volatility, then the fitted regression line should be satisfactory.

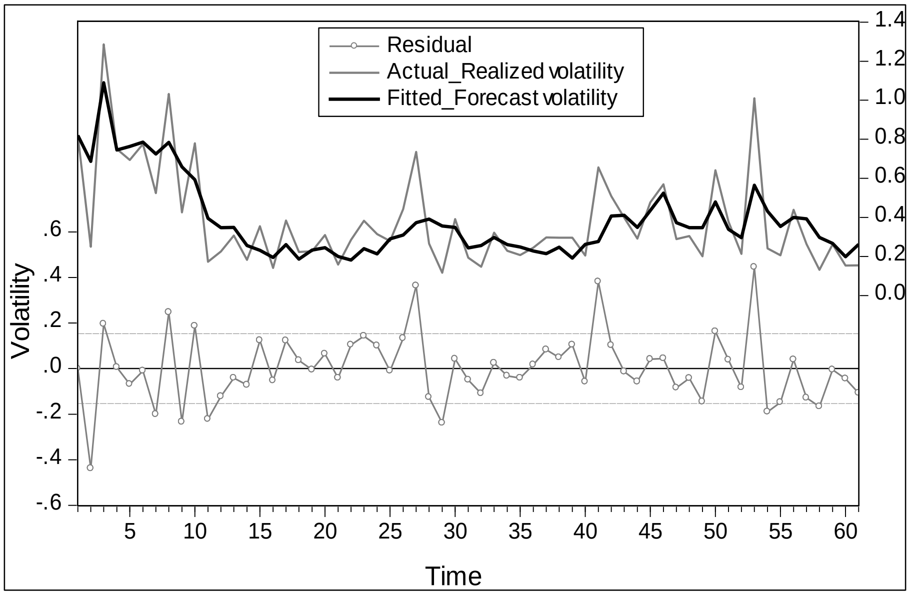

Figure 3.7: Visual representation of regression based efficiency test

Results for the regressions of realized volatility on forecast volatility are shown in Table four, where the values of the coefficients and coefficient of determination (R^2) were reported, also figure seven displays the fitted regression line along with actual, fitted and residual values of the regression line. As the figure seven reveals; the forecast volatility could capture the movement of realized volatility quite well. Results of the regression equation are promising with relatively high coefficient of determination and highly significant coefficients. The efficiency of the regression is analyzed based on the coefficient of determination, R^2. According to R^2, 62 % of the variations in forecast volatility is explained by realized volatility that indicates the adequacy of the GARCH model used in this study.

Table 3.4: Regression-based efficiency test results

Variable	*Coefficient*	*t-Statistic*	*Prob.*
$\boldsymbol{\alpha}$	0.25	13.14	0.00
$\boldsymbol{\sigma_t^2}$	0.42	9.87	0.00
R-squared	0.62		

3.12 CONCLUSION AND FUTURE WORKS

Among all the factors that lead to the deviation of the actual cost of a construction project from the original estimate, unprecedented price volatility of construction resources, namely materials and labors has been one of the major contributors (Hwang et al. 2012; Smith et al. 2011; Weidman et al. 2011; Xu and Moon 2013). Forecasting of the widely used cost indices in the construction industry such as the CCI is a way for cost estimators to address this problem. However, current forecasting methods assume that variations in price changes across the time are constant. After examining the CCI time series, results suggest that the variance is not constant throughout the years included in this study (January 1978-July 2014). This variation across time is referred to volatility in this study, which proves the existence of time-varying price fluctuations in the CCI. Over the past decade, this price fluctuation has been a main concern for all the parties involved in a construction project; in particular, contractors. Therefore, this study for the first time uses the GARCH (1, 1) method to calculate the variance of the CCI at each data point as a measure of the volatility of the CCI.

Estimating volatility of the CCI helps estimators to quantify the risk of over or underestimation and eventually integrate this measure into their original forecasts in order to calculate escalation factors and contingency amounts. This approach can be beneficial for long term projects such heavy infrastructure projects, were estimates are more vulnerable to price fluctuations. Moreover, thorough understanding of the current state of risk in construction projects helps contracting parties

to optimize their resource allocations. Findings of this study also help practitioners to become familiar with salient traits of the CCI. For example, estimated parameters of the variance equation indicate that an external shock at time t to the CCI series will persist for a relatively long period but eventually will die out.

The major limitation of using GARCH method lies in the fact that large historical data set with high frequency (at least monthly) is needed in order to capture the volatility across time. Second, it might be difficult to implement in broad scale, since it requires estimators having certain background knowledge on statistical techniques. This issue is one of the reasons that such statistical approaches are mostly discussed at the academic research level. Although running the GARCH method requires certain level of familiarity with time series analysis, the general findings of this study could be used by practitioners in the construction industry without the need to rerun the entire process again. For example, figure six has illustrated a decreasing trend over the past four years for the CCI volatility, which suggests less likelihood of over or underestimation of the construction cost estimation. In other words, contractors could consider lower premium or contingency amount in fixed price contracts or owners could set the lower trigger values in contracts with price adjustment clauses for compensation of the price escalations. In order to promote the use of such techniques in the construction industry, future studies should focus on developing fully automated programs, which select the optimal forecasting model among the candidates via auto-determination procedure and attempt to minimize the intervention of the user. To facilitate this matter, a clear flowchart of the used method along with simplified steps was presented in this study. Segregation of factors driving construction cost volatilities and performing sensitivity analysis on individual resources like labor and individual materials (e.g. Portland cement, steel, lumber, aggregate, oil), could also be an interesting subject for cost estimators and

construction stakeholders. Finally investigating spillover effect of construction cost index volatility on other construction variables, such as number of construction disputes or construction spending in different sectors, is another area that researchers could scrutinize based upon the results of this study.

3.13 REFERENCES

Aamodt, A., and Plaza, E. (1994). "Case-based reasoning: Foundational issues, methodological variations, and system approaches." AI communications, 7(1), 39-59.

Akintoye, A., Bown, P., and Hardcastle, C. (1998). "Macro-economic Leading Indicators of Construction Contract Prices." *Construction Management and Economics*, 16, 157-175.

Alam, M. Z., Siddikee, M. N., and Masukujjaman, M. (2013). "Forecasting Volatility of Stock Indices with ARCH Model." *International Journal of Financial Research*, 4(2).

Ashouri , B., and Lu, J. (2010). "Time Series Analysis of ENR Construction Cost Index." *Journal of Construction Engineering and Management*, 136, 1227-1337.

Ashuri, B., Shahandashti, S. M., and Lu, J. (2012). "Empirical tests for identifying leading indicators of ENR Construction Cost Index." *Construction Management and Economics*, 30(11), 917-927.

Balaban, E. (2004). "Comparative forecasting performance of symmetric and asymmetric conditional volatility models of an exchange rate." Economics Letters, 83(1), 99-105.

Blair, A. N., Lye, L. M., and Campbell, W. J. (1993). "Forecasting construction cost escalation." *Canadian Journal of Civil Engineering*, 20(4), 602-612.

CFMA.(2012). "Building Profit." (http://www.cfmabponline.net/cfmabp/20070708?pg=62#pg62).

Chen, H. L. (2007). "Developing Cost Response Models for company-Level Cost Flow Forecasting of Project-Based Corporations." *Journal of Construction Engineering and Management*, 24, 171-183.

Enders, W. (2008). *Applied econometric time series*, John Wiley & Sons.

Engle, R. (2004). "Risk and volatility: Econometric models and financial practice." *American Economic Review*, 405-420.

Engle, R. F. (1982). "Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation." *Econometrica: Journal of the Econometric Society*, 987-1007.

ENR (2014). "Construction Cost Index Histroy." http://enr.construction.com/economics/historical_indices/.

Fair, R. C., and Shiller, R. J. (1990). "Comparing information in forecasts from econometric models." *The American Economic Review*, 375-389.

Fung, A. (2009). "Construction costs tumble in NYC. " Crain's New Yourk Business. New Yourk city. http://www.crainsnewyork.com/

Hill, R. C., Griffiths, W. E., and Lim, G. C. (2008). *Principles of econometrics*, Wiley Hoboken, NJ.

Hwang, S. (2009). "Dynamic regression models for prediction of construction costs." *Journal of Construction Engineering and Management*, 135(5), 360-367.

Karmakar, M. (2005). "Modeling conditional volatility of the Indian stock markets." *Vikalpa*, 30(3), 21.

Kim, G.-H., An, S.-H., and Kang, K.-I. (2004). "Comparison of construction cost estimating models based on regression analysis, neural networks, and case-based reasoning." *Building and environment, 39(10), 1235-1242.Engineering and Management*, 135(5), 360-367.

Kuen, T., and Hoong, T. (1992). "Forecasting volatility in the Singapore stock market." *Asia Pacific J Manage*, 9(1), 1-13.

Lewis, S., and Grogan, T. (2013). "A Hundred Year of ENR Cost Indexes."

Lowe, D., Emsley, M., and Harding, A. (2006). "Predicting Construction Cost Using Multiple Regression Techniques." *Journal of Construction Engineering and Management*, 132(7), 750-758.

Maher, M. L., and Balachandran, B. (1994). "Multimedia approach to case-based structural design." *Journal of Computing in Civil Engineering*, 8(3), 359-376.

Martin Skitmore, R., and Thomas Ng, S. (2003). "Forecast models for actual construction time and cost." *Building and Environment*, 38(8), 1075-1083.

Morcous, G., Rivard, H., and Hanna, A. (2002). "Case-based reasoning system for modeling infrastructure deterioration." *Journal of computing in civil engineering*, 16(2), 104-114.

Ng, S. T., Cheung, S. O., Skitmore, M., and Wong, T. C. (2004). "An integrated regression analysis and time series model for construction tender price index forecasting." *Construction Management and Economics*, 22(5), 483-493.

Pierce, C., Huynh, N., and Guimaraes, P. (2012). "Cost Indexing and Unit Price Adjustments for Construction Materials."

Shane, J. S., Molenaar, K. R., Stuart Anderson, and Schexnayder, C. (2009). "Constructin Project Cost Escalation Factors." *Journal of Management in Engineering*, 25.

Smith, J. P., Miller, K., Christofferson, J., and Hutchings, M. (2011). "Best Practices for Dealing with Price Volatility in Utah's Residential Construction Market." *International Journal of Construction Education and Research*, 7(3), 210-225.

Tah, J., Carr, V., and Howes, R. (1999). "Information modelling for case-based construction planning of highway bridge projects." *Advances in Engineering Software*, 30(7), 495-509.

Touran, A., and Lopez, R. (2006). "Modeling Cost Escalation in Large Infrastructure Projects." *Journal of Construction Engineering and Management*, 853-860.

Wang, C.-H., and Mei, Y.-H. (1998). "Model for forecasting construction cost indices in Taiwan." *Construction Management & Economics*, 16(2), 147-157.

Webster, N. (2011). "The Merriam Webster Dictionary." Merriam-Webster, 11, ed., Merriam-Webster, New Yourk

Weidman, J. E., Miller, K. R., Christoffersen, J. p., and Newitt, J. S. (2011). "Best Practices for Dealing with Price Volatility in Commercial Construction." *International Journal of Construction Education and Research*, 7(4), 17.

Williams, T. P. (1994). "Predicting changes in construction cost indexes using neural networks." *Journal of Construction Engineering and Management*, 120(2), 306-320.

Wilmot, C. G., and Cheng, G. (2003). "Estimating Future Highway Construction Cost." *Journal of Construction Engineering and Management*.

Wilmot, C. G., and Mei, B. (2005). "Neural network modeling of highway construction costs." *Journal of construction engineering and management*, 131(7), 765-771.

Xu, J.-w., and Moon, S. (2013). "Stochastic Forecast of Construction Cost Index Using a Cointegrated Vector Autoregression Model." *Journal of Management in Engineering*, 29(1), 10-18.

CHAPTER FOUR: SHORT AND LONG RUN ESTIMATION OF THE ESCALATION FACTOR IN CONSTRUCTION PROJECTS USING VALUE AT RISK (PAPER 2)

4.1 INTRODUCTION

In cost analysis, escalation refers to an increase in the costs of any construction component from the original estimate, including both labor and material costs (Blair et al. 1993). Over the past decade, the majority of large and heavy construction projects, particularly those with longer durations have experienced cost overruns. This statement has been widely supported by previous studies and overall, it seems that more conservative approaches are needed in order to estimate cost escalation (Bhargava et al. 2010; Koushki et al. 2005; Shane et al. 2009; Touran and Lopez 2006). For example, Flyvbjerg (2007) and Flyvbjerg et al. (2002) performed a cost performance analysis on 258 transport infrastructure projects in 20 nations. Their study showed that the actual costs were on average 28% greater than estimated for all types of projects, 34% higher for tunnels and bridges, 45% higher for all rail projects, and 20% higher for all road projects.

Regardless of how the baseline cost of the construction project is estimated (stochastic or deterministic), cost estimators commonly apply a deterministic escalation rate or so-called "escalation factor" to their baseline estimation to account for the escalation due to the material price volatility and inflation in large construction projects. However, this method has been considered arbitrary (Cioffi and Khamooshi 2009). Therefore, upon Value at Risk (VaR) as an underlying methodology in this paper, two approaches are proposed for estimating escalation factors in a systematic way for construction projects: 1- Historical Method (HM), and 2- Variance-Covariance Method (VCM).

HM is based on a simple assumption that the past will repeat itself. It offers a direct, and relatively fast approach to forecasting the escalation factor. Due to its simplicity, and reliance on historical

data it suits long-term projections well. VCM is based on statistical assumptions. It utilizes advanced statistical techniques in a way that allows estimators to integrate short-term price volatilities into their forecasts of the escalation factor. Volatility in this context is defined using standard deviation of the escalation factor which is a good measure of uncertainty. In other words, higher volatility suggests a higher chance of underestimating construction cost.

For instance, Figure 1 shows tranquil periods over the 1990s and high fluctuation from 2000 to 2010. Logically, cost estimators should take into account periods of higher risk when determining an escalation factor to distinguish it from periods of lower risk.

In this study, cost escalation referrers to an increase in the base cost of a construction project, due to the material and labor price escalations over the course of a construction project, as well as the overall inflation in the construction sector. With this respect, construction cost indexes in general are good indicators (Wilmot and Mei 2005). These indexes are measured consistently at regular time intervals, while accounting for major materials and labor costs. This study uses the Engineering News Record Construction Cost Index (CCI) to create the escalation factor time series (*escci*) (Touran and Lopez 2006). Afterward, a set of systematic steps will be followed to create a dynamic stochastic approach to estimate the VaR of the escalation factors (upper bound escalation factor) for construction projects in both short and long run construction projects. The VaR estimation of the escalation factor help planners and cost estimators to calculate the escalation factor in a more conservative way.

4.2 ESCALATION FACTOR

A common way to integrate the impact of escalation is to assume a deterministic rate and apply that to the original cost estimation of the project using the conventional formulas (i.e. escalated

cost= original cost * $(1+i)^n$, i=escalation factor) (Touran and Lopez 2006). As it was noted this method has been considered rather arbitrary. There are but afew studies in the field of estimation of escalation factors, and even existing methods practiced so far suggest that there are not sufficient systematic methodologies for calculating escalation factors.

Previous studies related to the calculation of escalation factors can be divided into three groups. Studies in the first group rely on various forecasting methods (Ashouri and Lu 2010; Blair et al. 1993; Hwang 2009; Wang and Mei 1998; Xu and Moon 2013). Although a majority of these studies do not directly address the estimation of escalation factors, the results could be extended to the calculation of escalation factors. The second group, suggests using Monte Carlo Simulation as a tool to incorporate uncertainty into estimation of escalation factors (Chou et al. 2009; Diekmann 1983; Touran and Lopez 2006). While both of these proposed methods have been more or less adopted by the industry, both groups failed to address the problem of price volatility. In other words, these methods do not provide cost estimators with a concrete measure of risk as it pertains to price volatility which could be crucial in the process of risk analysis and cost estimation of a construction project. Finally, the third group focuses on finding and quantifying underlying causes of cost escalations in construction projects (Anderson et al. 2010; Bhargava et al. 2010; Guan and Liao 2014; Koushki et al. 2005; Nejat et al. 2010; Olatunji 2010). Although, studies in the third group have recognized various causes, unanimously acknowledged the role of market variations as a major source of price volatilities and cost escalation.

In this paper the CCI is used as the base time series for calculating the escalation factor. The CCI is published by Engineering News Records. It is an aggregate index published monthly, and has been calculated for over a century (Lewis and Grogan 2013). Therefore, it is one of the most well-recognized cost indexes by the construction industry. The escalation factor (*escci*) can be simply

calculated as the rate changes of the CCI from month to month according to Equation 1, which is referred to as the monthly escalation factor. Nevertheless, practitioners could calculate this for other intervals too (e.g. quarterly or annually). Figure 1 shows the CCI and the *escci* time series created according to Equation 1 for the period from July, 1978 to July, 2014.

$$escci = \frac{CCI_t - CCI_{t-1}}{CCI_{t-1}} * 100 \qquad (1)$$

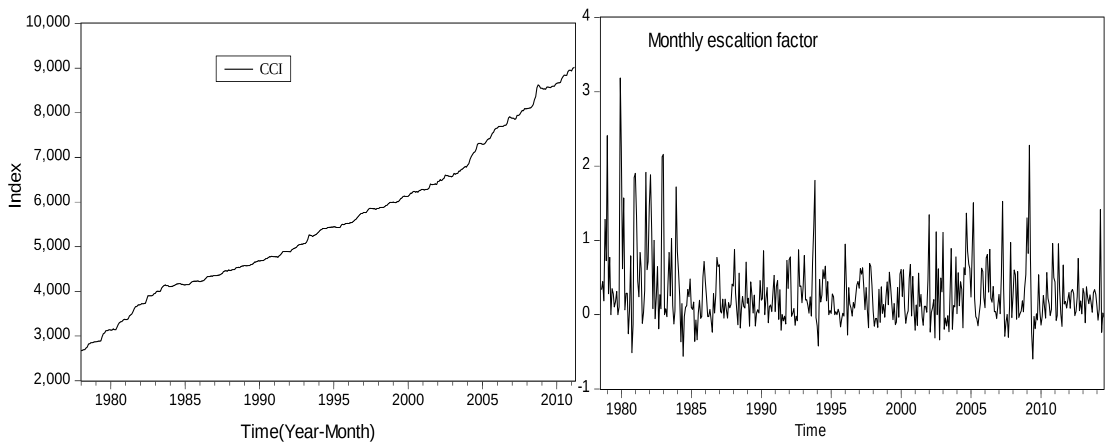

Figure 4.1: Original series of the CCI and series of the escaltion factor (escci)

4.3 VALUE AT RISK

VaR is a risk management technique to quantify risk, which ultimately gives risk managers a numeric number or series of numbers representing downside risk. VaR is able to characterize the worst case scenario of an event given a certain confidence level and a time frame, which is usually

referred to as the window size (Daníelsson, 2011). VaR_p suggests that with a probability of p, the actual escalation factor will not exceed the values of VaR.

One advantage of VaR compared to other stochastic forecasting methods as a measure of risk, lies in the fact that contractors are not distressed by price decreases. In this regard, VaR offers a stochastic forecasting of downside risks (Xie et al. 2012). Contracting parties have traditionally accepted price fluctuations in construction material and labor as one of the facts of the industry; However, what makes them experience considerable loss and stress in their projects are significant price spikes, where the VaR concept can come into play and answer the question of "what would be the highest escalation factor at a certain confidence level?" (i.e. worse case).

Although VaR is the main risk management technique in the financial industry; it is also gaining popularity in other sectors, as well as the construction industry. For instance, Caron et al. (2007) developed a decision making system for biding on a new construction project using VaR and Net Present Value distribution of the project over its lifecycle. They intended to obtain a better balancing of the overall portfolio of projects for a company operating in the engineering and contracting industry. In another study, Xie et al. (2012), used VaR to update the cost contingency budget for construction of a tunnel during project execution. They also applied their method to three different projects for the purpose of demonstration and validation. They noted that VaR minimizes human bias in risk assessment and produces close estimations, as for the first and second projects, the actual 95th percentile contingencies were 4% more than the forecasted; and for the third project the forecast is 16% less than the actual. Also, Zhou (2011) suggested that contracting parties in the construction industry could apply VaR to formal risk management in highway construction projects. He highlighted the strength of the VaR technique in quantifying unfavorable outcomes.

There are various ways to calculate VaR; however, Historical Method (HM), and Variance-Covariance Method (VCM) are two major ways briefly introduced here:

4.3.1 Historical Method(HM)

In this method all the values of a series are first simply sorted from smallest to largest, then for a specified period of time, and a specified level of probability (confidence), the down tail outcome is selected. HM is based on the assumption that past repeats itself. The selection of the confidence level and the window size is typically a subjective decision made by experts based on the type of industry and level of risk acceptance of project stakeholders. In this paper using HM in long-term forecasts is suggested (i.e. projects with duration more than 3 years).

4.3.2 Variance-Covariance Method (VCM)

The VCM is based on two major assumptions: 1- It assumes that the potential outcome is proportional to the series standard deviation (Cabedo and Moya 2003). 2- It assumes that the series of interest follows one of the known statistical distributions such as normal or student-t distributions. Equation 2 shows its general formula:

$$\mathrm{VaR}_c = Z_c\,\sigma \qquad (2)$$

Zc is a percentile of the standard normal distribution that corresponds to a pre-specified confidence level of c such as 90 or 95 percent. (e.g. $Z_{95\%}$= 1.64, c=95%, one tail)). This value is constant and is dependent on the probability level which itself could be subject to the cost estimator's opinion and the level to which he or she is willing to take risk. σ is the standard deviation of the series of interest.

Within the VCM, a few sub methods have been suggested which typically differ on how they address the calculation of the σ component of Equation 2. One approach assumes that the variance of the entire series remains constant throughout times. Whereas, the other approach allows for relaxing the assumption of constant variance, and accounts for time-varying variance, which is referred to as conditional variance or so-called volatility. One of the standard tools to calculate volatility of the series is Autorregressive Condition Heteroscedasticity family models (ARCH), or Generalized Autoregressive Conditional Heteroscedasticity family models (GARCH). These models allow us to estimate the variance equation for a time series (Engle 2004).

The benefit gained using ARCH or GARCH will be obvious; by using ARCH family methods, in fact we would incorporate the time-varying variance or volatility into our model. As Figure1 also illustrated, assumption of equal uncertainty does not seem to fit the current state of the construction industry quite well. Also, ARCH family models allow for richer specifications of the dynamic properties of volatility, and at the same time model volatility with high accuracy; therefore, leading to better VaR forecasts (Daníelsson 2011). Using this method in short-term estimations of escalation factors is proposed (i.e. projects with duration less than three years).

4.4 ARCH: MODELING VOLATILITY

The Autoregressive Conditional Heteroskedastic (ARCH) model captures the volatility of a time series. After fitting the regression line, assumption of the constant variance for the entire series does not always hold. Engle (2002) used the term conditional variance in contrast with unconditional variance. Conditional variance is dependent on time (σ_t), while unconditional variance is a constant numerical number for the entire series of the interest (σ). In reality, for the construction industry different time periods are associated with different risk values. Therefore, in

terms of risk management strategies, they should be treated differently. In this section, a brief review of the ARCH family models is presented, for more detailed information readers could refer to Joukar and Nahmens (2015) and (Enders 2008).

All the conventional regression models assume homogeneity of variance over the entire sample. For instance, in the equation $Y_t = m_t + e_t$, m_t stands for the mean equation (fitted regression line) of the time series of Y_t, and e_t is the vector of the residual terms for the specified regression line. Typically, it is assumed that e_t has a normal distribution with a constant variance. This assumption is denoted as $e_t \sim \mathrm{N}(0, \sigma^2)$, in which σ^2 is constant for all periods. In ARCH family models not only we relax this assumption, but we also start to fit a linear model for our variances or so-called volatility. In other words, variance itself will be applied as a dependent variable and is allowed to be a function of other variables. This family of models is able to provide us a dynamic risk measurement tools which can be used in different risk management scenarios including estimation and forecast of Value at Risk. As it was shortly noted before, GARCH is just a generalized form of the ARCH that was introduced two years after ARCH introduction, mostly for the sake of conformity to the principal of parsimony (Hill et al. 2008). It usually creates a more concise model with higher explanatory power.

By integrating volatility in the estimation of VaR, time dependent risk management is considered. Essentially three steps are followed in order to forecast the Value at Risk for the CCI based escalation factor time series using the VCM method:

Step 1: a regression line (mean equation) will be fitted to the *escci* time series.

Step 2: specifying a variance equation and modeling volatility of the *escci*.

Step 3: VaR quantification using results of the previous step and using Equation 2.

4.5 STEP 1: ESTIMATION OF A REGRESSION LINE (MEAN EQUATION) FOR THE ESCCI TIME SERIES

Although it is not the primary objective of this paper; the first step prior to estimating the variance equation for the *escci* time series is to find the most appropriate regression line or so-called mean equation for our time series of interest. Previous studies have offered various methods for fitting the mean equation of different time series in the construction industry (Ashouri and Lu 2010; Hwang 2009; Joukar and Nahmens 2015; Wang and Mei 1998; Xu and Moon 2013). Two major approaches are multiple regression and time series modeling. While each of these methods has their own pros and cons, time series due to their high accuracy and less dependence on other explanatory variables have gained a lot of popularity over the past few years. In this paper, the ARIMA (Autoregressive Integrated Moving Average) method is adopted for fitting the mean regression line of the *escci* series due to its high accuracy (i.e. Mean Absolute Error, Mean Absolute Percentage Error) and popularity. Moreover, within the broad family of time series techniques, ARIMA has a relatively simpler structure as well as easy implementations for practitioners.

An ARIMA model has essentially three parameters of p, d, and q. Parameters p and q determine the order of AR and MA. Parameter d represents the difference order required to transform the original dataset to a stationary time series. Since the mean equation estimation of the *escci* is not the main focus of this paper, readers should refer to Joukar and Nahmens (2015) or Ashouri and Lu (2010) for detailed information on this subject. After fitting quite few candidates and optimizing regression traits, eventually ARMA (p=2, d=0, q=1) as the best mean regression line is selected.

$$escci = escci_{t-1} + escci_{t-2} + e_{t-1} + e_t \qquad (3)$$

$escci_{t-1}$ *and* $escci_{t-2}$ are the first and the second order of the Autoregressive (AR) terms. e_{t-1} is the first order moving average (MA) term. Equation 3 can also be specified with this format: $escci = AR(1) + AR(2) + MA(1) + e_t$.

4.5.1 Test of Time-varying Volatility of the escci Time Series

After fitting the mean equation, in order to capture the time-varying volatility of the *escci* time series, the first point is to test if there are any signs of time-varying volatility in the fitted model. In fact, this is the moment of truth for volatility modeling using ARCH family methodologies. One of the standard tests for this purpose is Lagrange Multiplies or (LM) test (Engle 1982). It ensures whether the variances of *escci* have significant differences in magnitudes for different time periods. Elsewise, the assumption of the constant variance might be acceptable for the entire time series. More details on this test can be found in Enders (2008) (i.e. all the modern statistical softwares have built-in package for this statistics). As it was expected, result of the LM test approves strong signs of time-varying volatility for the *escci* time series. In fact, it suggests that cost estimators must consider different risk factors for different time horizons. In the next step we quantify volatility by specifying a separate variance equation for our fitted model.

4.6 STEP 2: VARIANCE EQUATION SPECIFICATION USING GARCH

In variance specification model, the decision is between ARCH (p) or GARCH (p,q). Equations 4 and 5 show the general specifications of ARCH (q) and GARCH (p, q).

$$\text{ARCH (q)}: h_t = var\,(escci_t) = \alpha_0 + \alpha_1\, e^2_{t-1} + \alpha_2\, e^2_{t-2} + \alpha_3\, e^2_{t-3} + \ldots. + \alpha_q\, e^2_{t-q} \qquad (4)$$

$$\text{GARCH (p, q)}: h_t = var\,(escci_t) = \alpha_0 + \alpha_1 e^2_{t-1} + \ldots + \alpha_q\, e^2_{t-p} + \beta_1 h_{t-1} + \ldots + \beta_p\, h_{t-q} \qquad (5)$$

GARCH (p, q) is a generalized form of ARCH (p). In fact, GARCH (p, 0) is just the same as ARCH (p). e_t is residual terms of the mean equation and h_t is conditional variance of these residuals. The magnitude of the parameters of α_i and β_i describe the short-term dynamic behavior of the escalation factor time series. Large β_i shows that a shock to the variance series take a long time to die out, therefore, uncertainty would persist for a longer period, large α_i means that volatility responds strongly to market drives (Karmakar 2005). α_1+β_1 determines stability of the system. If it is close to one, it implies that a shock at time t, will creates longer term instability.

Model selection criterial such as the Akaike information criterion (AIC) and Schwarz Information Criterion (SIC) will help us to select the best fitted model. They consider for both numbers of explanatory variables and goodness of fit. AIC and SIC with lower values are preferred. Generally, the procedure is to estimate the maximum combination of p and q, then start to optimize the SIC and AIC by dropping the order of the ARCH and GARCH terms. Two models of GARCH (1, 1), GARCH (1, 0) with the AIC 0.883311, and 0.911922, respectively, and SIC 0.990929, 0.990929, respectively, provided the lowest AIC and SIC. Therefore, GARCH (1, 1) was selected as the best model for modeling volatility of the escalation factor time series (*escci*).

4.6.1 Estimating the parameters

As it was explained, the CCI based escalation factor shows substantial evidence of the volatility. The basic GARCH (1, 1) results are given in Table 1. Coefficients in variance equation are listed

as ω the intercept, the α the first lag of the squared residuals and β, the first lag of conditional variance.

Table 4.1: Coefficients of fitted mean and variance equation (GARCH (1, 1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C_0	0.179	0.0159	11.26	0.00
C_1	-0.617	0.120	-5.11	0.00
C_2	0.163	0.038	4.26	0.00
C_3	0.787	0.119	6.58	0.00
ω	0.006	0.003	1.80	0.07
α	0.057	0.003	1.86	0.06
β	0.898	0.039	22.9	0.00

Sample: 1978 June-2012 July, 413 observations. Maximum Likelihood method of estimation,

Mean equation: = C_0 + $C1 escci_{t-1}$ + $C_2 escci_{t-2}$ + $C3 e_{t-1}$ + $C4 e_t$

Variance equation: $h_t = \omega + \alpha e_{t-1}^2 + \beta h_{t-1}$

Note that $\alpha + \beta$ is less than one, which is the requirement of a stable variance process. However, since the sum is close to one, it suggests that any external shock to the *escci* (e.g. recession or economic crises), creates a prolonged volatility in the escalation factor. The final variance model is estimated simultaneously with mean equation using the Maximum Likelihood process. As always, we must test the residuals of the final model. Residuals of the final model must completely follow a random process or white noise in order for model to be considered as applicable. Autocorrelation and Partial Autocorrelation Function, as well as the Ljung-Box Q test (Ljung and Box 1978) can be used for this purpose. In our final model, both of these tests are passed, indicating the model can be considered robust and reliable.

4.7 STEP 3: VAR QUANTIFICATION

Estimation of the variance equation using GARCH model, provides a series of the standard deviations (σ_t). σ_t is the key input for the VaR calculation using Variance Covariance method (equation 1).

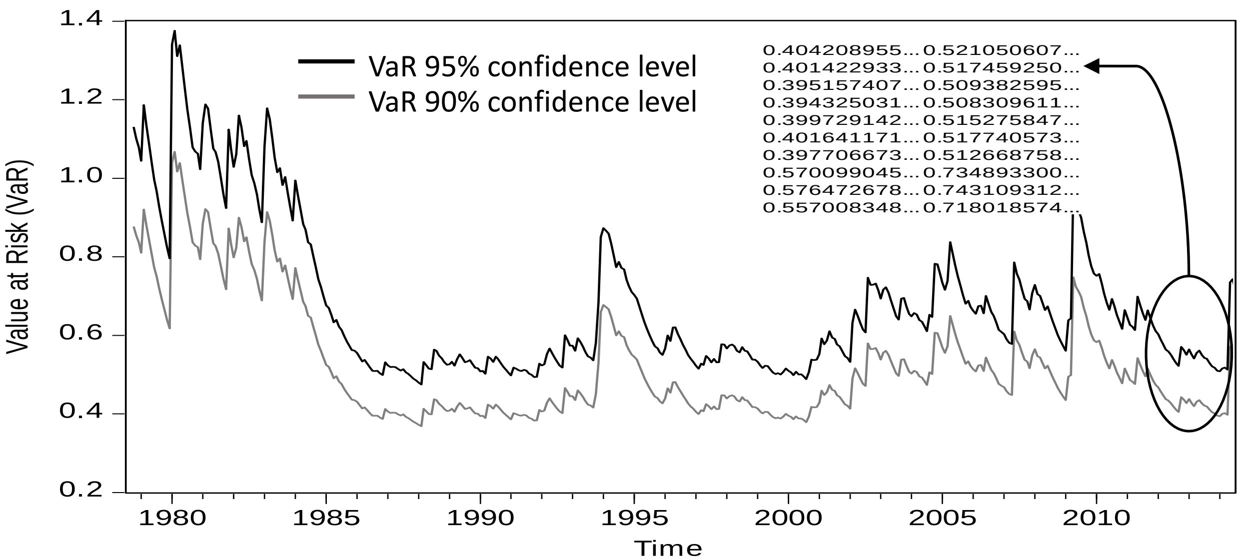

Figure 4.2: Monthly VaR of the escalation factor for 90% and 95 % confidence level

Figure 2 shows the calculated VaR for the entire sample series for 90 and 95 percent confidence interval respectively. Obviously, the VaR values for 90 % confidence level would be smaller than 95%. These VaR values have been calculated monthly. With probability of 90% or 95 % percent cost estimators could expect that real escalation factors for the particular month would not exceed the estimated VaR value. These values can be applied to the baseline or current budget of heavy construction projects by cost estimators instead of using deterministic escalation factors. This provides cost estimators a conservative approach. However, depending on their level of risk tolerance, they could adopt different probability levels.

4.8 HISTORICAL METHOD (HM)

In the HM the escalation factors are rearranged from worst to best in a histogram that compares the frequency of them.

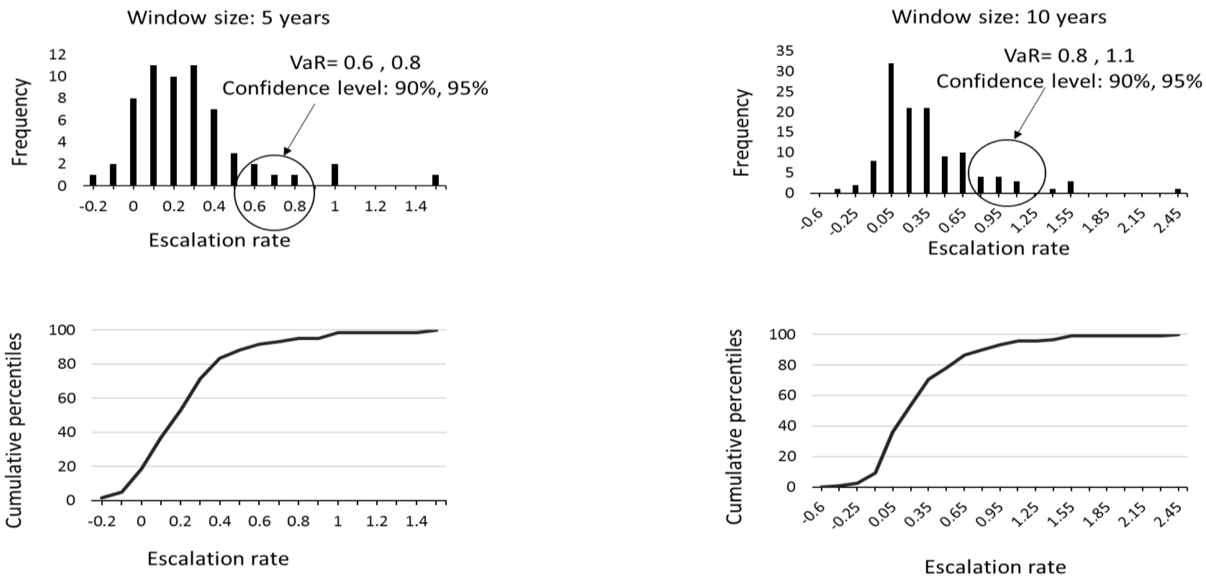

Figure 4.3: The monthly calculation of VaR of the escalation factors based on the HM for 5 and 10-year time frame

For example, at the highest point of the histogram shown in Figure 3, there are more than 10 months when the monthly escalation factor is between 0.1% and 0.4%. At the far right there are a few months with the escalation factors as high as 1.5% monthly within a period of five years which is referred to as window size. Below each histogram (Figure 3), its corresponding cumulative percentile graph has been illustrated as well.

The cumulative graph displays the probability level or the level of the confidence that is associated with its corresponding rate, and from which the escalation factor would not exceed.

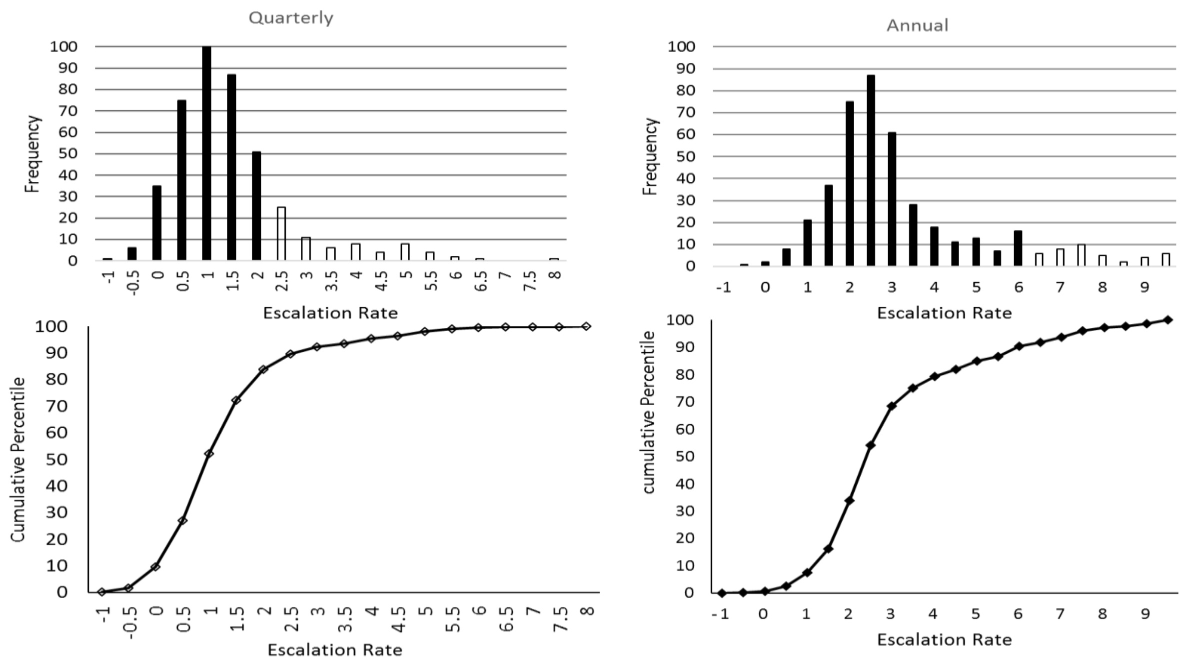

Figure 4.4: The quarterly and annually calculation of VaR based on HM for 26-year time frame

For instance, if we limit the time frame or window size of the analysis to five years, with 90% confidence we could conclude that monthly escalation factor would not exceed 0.6%. The escalation factor matching to 95% confidence level is 0.8%. Generally, there is a direct relationship between the confidence level and the escalation factor, meaning that higher confidence level is associated with higher escalation factor. Selection of confidence level corresponds to level of risk acceptance of the project stakeholders. It must be taken into account that that these graphs (Figure 3 and 4) demonstrate monthly escalation factor. Obviously one could calculate the semi-annually or annual escalation factor for various window sizes, meaning that instead of calculating monthly changes of the CCI which is essentially the lag one differences of the CCI values, one could calculate the quarterly escalation factor using the CCI which is the lag four differences,

semiannually (lag 6), or even annually (lag 12). The Figure 4 Shows escalation factor histograms calculated quarterly and annually. The quarterly Value at Risk value of the escalation factor corresponding to 90% confidence level is 2.1%, whereas the annual Value at Risk of the escalation factor for the same confidence level is 6.0%.

4.9 CASE STUDIES (HIGHWAY CONSTRUCTION PROJECTS)

In this section, two case studies will be presented to assess and demonstrate both methods presented in this paper: HM, and VCM. The case study entails two highway construction projects in the state of Louisiana. The first project is a roundabout with the length of 2,222 feet and a total cost of $2,396,426.29, and the second is a road with 3.6 miles with a total cost of $2,404, 273.54. Both projects were let in 2015. The bid histories for these projects were provided by the Louisiana Department of Transportation and Development (LA DOTD). In most highway projects, 80% of the overall cost of a project is attributed to a handful of items (e.g. superpave asphaltic concrete, Portland cement, class II base course) and all the other items make up the remaining 20% (minor items).

It is important to note that the escalation factor is intended to account for the price increases in material and labor market. Therefore, the comparison of the estimate and the actual cost of a project could be misleading, because the difference between actual and estimate cost of a project may differ not only due to the under or overestimation of the escalation factor, but also due to some other reasons, such as unforeseen ground conditions, change orders, poor project management and etc. Therefore, the focal point in this section will be on the differences between bid estimates of projects at different times which are good indicators of price volatilities and general inflation in

the construction sector (Dawood and Bates 2002). The following key steps are followed in order to compare bid estimates of a project at different times.

First, based on two years of bid history, the minimum, most likely, and maximum unit costs for each major item are estimated. The minor items' costs are kept at a small constant percentage of the overall cost. For all the items material and labor cost, overhead and profit were considered. Second, using these probable cost ranges and Monte Carlo Simulations, 10,000 probable total cost scenarios for each of these items were generated to get the most probable total base line bid estimate for each of these projects. Third, the Value at Risk of the escalation factor will be calculated using either HM or VCM. Forth, the baseline bid estimate will be escalated to the future time. Finally, the escalated amount and the actual future bid estimate of the project can be compared.

4.9.1 Project 1

Based on 2-year bid history prior to May 2005, the minimum, most likely, and maximum unit costs for each major and minor item of this project for May 2005 were estimated. Using Monte Carlo Simulation 10,000 probable total cost scenarios were generated. Of these scenarios, 70% had a 2005 total cost equal to or less than X_1= \$1,261,340.02. This amount is considered as the baseline cost estimation of project 1. This is nearly half of what it actually bid for on May2015, which was X_2=\$2,396,426.28 (actual future bid estimate of the project).

For bidding purposes, the 70th percentile works quite well and it has been a common practice at LA DOTD. In the next step, escalation factors using HM were calculated to escalate the baseline estimate of this project to 2015 using the same formula mentioned previously (i.e. escalated cost= original cost * $(1+i)^n$, i=escalation factor, time).

Table 4.2: Escalation factors (escci) calculated using VaR (HM) at different confidence levels and *time intervals*

Confidence level	*Monthly escci % , Escalated amount*	*Quarterly escci % , Escalated amount*	*Annual escci % , Escalated amount*
80 %	0.47, $X_1*(1+0.0047)^{120}$ **2214116.38**	1.7, $X_1*(1+0.017)^{40}$ **2475541.92**	4.5, $X_1*(1+0.047)^{10}$ **1996636.40**
85%	0.60, $X_1*(1+0.006)^{120}$ **2585769.77**	1.9, $X_1*(1+0.019)^{40}$ **2677931.9**	5.0, $X_1*(1+0.053)^{10}$ **2114053.04**
90%	0.69, $X_1*(1+0.0069)^{120}$ **2878677.88**	2.1, $X_1*(1+0.021)^{40}$ **2896422.09**	6.0, $X_1*(1+0.067)^{10}$ **2412550.22**
95%	0.80, $X_1*(1+0.008)^{120}$ **3281678.42**	2.7, $X_1*(1+0.027)^{40}$ **3661423.05**	7.5, $X_1*(1+0.077)^{10}$ **2648434.28**

Since the original bid estimate must be escalated 10 years to the future, HM was selected over the VCM.

It is important to note that the time component of the escalation formula (n) must be adjusted accordingly if the escalation factor is calculated monthly, quarterly or annually. For instance, the 10-year escalation period, and having monthly escalation factor (*escci*), n is equal to 120 (10 years * 12 months). Table 2 shows the results for escalation factors calculated for various confidence levels, various time intervals, as well as escalated bid cost.

4.9.2 Project 2

In the second project, asphalt makes up nearly 50% of its cost. The project was let in May 2015. The actual bid of the project in 2015 was 2,404,273.54. Similar to case 1, using 2-year bid history prior to May 2013, the cost estimate of the project for May 2013 was calculated at 2,287,190.36. Since the escalation period in this project is relatively short (2 years), it makes the prefect case for using VCM as the estimation method. Therefore, Value at Risk of the escalation factor is calculated for various confidence levels according to equation two ($VaR_c = Z_c\ \sigma_t$), the Z_c is a percentile of the standard normal distribution that corresponds to a pre-specified confidence level of c (e.g. $Z_{95\%}$= 1.64). This confidence level is essentially determined by the cost estimator's risk tolerance. Also, the σt (time-varying volatility) was calculated according to the VCM integrated GARCH method for May 2015.

$VaR_{95\%}$ = 1.64 (0.3147) = 0.27% $X_0\ (1+i)^{n}$ = 2287190.36 $(1+0.0027)^{2*12}$=2,440,094

$VaR_{90\%}$ = 1.28 (0.3147) = 0.32% $X_0\ (1+i)^{n}$ = 2287190.36 $(1+0.0032)^{2*12}$=2,469,465

$VaR_{85\%}$ = 1.03 (0.3147) = 0.40% $X_0\ (1+i)^{n}$ = 2287190.36 $(1+0.004)^{2*12}$=2,517,163

$VaR_{80\%}$ = 0.84 (0.3147) = 0.50% $X_0\ (1+i)^{n}$ = 2287190.36 $(1+0.005)^{2*12}$=2,578,028

Note that since the escalation factor using VCM method has been calculated monthly, the time component of the formula is adjusted accordingly (2*12).

4.9.3 Summary

In order to examine the performance of escalation factors calculated using HM for project 1 and VCM for project 2, Percentage Error Rate (PER) is employed. PER is calculated according to Equation 4.

$$PER = \left(\frac{escalated\ bid\ estimate - actual\ future\ bid\ estimate}{actual\ future\ bid\ estimate}\right)*100 \qquad (4)$$

PER shows the difference between actual and calculated value as a percent of the actual amount. Therefore, a PER value closer to zero implies higher accuracy in the estimate. The positive values of PER indicates the over estimation of the target value (i.e. actual future bid estimate), and negative values of PER indicates the under estimation of it. Figure 5 shows the percentage error rates calculated for both project 1 (the right side) and project 2 (the left side).

For project 1, VaR values of escalation factors were calculated at various rates (i.e. monthly, quarterly, and annual escalation factors) and four different confidence levels. As it is expected, by increasing the confidence level, the VaR of escalation factors will increase. As a result, the escalated bid estimate will increase and the likelihood of cost underestimation will decrease. For project 2, escalation factors were calculated only monthly, but for various confidence levels. By increasing the confidence level, a similar increasing trend is observed.

The range of error rate for project 1 was as low as 1% and as high as 37%; while this range for the second project was between 1.5 and 6.7 percent. However, one must notice that the time frame of prediction in the first project was 10 years. Whereas, in the second project this time frame only was 2 years.

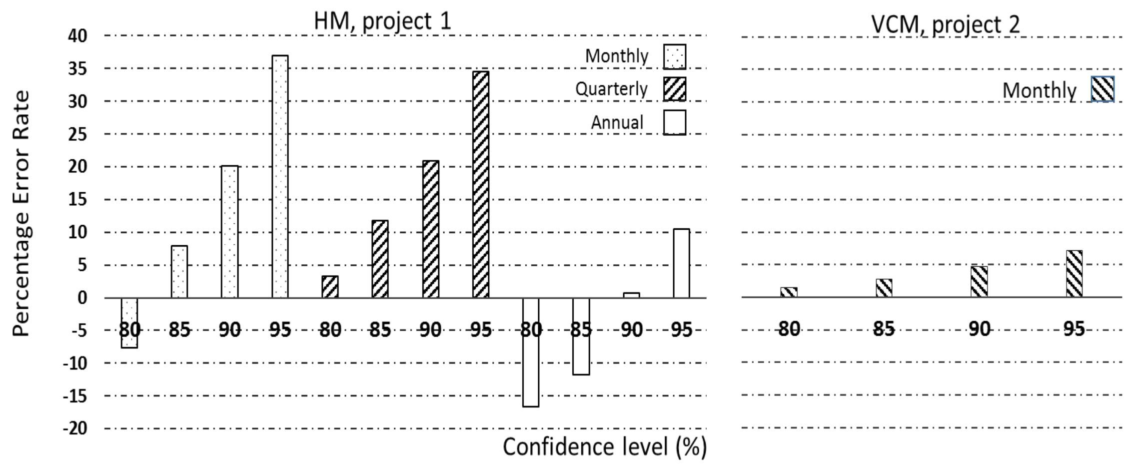

Figure 4.5: Percentage Error Rate of the escalated bid estimate of project 1 and 2 at various confidence levels

4.10 CONCLUSTION AND DISCUSSION

In this paper the Value at Risk methodology was adopted as a conservative risk assessment method to estimate the escalation factor. Historical Method (HM) and Variance and Covariance Method (VCM) as two popular approaches in calculation of the VaR were used. General Autoregressive Conditional Heteroscedastic (GARCH) was also integrated into the VCM to increase the efficiency and accuracy of the estimation by incorporating the risk of price volatility. In addition, two numerical projects with real data from the LA DOTD were presented to demonstrate application and performance of these methods.

For a given confidence level (probability) VaR suggests that the actual escalation factor will not exceed the estimated one. Therefore, unsurprisingly VaR tends to overestimate the escalation factor and directly address the problem of cost overrun. This fact was displayed in both case studies. Albeit, VCM shows higher accuracy and less variability across various confidence levels

in which the escalation factors are calculated in comparison with HM which demonstrates the much wider range of error rates. In general, it can be argued that VCM is capable of capturing the short-term dynamics of the escalation factor time series; therefore, it is suitable for projects with shorter durations. On the other hand, when there are long leaps between planning and construction stages of construction projects, HM can be used as a conservative way of calculating of the escalation factor.

The issue of overestimation, particularly for long-term projects can be moderated by adjusting the risk tolerance level of the project stakeholders. For instance, instead of adopting VaR at 95% confidence level, VaR at 80% Confidence level might be adopted. Another solution could be to calculate the VaR for various confidence levels and take the average of them as the final escalation factor.

Using the VaR method will help cost estimators to prepare more accurate bids. In this study the CCI was utilized for calculation of the escalation factor. However, the methodology can be applied to any other cost indices in the construction industry. The major limitation of using VCM lies in the fact that a large historical data set with relatively high frequency is needed for capturing price volatilities across time. Also, estimators need to be familiar with the foundation of statistical modeling in order to fully benefit from VCM. However, using HM helps them to some certain extent overcome both limitations, because HM does not hold any particular condition on the length and frequency of the data, its application is much simpler in practical case. In the case of the CCI, cost estimators and budget planners could directly use the results presented in this study. Finally using both methods for the purpose of cross validation is recommended.

In terms of future studies, cost indices are aggregate and contain various material markets which are not equal and may vary in volatility. Therefore, decomposing a cost index to its more volatile

components and calculating the VaR of escalation factor for those specific components could increase both reliability and accuracy of the estimation as a whole.

4.11 REFERENCES

Anderson, S. D., Damnjanovic, I., and Nejat, A. (2010). "Effects of Project Cost Reduction Methods." *Transportation Research Record: Journal of the Transportation Research Board*, 2151(-1), 28-35.

Ashouri , B., and Lu, J. (2010). "Time Series Analysis of ENR Construction Cost Index." *Journal of Construction Engineering and Management*, 136, 1227-1337.

Bhargava, A., Anastasopoulos, P. C., Labi, S., Sinha, K. C., and Mannering, F. L. (2010). "Three-stage least-squares analysis of time and cost overruns in construction contracts." *Journal of construction engineering and management*, 136(11), 1207-1218.

Blair, A. N., Lye, L. M., and Campbell, W. J. (1993). "Forecasting construction cost escalation." *Canadian Journal of Civil Engineering*, 20(4), 602-612.

Cabedo, J. D., and Moya, I. (2003). "Estimating oil price 'Value at Risk'using the historical simulation approach." *Energy Economics*, 25(3), 239-253.

Caron, F., Fumagalli, M., and Rigamonti, A. (2007). "Engineering and contracting projects: A value at risk based approach to portfolio balancing." *International Journal of Project Management*, 25(6), 569-578.

Chou, J.-S., Yang, I. T., and Chong, W. K. (2009). "Probabilistic simulation for developing likelihood distribution of engineering project cost." *Automation in Construction*, 18(5), 570-577.

Cioffi, D. F., and Khamooshi, H. (2009). "A practical method of determining project risk contingency budgets." *Journal of the Operational Research Society*, 60(4), 565-571.

Dawood, N. N., and Bates, W. (2002). "A decision support system specification for cost escalation in heavy engineering industry." *Computer‐Aided Civil and Infrastructure Engineering*, 17(5), 342-357.

Diekmann, J. E. (1983). "Probabilistic estimating: mathematics and applications." *Journal of Construction Engineering and Management*, 109(3), 297-308.

Enders, W. (2008). *Applied econometric time series*, John Wiley & Sons.

Engle, R. (2004). "Risk and volatility: Econometric models and financial practice." *American Economic Review*, 405-420.

Flyvbjerg, B. (2007). "Megaproject policy and planning: Problems, causes, cures." *Summary of Dissertation for Higher Doctorate in Science,(Dr. Scient.), Aalborg: Aalborg University*.

Flyvbjerg, B., Holm, M. S., and Buhl, S. (2002). "Underestimating costs in public works projects: Error or lie?" *Journal of the American planning association*, 68(3), 279-295.

Guan, Y., and Liao, H. (2014). "Studying the Reasons for Delay and Cost Escalation in Construction Projects: The Case of Iran Abstract ID."

Hill, R. C., Griffiths, W. E., and Lim, G. C. (2008). *Principles of econometrics*, Wiley Hoboken, NJ.

Hwang, S. (2009). "Dynamic regression models for prediction of construction costs." *Journal of Construction Engineering and Management*, 135(5), 360-367.

Joukar, A., and Nahmens, I. (2015). "Volatility Forecast of Construction Cost Index Using General Autoregressive Conditional Heteroskedastic Method." *Journal of Construction Engineering and Management*, 04015051.

Karmakar, M. (2005). "Modeling conditional volatility of the Indian stock markets." *Vikalpa*, 30(3), 21.

Koushki, P., Al-Rashid, K., and Kartam, N. (2005). "Delays and cost increases in the construction of private residential projects in Kuwait." *Construction Management and Economics*, 23(3), 285-294.

Kuen, T., and Hoong, T. (1992). "Forecasting volatility in the Singapore stock market." *Asia Pacific Journal of Management*, 9(1), 1-13.

Lewis, S., and Grogan, T. (2013). "A Hundred Year of ENR Cost Indexes."

Nejat, A., Anderson, S. D., and Damnjanovic, I. (2010). "Effects of Project Cost Reduction Methods." *Transportation Research Record: Journal of the Transportation Research Board*, 2151(-1), 28-35.

Olatunji, O. A. (2010). "The impact of oil price regimes on construction cost in Nigeria." *Construction Management and Economics*, 28(7), 747-759.

Shane, J. S., Molenaar, K. R., Stuart Anderson, and Schexnayder, C. (2009). "Constructin Project Cost Escalation Factors." *Journal of Management in Engineering*, 25.

Touran, A., and Lopez, R. (2006). "Modeling Cost Escalation in Large Infrastructure Projects." *Journal of Construction Engineering and Management*, 853-860.

Wang, C.-H., and Mei, Y.-H. (1998). "Model for forecasting construction cost indices in Taiwan." *Construction Management & Economics*, 16(2), 147-157.

Wilmot, C. G., and Mei, B. (2005). "Neural network modeling of highway construction costs." *Journal of construction engineering and management*, 131(7), 765-771.

Xie, H., AbouRizk, S., and Zou, J. (2012). "Quantitative Method for Updating Cost Contingency throughout Project Execution." *Journal of Construction Engineering and Management*, 138(6), 759-766.

Xu, J.-w., and Moon, S. (2013). "Stochastic Forecast of Construction Cost Index Using a Cointegrated Vector Autoregression Model." *Journal of Management in Engineering*, 29(1), 10-18.

Zhou, X. (2011). "Managing commodity risks in highway contracts: Quantifying premiums, accounting for correlations among risk factors, and designing optimal price-adjustment contracts." Texas A&M University.

CHAPTER FIVE: PRIORITIZATION OF PRICE VOLATILIYT MANAGEMENT STRATEGIES IN CONSTRUCTION PROJECTS (PAPER 3)

5.1 INTRODUCTION

In the past decade, the construction industry has undertaken unprecedented price volatility, which has severely impacted the industry. It has caused Construction companies' bankruptcies, disputes, cost and time overruns (Rows, 2009). The construction Financial Management Association in a recent study has reported approximately 70% of general contractors have mentioned fluctuations in material prices as the main project risk (2012). The construction industry, particularly highway construction is an energy intensive economic sector. Therefore, even in a stable construction material market, the dynamics of other market elements such as oil prices cause unexpected fluctuations in the material market. For instance, about a 4 % increase in the price of asphalt cement is usually considered within normal range; however, over the past decade industry has experienced very often price jumps as high as 60% (Zhou, 2014).

Although a number of strategies have been used by the construction industry to deal with material price volatility, still the impact of various project factors (criteria) is not clear for parties involved in the contract. Due to limited knowledge, in many cases companies fail to select an adequate approach to better manage volatilities of material prices. Therefore, it is imperative for the industry to have access to a systematic approach that will allow for decision-making at a broader level while it includes all the possible price volatility management strategies and relevant project criteria (such as total project duration or total number of claims).

In this study a selection model based on Analytic Hierarchy Process (AHP) is used to consider both price volatility management strategies and project criteria concurrently. The AHP methodology applies objective mathematical model in order to formalize the knowledge of an

expert panel. This study intends to provide a decision making support system, as well as a practical guideline to help various parties to make consistent, logical decisions. The objective of this study is twofold: 1) document current strategies and criteria used by contractors and owners to manage material price volatilities, based on an extensive literature review and industry experts' interviews; 2) prioritize price volatility management strategies with respect to a number of criteria, using AHP as a selection tool. Lessons learned from this study are discussed and used to propose practical guidelines to deal with price volatility.

5.2. MANAGEMENT STRATEGIES FOR PRICE VOLATILITY

The lack of a plan to manage the risk of material price volatility, typically leads to price speculations or exaggerated premiums that contractors add to the bid prices to cover their risks. Furthermore, it could be the source of other problems, like cost escalation, schedule delays, disputes and material shortages (Skolnik 2011). This section discusses the most common strategies that are currently used in the construction industry or have been proposed in previous studies as viable options in order to deal with this issue.

5.2.1 Price Adjustment Clauses (PAC):

Price adjustment clauses (PAC) are usually provided for specific items in construction projects contracts (e.g. fuel price in highway projects contracts, steel price for commercial construction projects). The specification of the clauses usually varies depending on the amount of material required, total duration of the contract or type of the material. By including PAC in the contract, the owner promises an adjustment to or from the contracting parties contingent on the direction of the price change either inclusively or exclusively (Brown and Randolph 2011; Kosmopoulou and

Zhou 2014). The inclusive PAC allows for the entire price difference while the exclusive PAC allows only for the partial price adjustment.

Many PACs require floor (trigger) and ceiling value (cap). Adversaries of this strategy claim that these kinds of price adjustments define new extra role of insurer for the owners and provides protection and support to less productive firms (Kosmopoulou and Zhou 2014). They also emphasize the role of a trigger value as a tool in support of owners. There have been a few systematic studies on how motivations and bidding behavior of contracting parties are influenced due to these price adjustment policies or how this strategy influences projects with respect to other projects' factors such as cost and duration (Brown and Randolph 2011; Kosmopoulou and Zhou 2014).

Historically, highway construction sector has been the first sector to notice the importance of minimizing the effects of price volatilities (Pierce et al. 2012), mainly due to intensive use of fuel in this industry. However, the requirement for price adjustment clauses in 80s and 90s had been very strict, and it has been limited to specific projects under certain conditions. Eckert and Eger III (2005) highlighted that using PAC helps smaller contractors to compete against larger companies and enables them to submit their bids. They also noted that using PAC may reduce legal fees due to litigation arising from severe price changes in a project. This view is also supported by Kosmopoulou and Zhou (2014). Using a six-year data set provided by the Oklahoma Department of Transportation, they evaluated the price adjustment clauses for the specific fuel based items and its potential effects on bidding behaviors of contractors. They concluded that the bidding became more competitive after the implementation of the PAC policies, as well as decreasing the risk of price uncertainties for contractors. However, they emphasized the trigger value as the most critical factor in the success of this policy. Similarly, Zhou (2011) notes that in

the absence of such clauses most likely contractors inflate their bid prices to the point that it might cost owners even more than the actual cost escalation amount. Since the true direction of price changes is not determined, it might pose owners who do not adopt this strategy to an even higher risk.

The results of a study by the National Cooperative Highway Research Program (2012) indicated that using similar clauses are moderately positive. The report revealed that, while this mechanism could be effective for certain materials (i.e. asphalt and fuel); it cannot provide a reliable way for dealing with price volatilities for other construction materials like steel and concrete; mainly because of the large number of such products are manufactured. Application of aggregate indices like Constructing Cost Index (CCI), Building Construction Index (BCI) or multiple price indices could help to manage this problem (Pierce et al. 2012). The report also lists some benefits of PAC including "positive effect on bid prices, number of bidders, market stability and supply chain". Nevertheless, the study points out that there is not enough evidence showing that contractors tend to withdraw their bids in absence of PAC. Furthermore, the report recommended the use of PAC for only projects that last longer than six months. Interestingly the study did not recommend the use of a trigger value in the use of PAC. Whereas other studies' focus is on the trigger value as a critical element of such clauses (Pierce et al. 2012; Zhou and Damnjanovic 2011).

5.2.2 Alternative Project Delivery Methods:

In regard to alternative project delivery methods with respect to price volatility in highway construction projects, Lean Project Delivery (LPD) and Project Fast Track methods have been explored in previous studies (Smith et al. 2011; Weidman et al. 2011). LPD emerged in 2000 from abstract and applied information (Ballard 2008). It encourages all the parties involved in the construction project to behave as a team for the success of the project and it involves tactics that

construct on the relational principles (Forbes and Ahmed 2010). According to the Lean Construction Institute, LPD decreases the risk in projects of long duration, high uncertainty and complexity. If an unexpected price spike occurs down the road, for the sake of the project, parties are willing to share the consequences instead of trying to shift it entirely toward each other. Furthermore, IPD methods enhance the communication among the project players, which helps to control the amount of fluctuation in certain situations.

Smith et al. and Weidman et al. (2010) in separate studies interviewed commercial and residential contractors in the state of Utah regarding the effectiveness of the Integrated Project Delivery (IPD) which is a subset of LPD in managing material price volatility. The results suggest that contractors overall have positive attitude toward using IPD as a systematic way to deal with variety of risks including material price volatility in construction projects. However, the majority of participants mentioned that LPD is a new concept to the construction industry, and it requires cultural changes for its successful implementation. Using LPD, several studies have addressed different factors including: many different aspects of projects (Ballard and Howell 2003); scheduling and total duration of construction projects (Khanzode et al. 2005); numbers of disputes throughout a project (Lichtig 2006); logistic and supply chain of a construction project (Thomas et al. 2004); total cost of a project (Ballard 2008); and safety and productivity (Nahmens and Ikuma 2009). Although none of these studies addressed the specific case of price volatility and potential impact of LPD on long-term projects. However, a major theme emerged from reviewing the current literature on LPD. LPD can act as an independent strategy of managing material price volatility, as well as a promising platform on which other price volatility management strategies could be conducted with lower risk and essentially with higher influence.

Project fast tracking is another delivery method that reduces the possibility of price fluctuations by minimizing project duration (Allen and Iano, 2013). In fast track, construction of the project starts while the design phase of the project still is in progress. This method can be utilized in manufacturing built construction to achieve the ultimate pace (Kasim et al. 2005). Similar to IPD, project fast tracking requires high communication and collaboration of the parties involved in the project for the successful implementation.

5.2.3 Price Cap Contract

Typically, contractors buy a certain amount of materials every year. Price cap agreements provide the contractors with the opportunity to place a cap on the price of construction materials (Ng et al., 2004). The price cap option allows contractors to minimize their inventory cost, as well as the risk of price volatility, while it helps suppliers to retain their market share and smooth their production schedule (Weidman et al. 2011). Price cap contract for material procurement essentially is similar to "call option" in financial markets. A call option is a financial contract between two parties in which the buyer of the "call option" has the "right but not the obligation to buy an agreed quantity of a particular commodity or financial instrument from the seller. On the other hand, seller is obligated to sell the commodity or financial instrument to the buyer if the buyer decides. The buyer pays the fee for this premium" (O'Sullivan and Sheffrin 2007). Apparently, this option stresses on long run agreements between buyer and seller and relationships become significantly vital.

Ng et al. (2004) compared the cost of long-term contract with a price cap to spot purchases in the construction material market. They attempted to quantify the savings that contractors can achieve by entering into a long-term material contract with a price cap rather than making spot purchases. They concluded using this approach that while suppliers benefit from steady demand and long term contracts, it secures contractors from the price volatilities and reduce the contingency value

of the contract. Similarly, Weidman et al. (2011) suggested price cap contract as one of the approaches that commercial construction industry can utilize to manage price fluctuations. However, the result of their study did not demonstrate the broad adoption of this strategy in commercial construction market. Dong and Chiara (2010) in their study, highlighted the role of price cap contracts and real options as a risk management device for risk mitigation in infrastructure projects.

5.2.4 Contingency

Contingency in cost estimation entails items such as minor price fluctuations or changes within the scope (Upp 2010), and it is generally determined either by expert judgment or stochastic methods. Recently due to increase of price volatility, many contractors rely on a contingency plan to deal with volatile prices, particularly for contracts without PAC (Zhou 2011). It is discussed that in fixed price contracts, contractors include large contingencies in their initial estimate in order to cover changes in prices and hedge against the risk exposures. On the other hand, it is also argued that if contractors overestimate the contingency amount, the prices of fixed price contracts could go above those contracts with adjustment clauses. Farid and Boyer (1985) introduced the Fair and Reasonable Markup (FaRM) pricing model in fixed contracts, in particular in commercial projects. FaRM is the smallest fee that fulfills the required rate of return based upon minimum acceptable price for the contract. The study noted that the FaRM pricing model could provide contracts with a substitute method for subjective estimation of contingencies. However, this approach has not gained in popularity in commercial construction (Smith et al. 2011).

In order to eliminate the subjectivity from the contingency calculation, using quantitative methods such as Monte Carlo simulation, regression analysis, time series techniques and Artificial Neural Network have been proposed (sources). Nevertheless, in practice this number is most likely

subjectively determined based on past experience. Some shortcomings of using contingency to deal with material price volatility are: 1) full reliance of this method on estimator, 2) double counting risk, in particular in projects with various subcontractors, any of them include contingencies and premiums in their calculation, and 3) not providing any confidence interval for the results (Chapman 2001; Smith et al. 2011; and Zou et al. 2009).

5.2.5 Risk Management Methods

Risk Management methods refer to utilizing either quantitative or qualitative techniques in order to assess and measure the risk that is associated with the material price fluctuations in highway construction projects. Examples of quantitative methods include forecasting and modeling future trends of the market and cost indexes using statistical modeling. Both modern methods, such as time series analysis, Neural Networks and conventional ones, like Multiple Regression analysis and Monte Carlo simulation have been widely used (Ashouri and Lu 2010; Hwang 2009; Joukar and Nahmens 2015; Wilmot and Cheng 2003; Xu and Moon 2013).

Qualitative techniques of risk management, however, remain mostly subjective to experts' opinions, as well as using confidence indexes that have been developed by the construction news agencies and associations such as Associated Builders and Contractors and Engineering News Records.

Risk management methods not only provide cost estimators with more accurate estimates of the probable cost of the projects, but it also helps them in making other critical decisions. Decisions include managing price volatility such as estimation of contingency amount, need for stockpiling materials in advance, selection of the desired method of project delivery, inclusion of any particular clause in the contract language and etc (Mehdizadeh 2012; Touran and Lopez 2006).

5.2.6 Other practices

In addition to strategies previously mentioned for managing material price volatility, there are a few other simple, yet effective alternatives that can be found in previous studies. Pierce et al. (2012) noted that many highway agencies break the projects into smaller pieces or into smaller phases in order to limit the time and scope of the project and minimize the risks of price uncertainties and material shortages; particularly, in more complex projects. Another strategy documented in the literature is considering alternative designs with respect to material prices and availability for minimizing the effects of price spikes (Skolnik 2011).

Early material procurement method is another way of dealing with price volatilities. With these method materials are purchased upon approval of the project or at least those materials that are most susceptible to price fluctuations are purchased. In this scenario contractors attempt to either separate the volatile price material from the rest of the job and they place the order within the hour of signing the contract (Koushki et al. 2005; Moore 2008). The major concern with this method is the potential for dispute between the owner and the contractor over where to store the materials or the cost of warehouse space for stockpiling of materials. However, typically owners are willing to come up with some policies to pay for contractors to stockpile the materials as a way to manage the risk of price volatilities (Smith et al. 2011). The second issue related to this strategy is the risk of theft and overall risk of material management.

5.3 ANALYTIC HIERARCHY PROCCESS APPLICATIONS IN THE CONSTRUCTION INDUSTRY

Various methods of dealing with material price volatility have been proposed or practiced over the past few years (Weidman et al. 2011). Nevertheless, each of which has upsides and downsides with respect to different criteria or projects' factors. For instance, although PAC has gained recent

popularity, the downside is that the entire risk is transferred to the owner, and in projects with long duration this could be significant. Moreover, these types of clauses usually cannot be applied to any contract or any material. On the other hand, the method is accurate and potentially minimizes the number of disputes over the course of a construction project. In this case or many similar decision-making situations, the final decision is dependent on the assessment of a number of alternatives (solutions) with respect to a number of tangible or intangible criteria. This decision-making problem is referred to as Multi Attribute Decision Making problem (MADM). Analytic Hierarchy Process (AHP) is a method that provides a systematic approach for making the best-informed decision in such complex problems. Since AHP introduction (Saaty 1977), it has been widely used by many researchers in different areas like manufacturing, construction, computer science, data science, engineering, and management (Al-Harbi 2001; Anderson et al. 2010; Dey 2010; Hsu and Pan 2009). This section provides a brief review on previous application of AHP in process of decision making in the construction industry.

Mustafa and Al-Bahar (1991) conducted one of the first studies using AHP in the field of project risk management. The study underlined the potential benefit of AHP in the construction industry, where presence of various qualitative factors makes it hard for the construction entities to make systematic and formalized decisions. In another study, Al-Harbi (2001) addressed the problem of selecting the best contractor among bidders. The study also highlights the ability of performing sensitivity analysis within the AHP method. Shapira and Goldenberg (2005) established an AHP model for construction equipment selection. Their study first points out that previous methods in selecting an appropriate construction equipment could not address all influential factors properly due to lack of considering soft factors.

An et al., (2007) used the AHP methodology along with Case Based Reasoning (CBR) model in order to include experience in all processes of cost estimating for construction projects, particularly in determining the important weights of criteria in the CBR model. The study noted that AHP is a reliable tool for measuring experience. Similarly, Dey (2010) by integration of AHP and risk map developed a framework for risk management of projects. In a very recent study, Li and Zou (2012) applied fuzzy AHP in a unique case of public private partnership infrastructure projects like motorways, bridges, tunnels and railways for risk identification and assessment with respect to project life cycle.

Surprisingly, just during the past two years AHP has drawn increased attention of researchers and practitioners in the construction industry. Aminbakhsh et al. (2013) used AHP in ranking of safety risks in construction projects. Janackovic et al. (2013) applied fuzzy AHP for ranking the indicators of occupational safety throughout a case study in road construction companies and supported the results of Aminbakhsh et al. (2013). Liu et al. (2011) and Hosseinijou et al. (2014) used a combination of AHP and fuzzy theory in order to create an evaluation system of concrete pavement and material selection. Zhang-yin and Sheng-hui (2013) as well as Whang and Kim (2014) used AHP in the context of sustainable design management.

Collectively, these studies outline a critical role for AHP in construction management, particularly areas that require integrating soft factors and personal experience into the problem. This study, intends to introduce the application of AHP to another critical area, in which the construction industry is also struggling - material price volatility.

5.4 METHODOLOGY

This study intends to provide a decision-making guideline to help various parties to make consistent, logical decisions for mitigating the risk of material price volatility. The objective of this study is twofold: 1) document current strategies and criteria used by contractors and owners to manage material price volatilities; and, 2) prioritize price volatility management strategies with respect to a number of criteria. These two objectives account for two major phases in this paper.

Phase one is completed through a comprehensive literature review, as well as semi structured interviews with a panel of experts. In fact, this phase comprises of information gathering and generation of feasible alternatives. A panel of seven transportation builders' experts was used for both phases of this study. Experts were selected carefully from the major players in highway construction projects within the state of Louisiana: contractors, Louisiana Department of Transportation Engineers and material suppliers. The industry experts were selected based on the years in the industry (minimum 10 years) and they also had to be active in the highway construction industry at the time of the interview. Also it is worthwhile to note that the reliability of results at either phase is not dependent on the quantity of sample size, but its (the sample's quality as in the experts) quality (Saaty and Vargas, 2012). Two separate meetings with each member of the panel were held.

I would like to see more discussion on the experts…this can be an area the people can attack and if you don't show them you have a strong representative group then all else is for naught….

The first round of meetings is dedicated to phase 1. It primarily consisted of brainstorming and generating an exhaustive list of the alternative price volatility management strategies and project criteria in any large highway construction project, discussing all the alternative strategies and

criteria that have already been found in the literature, and their advantages and disadvantages. As it was noted, criteria in this study can be considered as project performance indicators such as ?. In the context of material price volatility, various criteria can be considered by parties to evaluate the performance of any potential strategy. Impact of a strategy on total project cost, total project duration or the performance of a strategy in terms of risk allocation, chance of dispute arising, accuracy, and institutional barriers to implement the strategy are some instances of these criteria. The second round of meetings was allocated to the AHP process which comprised phase two of this research. This study used Expert Choice 11 software for conducting AHP analysis. The following section briefly reviews AHP concepts and its methodology. However, readers could refer to Saaty (1981); Saaty (2003); Saaty and Vargas (2012) for more detailed information.

5.5 ANALYTIC HIERARCHY PROCESS (AHP)

The AHP takes advantage of the psychological fact that, an individual is typically good and rational at pairwise comparisons. Therefore, AHP essentially offers a framework in which making simple pairwise comparisons enable decision makers to overcome the entire problem. As outlined in the Figure 1, the AHP methodology comprises three major steps.

Step 1 is decomposition of the problem. Outputs from phase one provided major inputs to this step. Round two meetings with the panel of experts starts with the screening process and creating the hierarchy structure of the decision problem. Out of a total of ten identified strategies, four strategies ultimately were selected as the final candidates for AHP analysis based on their effectiveness, current popularity, future perspective of the industry, and experts' personal experience.

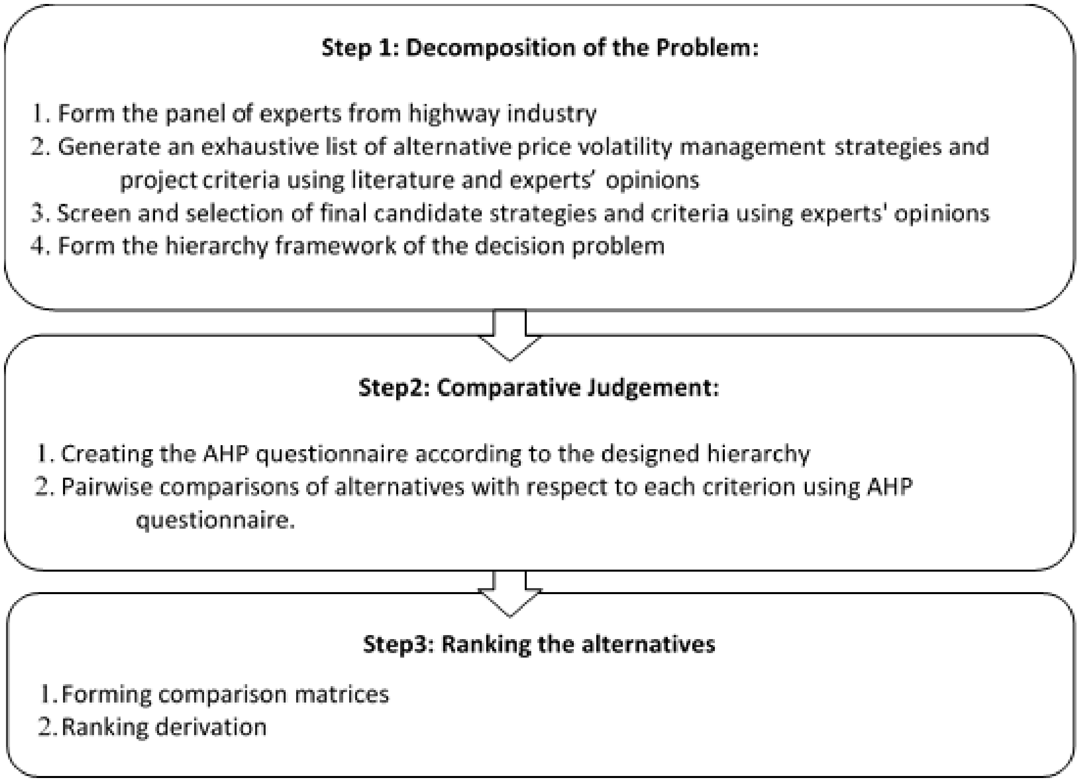

Figure 5.1. Tailored AHP Methodology

These four strategies were: 1- Price Adjustment Clauses (PAC), 2- Integrated Project Delivery methods (IPD), 3- Price Cap Contracts, and 4- Quantitative Risk Management methods. Furthermore, three criteria of 1-project total cost, 2-risk allocation and liability sharing, and 3-project duration were selected by the panel of experts with which strategies will be compared. These project criteria were considered as the top three performance indicators in highway construction projects by the panel of experts. Figure 2 illustrates the hierarchy structure of the decision problem.

Consequently, The AHP questionnaires was completed and pairwise comparisons were made (step 2). Step 3 (Figure 1) entailed making the final analysis and actual ranking of the alternatives with respect to each criterion.

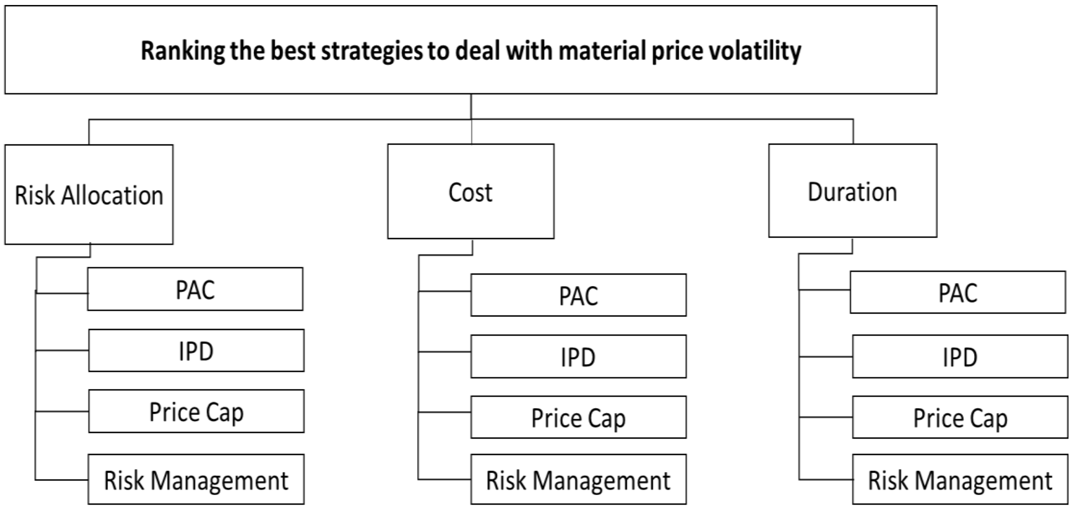

Figure 5.2: Hierarchy of project criteria and risk management strategies

5.5.1 Theoretical Background of AHP:

Once the hierarchy structure of the decision making problem is mapped, step 3 (Figure 1) begins. It first starts by comparing criteria in pairs, and then it continues by comparing alternatives in pairs with respect to each criterion. The pairwise comparison is done using the AHP standard numerical scale presented in Table 1. Results are recorded for each set in a separate matrix which is referred to as "decision matrix" denoted by DM (1). Since there are 3 criteria and four alternatives, a total of four decision matrices must be filled out by each expert. The term a_{ij} in DM (equation 1) expresses an expert's preference of strategy A to B according to the scale presented in table one. a_{ij} is reciprocal of a_{ji}.

$$DM = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nn} \end{bmatrix} \qquad (1)$$

Each entry of the matrix DM determines two major facts regarding each criterion or alternative in comparison with another one: 1- which one is more important, 2-the importance intensity of that comparison.

Table 5.1: The standard numerical and verbal scale for pairwise comparisons in AHP

Value of the entry	Interpretation (verbal intensity)
1	***Equal*** importance of two alternatives
3	One alternative is ***slightly*** more important than another one
5	One alternative is more ***important*** than another one
7	One alternative is ***strongly*** more important than another one
9	One alternative is ***absolutely*** more important than another one
2, 4, 6, 8	These are intermediate scales between two adjacent judgements
Reciprocals (1/x)	A value attributed when alternative A is compared to alternative B, becomes the reciprocal when B is compared to A

After forming decision matrices, each element of the decision matrix is normalized across its column (i.e. = $\frac{\alpha_{ij}}{\sum_{k=1}^{n}\alpha_{kj}}$, n=numbers of columns which are equal to number of strategies) producing the Normalized Column Matrix (NCM), and then the average of each row for the NCM is calculated. Taking averages across NCM rows according to equation two is the most popular way to estimate the eigenvector of a decision matrix which is referred to as weight vector for criteria ($\overrightarrow{\boldsymbol{\omega}}$), and local priority vector for alternatives ($\overrightarrow{\boldsymbol{\beta}}$). Saaty's core theory states that the eigenvectors of the decision matrices are the priority vectors.

$$\omega_i = \frac{1}{n}\sum_{k=0}^{n}\frac{\alpha_{ij}}{\sum_{k=1}^{n}\alpha_{kj}} \qquad (2)$$

Once vector of $\overrightarrow{\boldsymbol{\omega}}$ for criteria, as well as alternatives ($\overrightarrow{\boldsymbol{\beta}}$) are calculated, the global score of each alternative which indicates the overall ranking of one strategy is obtained. This aggregation is

achieved by multiplying local priority vectors by the relative weights of the respective criteria ($\vec{\boldsymbol{\omega}} * \vec{\boldsymbol{\beta}}$).

Consistency Index (CI) which is calculated according to equation 3 is a tool for handling the consistency of pairwise comparisons. Although the absolute consistency should not be expected, researchers must be able to control the inconsistency to some certain extent. The acceptable range for the CI is equal or less than 0.10 (Saaty and Vargas, 2012). If this condition is not met, revisions of the comparisons are suggested. λ_{max} is the maximum eigenvalue of matrix D.

$$\text{Consistency Index (CI)} : \frac{\lambda_{max} - n}{n-1} \qquad (3)$$

5.6 RESULTS

The first objective of the current study was to document strategies on which the construction industry could rely to manage price volatility. Through literature review and interviews with panel of experts, a total of 10 strategies were collected. Table 1 list these strategies, as well as their advantages and disadvantages.

The second objective of this study was to prioritize price volatility management strategies with respect to the most important criteria of highway construction projects. Out of 10 strategies identified in phase 1 of this study, the panel of experts selected the top four. In addition, cost, duration, and risk allocation were selected as the top projects' criteria.

The first pairwise comparisons were made among the criteria to determine their relative importance in the overall decision making frame.

Table 5.2: List of alternative strategies and their advantages and disadvantages

Strategies	Advantages	Disadvantages
PAC	• Increase the competition among the contractors • Enable small contractors to compete. • High accuracy • Minimize the chance of arising disputes due to material price volatility	• Owner plays the role of insurer • Cannot be applied to any contract • Cannot be applied to any material • It is popular with contractors during periods of escalation but not during periods of price drops.
LPD	• Sharing the entire risk of the project among contracting parties • Positive impacts on other aspects of the project	• Requires mutual trust and cultural requirements • Not applicable to all kinds of projects
Fast Track	• Save time • Facilitate some other strategies such as early material procurement • Increases the accuracy of some other methods due to shortening the project duration	• Increase the chance of design revision and change orders • Quality concerns • Cost concerns
Price Cap	• Decrease the price uncertainty for contractors • Provide steady demand and market share for material supplier • Reduce the waste • Provide operating flexibility for buyers including minimizing inventory cost	• Requires long-term relationship between contractor and material supplier • Not suitable for complex projects with very long durations.
ICT	• Provide comprehensive tools for all aspects of construction management including cost and price volatility. • Save time • Provide information and eliminate the middle men.	• Not directly address the material price volatility. • Not adequate in the case of price spikes. • Depends on other factors such as training
Contingency	• Easy implementation • Applicable in long term projects	• Subject to personal opinions, usually estimator • It does not manage / mitigate the risk but it allocates money to it • Double counting the risk
Quantitative risk management	• High accuracy • High variety of methods and techniques • Provide confidence interval for estimation.	• Difficult implementations • Lower accuracy in long-term projects.
Qualitative risk management	• Easy implementation • Applicable in long-term projects. • Using qualitative indexes produced by prominent agencies increases accuracy and consistency of these methods.	• Subject to expert's opinions

Table 5.2. continued

Strategies	Advantages	Disadvantages
Early material procurement	• It is cost effective	• Dispute over the warehouse rent • Safety concerns • Not feasible in more complex projects • Not feasible for some materials in highway construction such as asphalt
Breaking the project into smaller phases	• Facilitates some other strategies such as early material procurement • Increases the accuracy of other methods due to shortening the duration of the project	• Not feasible in many projects, most of the projects are best handled as a single project • Project duration concerns in public projects • Coordination and communication concerns • It cuts back on large scale savings

Table three summarizes the final weights, as well as the Consistency Index (CI) obtained at this level. These weights represent marginal contributions or importance. The higher the weight, the more important the corresponding criterion. Project cost was perceived as the most significant criterion (0.435), followed by the risk allocation and liability sharing (0.329), and project duration (0.236).

Table 5.3 Criteria weight vector and its CI

Criteria	**Weight vector ($\vec{\omega}$)**
Cost	0.435
Duration	0.236
Risk allocation	0.329
CI	0.01

The CI calculated for the entire participants at this level is 0.01, which is well below the threshold of 0.10. Next, pairwise comparisons were made between the four identified strategies with respect to the three project criteria. Six pairwise comparisons for each combination. These are called local comparisons that from which eigenvectors or so-called local priority vectors are extracted. The first three columns of table four summarizes the local priority vectors obtained from pairwise

comparisons for each criterion $(\overrightarrow{\boldsymbol{\beta_i}})$. Also the numbers in the last row are CIs for each set which are well below 0.10.

Table 5.4: Local priority vectors for alternatives with respect to each project's criterion and global rankings

	Local priorities (eigenvectors)			**Global priorities** $(\vec{\boldsymbol{\omega}} * \overrightarrow{\boldsymbol{\beta}})$
	Cost $(\overrightarrow{\beta_1})$	Duration$(\overrightarrow{\beta_2})$	Risk allocation$(\overrightarrow{\beta_3})$	
Risk Management	**0.45**	**0.32**	**0.24**	0.337
PAC	**0.30**	**0.15**	**0.44**	0.311
IPD	**0.20**	**0.46**	**0.27**	0.280
Price Cap	**0.05**	**0.07**	**0.05**	0.078
Consistency Ratio	0.03	0.057	0.07	0.045

Final evaluation of the pairwise comparisons indicates that with respect to project cost, which was recognized as the most important criterion of our decision making model, the highest priority strategy was quantitative risk management methods (0.45), followed by the PAC (0.30), IPD (0.20) and price cap (0.05). With respect to risk allocation and liability sharing, PAC ranked number one strategy (0.44) to deal with material price volatility followed by the IPD (0.27), risk management (0.24) and price cap (0.07). Finally, with respect to duration; experts gave their highest priority to IPD (0.46). Risk management methods was selected as the second most important alternative (0.32), followed by the PAC (0.15) and price cap (0.07).

Moreover, AHP can aggregate the local rankings across all criteria to determine the global rankings by multiplying $\vec{\omega}$ and $\vec{\beta}$. The last column of table four shows the global strategies' rankings. Risk

management gained the first place (0.337), PAC the second place (0.311), IPD (0.280) and Price cap (0.078) the third and fourth places respectively. Also, the overall CI is 0.045 which is within acceptable range.

A sensitivity analysis was also conducted to help with the uncertainty surrounding the decisions. In order to determine the sensitivity of the experts' responses, the criteria percentage ranking was altered slightly to observe any changes in the strategies' rankings. For instance, if we increase the percentage weight of cost by 10%, from 43.5 % to 53.5 %, no changes will occur in the ranking of the priorities. Overall, by increasing the priority percentage of the cost, no changes will occur in ranking of alternative strategies. However, if we decrease the relative weight of the cost, risk and liability sharing will replace the cost as the most important criterion of the decision making model. This change will influence the overall rankings. In the new scenario PAC will gain the highest priority among the four candidate strategy. As it was shown in table four, final scores for these two strategies in overall rankings have been very close. Therefore, by reducing the weight of cost, PAC immediately replaces the risk management methods as the number one strategy in dealing with material price volatility. Furthermore, if we increase the importance (weight) of the criterion of project duration which is the last one in original ranking, IPD will be the number one strategy to manage material price volatility.

5.7 CONCLUSIONS AND DISCUSSIONS

Material price volatility has become one of the major risks in highway construction projects mostly because of its dependence on energy prices and other macroeconomic factors. This study for the first time aimed to document and rank all the strategies that have been used or proposed to manage material price volatility. According to the results, quantitative risk management methods due to

their high accuracy outweigh other strategies when total cost of the project is the primary concern. Systematic quantitative risk management methods are more prevalent in the highway projects, while Weidman et al. (2011) noted that in the residential and commercial projects subjective price speculation is a more common practice. Also, in terms of project cost, PAC showed the satisfactory performance, mainly because it helps contractors to reduce the contingency portion that is related to price volatility.

With respect to the risk allocation and liability sharing, PAC was selected as the best strategy. Although some studies had noted that Price Adjustment Clauses transfer the entire risk of price volatility to the owners (Brown and Randolph 2011; Kosmopoulou and Zhou 2014), the panel of experts in this study unanimously believed that owners have control tools such as setting trigger values and imposing ceiling values (cap) to utilize PAC in a way that each party be exposed to a fair share of risk as it pertains to price volatility. . IPD was regarded as the second best strategy to address material price volatility when risk allocation is performance indicator. It was underlined that IPD covers broader range of issues and it is not applicable to all types of projects. However, in terms of the project duration, IPD was selected unanimously as the number one strategy that has significant impact on duration of the projects. Similarly, Smith et al. (2011) had noted the role of "communication" between contractors and suppliers in residential and commercial construction projects in dealing with the risk of price volatility.

Figure 3 consolidates the results of this study in a decision tree, which is further integrated in a decision-making guideline to help various parties to make consistent, logical decisions for mitigating the risk of material price volatility in highway construction projects. The ranking produced in this paper is the starting foundation knowledge and guidance on how each of these methods of managing price volatility could be more preferable in different situations

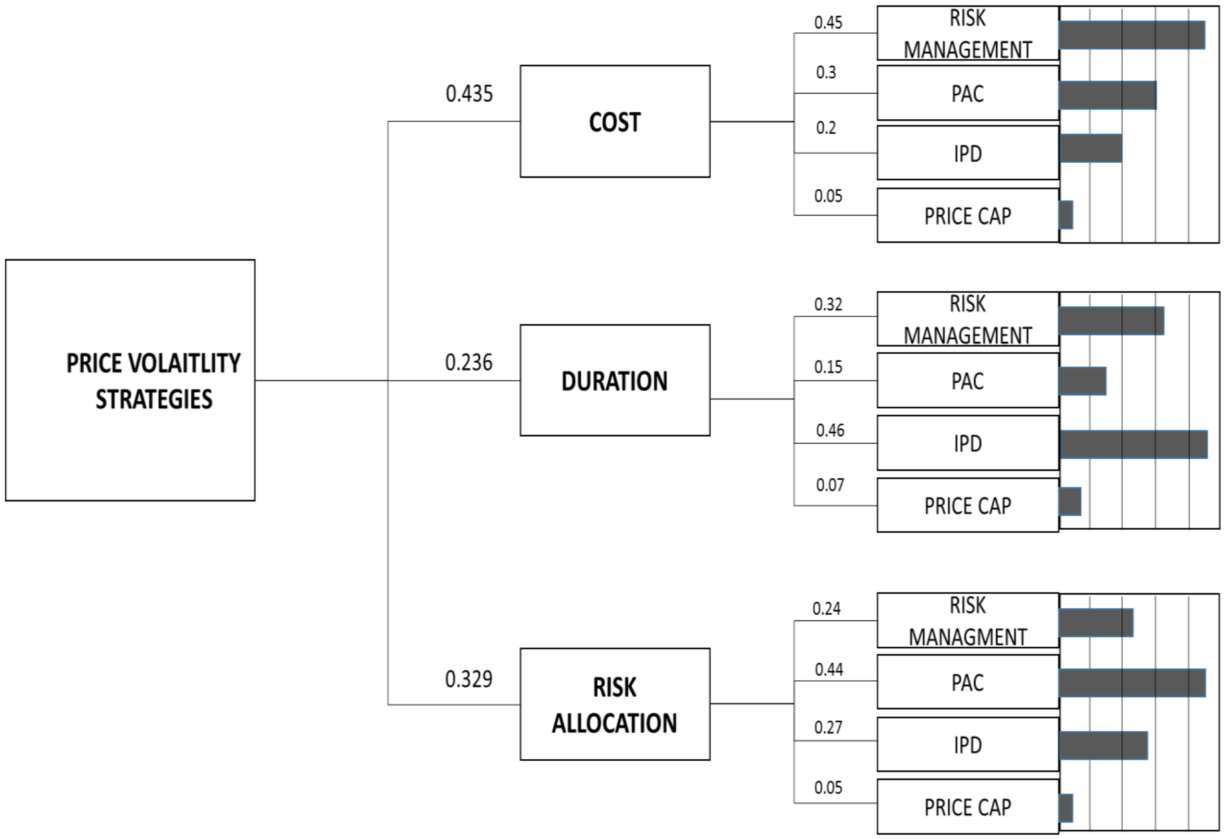

Figure 5.3: Weighted decision tree with criteria, alternatives and allocated weights

where one or two criteria may have higher relative importance. The results surely could vary in different scenarios in different projects with different priorities. Contracting parties in highway construction projects not only can directly benefit from the results of this study, but also they can utilize the AHP methodology as a platform in their own customized way in highway construction projects using strategies and criteria discussed in order to gain early insight and better understanding regarding feasible alternative strategies and project's criteria in terms of price volatility management. AHP methodology takes advantage of both subjective ideas of experts and objective rigorous mathematical modeling at the same time. Therefore, it is able to handle both simple and complicated models along with various options for post analyzing the critical elements of the decision. This paper focuses on constructing a simple, straightforward and systematic

selection method for cost estimators and risk managers by including the top four risk management strategies and the top three project criteria. Adding more complexities such as increasing the numbers of criteria and sub levels for alternatives, replicating the study in other geographical regions, as well as considering other selection strategies such as Delphi methodology could be the next steps for future researchers interested in this field.

5.8 REFERENCES

Al-Harbi, K. M. (2001). "Application of the AHP in project management." *International journal of project management*, 19(1), 19-27.

Allen, E., and Iano, J. (2013). *Fundamentals of building construction: materials and methods*, John Wiley & Sons.

Aminbakhsh, S., Gunduz, M., and Sonmez, R. (2013). "Safety risk assessment using analytic hierarchy process (AHP) during planning and budgeting of construction projects." *Journal of safety research*, 46, 99-105.

An, S.-H., Kim, G.-H., and Kang, K.-I. (2007). "A case-based reasoning cost estimating model using experience by analytic hierarchy process." *Building and Environment*, 42(7), 2573-2579.

Anderson, S. D., Damnjanovic, I., and Nejat, A. (2010). "Effects of Project Cost Reduction Methods." *Transportation Research Record: Journal of the Transportation Research Board*, 2151(-1), 28-35.

Ashouri , B., and Lu, J. (2010). "Time Series Analysis of ENR Construction Cost Index." *Journal of Construction Engineering and Management*, 136, 1227-1337.

Ballard, G., and Howell, G. (2003). "Lean project management." *Building Research & Information*, 31(2), 119-133.

Brown, I., and Randolph, L. (2011). "Evaluation of Price Adjustment Clauses for Construction Materials."

Dey, P. K. (2010). "Managing project risk using combined analytic hierarchy process and risk map." *Applied Soft Computing*, 10(4), 990-1000.

Eckert, C., and Eger III, R. J. (2005). "Study of liquid asphalt price indices applications to Georgia contracting."

Eger III, R. J., and Guo, H. (2008). "Financing Infrastructure: Fixed price vs. Price Index Contract." *Journal of Public Procurement*, 8(3).

Farid, F., and Boyer, L. (1985). "Fair and reasonable markup (farm) pricing model." *Journal of construction engineering and management*, 111(4), 374-390.

Forbes, L. H., and Ahmed, S. M. (2010). *Modern construction: lean project delivery and integrated practices*, CRC Press.

Hosseinijou, S. A., Mansour, S., and Shirazi, M. A. (2014). "Social life cycle assessment for material selection: a case study of building materials." *The International Journal of Life Cycle Assessment*, 19(3), 620-645.

Hsu, T.-H., and Pan, F. F. C. (2009). "Application of Monte Carlo AHP in ranking dental quality attributes." *Expert Systems with Applications*, 36(2), 2310-2316.

Hwang, S. (2009). "Dynamic regression models for prediction of construction costs." *Journal of Construction Engineering and Management*, 135(5), 360-367.

Janackovic, G. L., Savic, S. M., and Stankovic, M. S. (2013). "Selection and ranking of occupational safety indicators based on fuzzy AHP: A case study in road construction companies." *South African Journal of Industrial Engineering*, 24(3), 175-189.

Joukar, A., and Nahmens, I. (2015). "Volatility Forecast of Construction Cost Index Using General Autoregressive Conditional Heteroskedastic Method." *Journal of Construction Engineering and Management*, 04015051.

Kasim, N., Anumba, C., and Dainty, A. "Improving materials management practices on fast-track construction projects." *Proc., Proceedings Twenty First Annual Association of Researchers in Construction Management (ARCOM) Conference, Khosrowshahi*, 793-802.

Khanzode, A., Fischer, M., and Reed, D. "Case study of the implementation of the lean project delivery system (LPDS) using virtual building technologies on a large healthcare project." *Proc., 13th International Group for Lean Construction Conference: Proceedings*, International Group on Lean Construction, 153.

Kosmopoulou, G., and Zhou, X. (2014). "Price Adjustment Policies in Procurement Contracting: An Analysis of Bidding Behavior." *The Journal of Industrial Economics*, 62(1), 77-112.

Kul B. Uppal PE, E., , (2010). "Contingency." *AACE International*AACE International.

Li, J., and Zou, P. (2012). "Risk identification and assessment in PPP infrastructure projects using fuzzy Analytical Hierarchy Process and life-cycle methodology." *Australasian Journal of Construction Economics and Building*, 8(1), 34-48.

Lichtig, W. A. (2006). "Integrated Agreement for Lean Project Delivery, The." *Constr. Law.*, 26, 25.

Liu, Z. B., Fei, W. S., Wu, P. G., and Chen, F. (2011). "The research on building up the hierarchy process and fuzzy evaluation model and evaluation system about the cement concrete pavement on the basis of the fuzzy mathematics theory." *Advanced Materials Research*, 255, 3228-3233.

Mehdizadeh, R. (2012). "Dynamic and multi-perspective risk management of construction projects using tailor-made Risk Breakdown Structures." Université Paris-Est Marne la Vallée.

Mitropoulos, P., Abdelhamid, T. S., and Howell, G. A. (2005). "Systems model of construction accident causation." *Journal of Construction Engineering and Management*, 131(7), 816-825.

Mustafa, M. A., and Al-Bahar, J. F. (1991). "Project risk assessment using the analytic hierarchy process." *Engineering Management, IEEE Transactions on*, 38(1), 46-52.

Nahmens, I., and Ikuma, L. H. (2009). "An empirical examination of the relationship between lean construction and safety in the industrialized housing industry." *Lean Construction Journal*, 2009, 1-12.

Ng, F. P., Björnsson, H. C., and Chiu, S. S. (2004). "Valuing a price cap contract for material procurement as a real option." *Construction management and economics*, 22(2), 141-150.

O'Sullivan, A., and Sheffrin, S. M. (2007). *Economics: Principles in action*, Boston, Mass.: Pearson/Prentice Hall.

Pierce, C., Huynh, N., and Guimaraes, P. (2012). "Cost Indexing and Unit Price Adjustments for Construction Materials."

Redd, L., and Hibbard, T. (2009). "Asphalt Risk Management at the Wyoming Department of Transportation."WYDOT.

Saaty, T. L. (1981). *Decision Making for Leaders: The Analytical Hierarchy Process for Decisions in a Complex Work*, Lifetime Learning Publications.

Saaty, T. L. (2003). "Theory of the analytic hierarchy process. Part 2.1." *Системні дослідження та інформаційні технології*.

Saaty, T. L., and Vargas, L. G. (2012). "The Seven Pillars of the Analytic Hierarchy Process." 175, 23-40.

Shapira, A., and Goldenberg, M. (2005). "AHP-based equipment selection model for construction projects." *Journal of Construction Engineering and Management*, 131(12), 1263-1273.

Skolnik, J. (2011). *Price Indexing in Transportation Construction Contracts*, Jack Faucett Associates.

Smith, J. P., Miller, K., Christofferson, J., and Hutchings, M. (2011). "Best Practices for Dealing with Price Volatility in Utah's Residential Construction Market." *International Journal of Construction Education and Research*, 7(3), 210-225.

Thomas, H. R., Horman, M. J., de Souza, U. E. L., and Završki, I. (2004). "Closure to "Reducing Variability to Improve Performance as a Lean Construction Principle" by H. Randolph Thomas, Michael J. Horman, Ubiraci Espinelli Lemes de Souza, and Ivica Zavrski." *Journal of Construction Engineering and Management*, 130(2), 300-301.

Touran, A., and Lopez, R. (2006). "Modeling Cost Escalation in Large Infrastructure Projects." *Journal of Construction Engineering and Management*, 853-860.

weidman, J. E., Miller, K. R., Christoffersen, J. p., and Newitt, J. S. (2011). "Best Practices for Dealing with Price Volatility in Commercial Construction." *International Journal of Construction Education and Research*, 7(4), 17.

Whang, S.-W., and Kim, S. (2014). "Determining sustainable design management using passive design elements for a zero emission house during the schematic design." *Energy and Buildings*, 77, 304-312.

Wilmot, C. G., and Cheng, G. (2003). "Estimating Future Highway Construction Cost." *Journal of Construction Engineering and Management*.

Xu, J.-w., and Moon, S. (2013). "Stochastic Forecast of Construction Cost Index Using a Cointegrated Vector Autoregression Model." *Journal of Management in Engineering*, 29(1), 10-18.

Zhang-yin, L., and Sheng-hui, J. (2013). "Evaluation Method on Effectiveness of Sustainable Engineering Construction Project Management." *International Journal of Applied Environmental Sciences*, 8(9).

CHAPTER SIX

This section summarizes the results, discusses the limitations, and puts forward the directions for future studies. The section is organized into two primary sub sections; in the first subsection, summary of each paper is presented, and in the second subsection, the limitations and directions for future works are presented.

6.1 SUMMARY:

This dissertation has investigated the issue of price volatility in the material and labor markets from both perspectives of risk management, and risk analysis in the three independent papers, which comprise of three major chapters of this dissertation. The central objective of this dissertation are addressing volatility, as well as helping cost estimators, risk managers, planers, and other parties involved in a construction project to measure, quantify, and manage price volatility. The following is a brief summary of each paper, as well as its key insights.

In the first paper (chapter three), the Engineering News Record Construction Cost Index (ENR CCI), as a widely used cost index in the construction industry has been employed for the purpose of quantifying and forecasting price volatility. In order to achieve this objective, General Autoregressive Conditional Heteroscedastic (GARCH) family models were used. Using these models allows cost estimators to relax one of the assumptions of the previous forecasting models: equal amount of uncertainty (risk) through passage of time, which technically is known as the homogeneity of variance assumption. Examining the CCI over the past 36 years (1978-2014) proves that magnitude of uncertainty throughout the years is not constant and experience significant variations. Therefore, cost estimators need to be able to incorporate these variations

into their modeling process. This integration first increases the reliability and accuracy of the forecast, second it provides them with numerical indicators of risk in relation to the price volatility which can be used in estimation of the escalation factor and contingency amounts. Quantifying risk also helps project stakeholders to optimize their resource allocations. Another benefit of using GARCH models for forecasting is that it helps practitioners to become familiar with the salient features of the cost indices, and the economic intuition that could be gained out of it. For instance, as it was noted in great details in the first paper, the estimated parameters of the variance equation indicate that an external shock at time t to the CCI series will persist for a relatively long period but eventually will die out and market will go back to its normal condition.

The second paper (chapter four) intended to provide a practical application for the GARCH model that was introduced in the first paper in the context of the escalation factors estimation. This chapter used the Value at Risk as its principal methodology, and ENR CCI as the input data set. The VaR allows cost estimators to keep their eyes on the downside of risk in terms of the price volatility. Considering the high volume of the projects suffering from cost overrun, being cognizant of the downside risk, particularly when economic outlook is not promising could be enormously beneficial for cost estimators, as well as project stakeholders. On the other hand, the integration of the VaR and GARCH helps them to account for the impact of the volatility in their calculation which will enhance their estimation in terms of reliability and accuracy. Moreover, Historical Method (HM), which is another way of calculation of the VaR was estimated. The core principal of HM is based on the assumption that past repeats itself; therefore, it is argued that it could be more appropriate for very long term forecast, when the accuracy of the (e.g. over 3 years) statistical forecasts decreases. The results of the study showed both approaches could provide satisfactory estimations of the escalation factors. Escalation factors calculated using both methods

across various confidence levels were applied to two real construction projects in the state of Louisiana and percentage error rates were calculated subsequently. According to the percentage error rates, VCM in short-term estimations is capable of producing escalation factors with higher accuracy and less variability (i.e. 1.5% -6.7 %) across various confidence levels compared to HM (i.e. 1.0% - 37%).

Finally, in the third paper two major objectives were outlined. 1- for the first time an information bank was created covering all the risk management strategies that could be used either alone or combined with other strategies to deal with the issue of the price volatility. 2- Based on the findings in the step one, and help of a panel of experts, a formalized, but simple decision making guideline was produced that can be replicated or used for the purpose of the selecting the most suitable risk management strategy for dealing with price volatility issue while considering the major criteria of a construction project. As it was noted in chapter four, the project criteria in this study are referred to as project indicators upon which the impacts of a strategy were compared with other alternative strategies. The first section of this study relied on an extensive review of the literature, and semi-structured interview with the high profile panel of experts that was formed for the sake of this research. The second section of the study used Analytic Hierarch Process (AHP) as a selection tool. AHP is a strong decision making tool which is based on pairwise comparisons of the alternative strategies by panel of experts. Panel of experts in this study selected project duration, risk allocation and liability sharing, and project cost, as the major project criteria. They also selected quantitative risk management methods such as those discussed in the first paper, Price Adjustment Clauses (PAC), Integrated Project Delivery (IPD) methods, and price caps as the top potential risk management strategies for dealing with the issue of the price volatility.

According to the final results, quantitative risk management methods outweigh other strategies when total cost of the project is the primary concern due to its high accuracy. Also, in terms of project cost, PAC showed the satisfactory performance. With respect to the risk allocation and liability sharing, PAC was selected as the best strategy. IPD was regarded as the second best strategy to address material price volatility when risk allocation is performance indicator. It was underlined that IPD covers broader range of issues and it is not applicable to all types of projects. However, in terms of the project duration, IPD was selected unanimously as the number one strategy that have significant impact on duration of the projects. Results from this paper were compiled in a decision making guidelines to aid contracting parties in their evaluation of potential projects.

6.2 LIMITATIONS AND DIRECTIONS FOR FUTURE WORKS:

Dealing with the material and labor price volatility has been the primary focus of this dissertation. The first two papers aimed to assist cost estimators with the risk analysis process by forecasting and measuring the price volatility risk via statistical tools. Generally, for the purpose of predictive modeling a large historical data set is needed. Specifically, GARCH methodology requires a large historical data set with high frequency to capture volatilities of a price index accurately. Also, for a wide application of GARCH methodology, higher knowledge of statistical modeling is favored for cost estimators.

On the other hand, the third paper focused on risk management and decision making side of the price volatility subject. In this regard, since all the experts in this study were selected from the state of Louisiana, it would be helpful to replicate the study in other states as well to obtain other experts' experience across the country.

The results of the work opened up many topics for future research including:

• Material price volatility is one of the major sources of the price volatility. However, volatilities within the material market varies among different materials. Segregation of the materials in order to determine an extent to which any material plays a role in the price volatilities could be an interesting topic.

• Although the sudden movements in the material and labor markets are the major contributors to the price volatility in the construction industry; however, a comprehensive research to identify other potential factors could be an interesting topic for the future researchers.

• The spill over impact of the price volatility in the construction industry on the other construction variables such dispute arises throughout the construction project.

• To quantify the relationship between the complexity level of a project and the confidence level that a cost estimator should adopt for relatively accurate results in estimation of the escalation factor using Value at Risk methodology.

• To create weight escalation factor based on the importance of the items causing escalation in the construction projects.

• To determine the impact of the news on the price volatility; in order to determine how responsive construction material and labor market is to an external political and economic shocks and news. Also researchers could scrutinize symmetrical impact of the news on the price volatility to answer the question of whether good and bad news has equal impacts on the price volatility.

- One of the major variables, in particular in the highway construction industry, is oil price, which itself is quite volatile. To determine the impact of the oil price volatility, and its spill overs on the construction market could be another research topic for the future researchers.

- To develop fully automated programs for the purpose of auto selection and minimizing the user interaction in developing forecasting models proposed in paper 1 and paper 2.

- In the third paper of this dissertation, the experts' opinions were formalized in order to rank the alternative strategies in dealing with the price volatility via AHP as a selection tool. However, researchers could use other similar methods such as Delphi as well, and compare the results.

- Replicating the third paper in other states could be another informative idea in the sense of decision making and scrutinizing the impacts of geographical variables on the decision making process.

APPENDIX: CHAPTER 3 DIAGNOSTIC AND APPPLICABILITY TESTS

Table 5 shows the results of the Lagrange Multiplier (LM) test in order to check if there is any remaining conditional volatility in the residuals of the mean equation. The null hypothesis (H_0) in this test is "having no conditional volatility or ARCH effect." The EViews software reports F statistics for the whole test as well as t statistics for the individual lags (three lags) with corresponding probabilities.

Table A.1: ARCH effect test for detecting remaining conditional volatilities of the CCI after the fitting the GARCH (1,1) model

F-statistic	0.401752	Prob. F(3,406)	0.7518
Obs*R-squared	1.213529	Prob. Chi-Square(3)	0.7498

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Sample (adjusted): 1978M06 2012M07
Included observations: 410 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.059288	0.148231	7.146202	0.0000
RESID^2(-1)	-0.020447	0.049581	-0.412407	0.6803
RESID^2(-2)	0.020518	0.049571	0.413919	0.6792
RESID^2(-3)	-0.044963	0.049573	-0.907007	0.3649

In order for the final model to be applicable, residuals of the final model must show no sign of serial autocorrelation. Ljung-Box Q test check for this condition. The null hypothesis is “NO Autocorrelation". The Q statistic shown in the figure 8 follows chi-square distribution and corresponding probability values should be all above 0.05 for “failing to reject the null hypothesis". In accordance with stated hypothesis, visually all the autocorrelation, as well as partial correlation values should fall within the dashed boundary.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.005	-0.005	0.0104	
		2	0.008	0.008	0.0376	0.846
		3	-0.051	-0.051	1.1124	0.573
		4	0.020	0.020	1.2807	0.734
		5	-0.013	-0.012	1.3515	0.853
		6	0.020	0.017	1.5170	0.911
		7	0.067	0.069	3.4010	0.757
		8	0.074	0.073	5.6885	0.577
		9	0.015	0.018	5.7829	0.672
		10	0.006	0.012	5.7990	0.760
		11	0.040	0.046	6.4783	0.774
		12	0.061	0.063	8.0791	0.706
		13	0.078	0.080	10.680	0.557
		14	0.052	0.053	11.841	0.541
		15	-0.036	-0.040	12.393	0.575
		16	-0.051	-0.054	13.501	0.564
		17	0.085	0.085	16.596	0.412
		18	-0.016	-0.026	16.702	0.475
		19	0.006	-0.016	16.717	0.543
		20	0.023	0.010	16.949	0.593

Figure A.1: Autocorrelation and Partial Autocorrelation of residuals of the final model.

In order for final GARCH model to be applicable, squared residuals of the final model must show no sign of serial autocorrelation. Otherwise, it would suggest existence of remaining conditional volatility. Ljung-Box Q test check for this condition. The null hypothesis is “NO Autocorrelation". The Q statistic follows chi-square distribution and corresponding probability values should be all above 0.05 for “failing to reject the null hypothesis". In accordance with stated hypothesis, visually all the autocorrelation, as well as partial correlation values should fall within the dashed boundary.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.022	-0.022	0.1949	
		2	0.022	0.021	0.3930	0.531
		3	-0.046	-0.045	1.2707	0.530
		4	-0.023	-0.025	1.4831	0.686
		5	0.089	0.091	4.8367	0.304
		6	0.008	0.011	4.8635	0.433
		7	0.037	0.032	5.4546	0.487
		8	-0.001	0.008	5.4548	0.605
		9	-0.031	-0.028	5.8629	0.663
		10	0.059	0.054	7.3471	0.601
		11	0.039	0.044	8.0007	0.629
		12	0.053	0.044	9.1975	0.604
		13	0.087	0.092	12.426	0.412
		14	0.080	0.095	15.148	0.298
		15	-0.011	-0.013	15.199	0.365
		16	-0.008	-0.007	15.224	0.435
		17	0.074	0.077	17.613	0.347
		18	0.019	0.007	17.766	0.404
		19	-0.015	-0.035	17.859	0.465
		20	0.070	0.073	19.968	0.397

Figure A.2: Autocorrelation and Partial Autocorrelation of squared residuals of the final model.

VITA

Alireza Joukar was born and grew up in Esfahan, Iran. In 2011 he finished his Bachelor and Master of Economics from University of Isfahan. Afterward he moved to the United States, Louisiana where he started his Ph.D.in Engineering Science with the concentration on statistics and quantitative methods. His interests include applied econometrics, statistical methods and data science.