ANALYZING UNCERTAINTY IN THE PRICE OF MATERIALS AND FINANCIAL RISK MANAGEMENT STRATEGIES

A Dissertation
Presented to
The Academic Faculty

By

Mohammad Ilbeigi

In Partial Fulfillment
of the Requirement for the Degree
Doctor of Philosophy in the
School of Building Construction

Georgia Institute of Technology
August 2017

ANALYZING UNCERTAINTY IN THE PRICE OF MATERIALS AND FINANCIAL RISK MANAGEMENT STRATEGIES

Approved by:

Dr. Daniel Castro-Lacouture, Advisor
School of Building Construction
Georgia Institute of Technology

Dr. Bistra Dilkina
School of Computational Science and Engineering
Georgia Institute of Technology

Dr. Timothy Welch
School of City and Regional Planning
Georgia Institute of Technology

Dr. Xinyi Song
School of Building Construction
Georgia Institute of Technology

Mr. David Jared, P.E.
Office of Research
Georgia Department of Transportation

Date Approved: March 31, 2017

Dedicated to my beloved father and mother,

Mostafa and *Jaleh*

and my lovely sister

Shima

ACKNOWLEDGMENTS

I would like to express my deepest gratitude to my advisor, Dr. Daniel Castro-Lacouture, for his guidance, support, and supervision throughout all the stages of this dissertation. This dissertation would not have been possible without his guidance and continuous help. He has been not only my advisor but has been and will continue to be my role model.

I would like to extend my thanks to my committee members. I wish to express my warm and sincere thanks to Dr. Bistra Dilkina from the School of Computational Science and Engineering for her unwavering support and encouragement over the years. I am deeply grateful to Dr. Xinyi Song from the School of Building Construction for her constructive comments and amazing support. I warmly thank Dr. Timothy Welch from the School of City and Regional Planning for his enormous support and guidance. I would like to express my deepest appreciation to Mr. David Jared, Manager of the Office of Research at the Georgia Department of Transportation, for his invaluable and unstinting support.

I would like to include a special note of thanks from the bottom of my heart to Dr. Laura Hollengreen for helping me right when I needed it most. I would like to express my heartfelt gratitude to Dr. Laurie Garrow; I cannot thank her enough for everything she has done for me. I am also eternally grateful for everything that Dr. Kamran Paynabar has taught me. I will never forget his help.

I am extremely thankful to my friends and colleagues at Georgia Tech for all of the amazing moments and fun we had: Kia Mostaan, Masoud Gheisari, Habib Fathi, Sami

Kolahdoozan, Abbas Rashidi, Soheil Shayegh, Minsoo Baek, Jordan Sturgis, Saman Yarmohammadi, Mostafa Reisi, Ebrahim Karan, Amirabbas Pirouz, Mehdi Nourbakhsh, Samaneh Zolfagharian, John Fard, and Arya Sedehi.

Last but not least, I want to thank my parents, Mostafa and Jaleh, and my supportive sister, Shima, for their endless patience and support. Without their support and guidance, I would not be where I am today.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF SYMBOLS AND ABBREVIATIONS

AASHTO	American Association of State Highway and Transportation Officials
ACF	Autocorrelation Function
$ACPI_t$	Asphalt Cement Price Index at Time t
ADF	Augmented Dickey-Fuller
AIC	Akaike Information Criterion
ANOVA	Analysis of Variance
AR	Autoregressive
ARCH	Autoregressive Conditional Heteroscedasticity
ARIMA	Autoregressive Integrated Moving Average
BIC	Bayesian Information Criterion
CCI	Construction Cost Index
CUSUM	Cumulative Sum
D	Difference order required to remove seasonality
DOT	Department of Transportation
ES	Exponential Smoothing
ENR	Engineering News Records
FACs	Fuel Adjustment Clauses

FHWA	Federal Highway Administration
GARCH	Generalized Autoregressive Conditional Heteroscedasticity
GBAP	Georgia Base Asphalt Price
GDOT	Georgia Department of Transportation
LBAP	Local Base Asphalt Price
LCL	Lower control limit of the control chart
MA	Moving Average
MAPE	Mean Absolute Percentage Error
MAE	Mean Absolute Error
MLE	Maximum Likelihood Estimation
MSE	Mean Square Error
NAPA	National Asphalt Pavement Association
NBAP	National Base Asphalt Price
NCTSPM	National Center for Transportation Systems Productivity and Management
ODOT	Oklahoma Department of Transportation
P	Orders of seasonal autoregressive
PACs	Price Adjustment Clauses
Q	Orders of seasonal moving average
SAR	Seasonal Autoregressive

SMA	Seasonal Moving Average
VAR	Vector Autoregression
VIF	Variance Inflation Factor
UCL	Upper control limit of the control chart
α	Trend smoothing parameters
β	Mean smoothing parameters
d	Difference order
p	Order of AR
q	Order of MA
γ	Seasonal smoothing parameter

SUMMARY

The United States has more than 2.6 million miles of paved roads and highways (FHWA 2013), and 93% of this infrastructure is surfaced with asphalt. Maintenance of paved roads and highways, in addition to new projects, requires a significant amount of asphalt. Each year, more than 500 million tons of asphalt mixture are produced in the United States (NAPA 2015), and the demand is forecasted to increase 3.3% annually (Freedonia 2015). However, significant volatility and unprecedented uncertainty in the price of asphalt cement is a serious challenge for both contractors and state departments of transportation (DOTs) with regard to proper cost estimation and budgeting of transportation projects (Damnjanovic et al. 2009). Previous studies indicate that owner organizations often overpay for projects under fixed-price contracts that transfer the material price risk to contractors due to increased risk premiums and hidden contingencies in contractors' submitted bid prices. A common method widely used by state DOTs to handle the issue of extra risk premiums in submitted bid prices and to avoid overpayment to contractors is to offer price adjustment clauses (PACs) in contracts. A PAC is a risk-sharing contractual mechanism that guarantees an adjustment in payment to contractors based on the size and direction of the material price change.

Although volatility and uncertainty in the price of asphalt cement is a serious challenge for both contractors and state DOTs, there is little knowledge about how asphalt cement prices fluctuate over time. The ability to forecast asphalt cement price can result in more accurate cost estimations and budgeting. The first research objective of this thesis is to develop appropriate univariate time series models to forecast the price of asphalt cement.

In chapter 3, after identifying the characteristics of historical records of asphalt cement price index, four univariate time series forecasting models, Holt Exponential Smoothing, Holt-Winters Exponential Smoothing, Autoregressive Integrated Moving Average (ARIMA), and seasonal ARIMA, are created to forecast future values of asphalt cement price. The results indicate the future price of asphalt cement can be predicted with less than 2% error.

Second, there is little knowledge about measuring, analyzing, and forecasting asphalt cement price volatility. This gap in knowledge makes it difficult to develop material price risk management strategies properly. The second research objective of this thesis therefore is to measure, model, and forecast asphalt cement price volatility. In chapter 4, Autoregressive Conditional Heteroscedasticity (ARCH) and Generalized Autoregressive Conditional Heteroscedasticity (GARCH) time series models are created to model the conditional volatility of asphalt cement price over time. The results indicate that uncertainty in the price of asphalt cement can be modeled and forecasted with less than 3% error.

Although PAC is a very common risk management strategy to address the consequences of material price uncertainty, it is not clear how offering PACs in transportation contracts affects the submitted bid prices for major asphalt line items. The third research objective of this thesis is to examine the effect that offering of PACs has on variation in contractors' submitted bid prices for major asphalt line items in transportation projects via multivariate regression models. In chapter 5, multivariate regression models that have the power to explain variations in the submitted bid prices for major asphalt line items are used to empirically assess the impact of PACs on bid prices. No evidence was found to support the hypothesis that offering PACs would reduce submitted bid prices for major asphalt line items.

Finally, there is little knowledge about the effects of PACs on the level of competition among bidders. The fourth research objective of this dissertation is to empirically analyze the effects that offering PACs has on the competition among bidders for transportation projects. The level of competition is quantified based on the number of bidders and the dispersion of the submitted bid prices. In chapter 6, a system monitoring process is conducted to empirically examine the impact of the offering of PACs on number of bidders and the dispersion of submitted bid prices. The results show that there is no empirical evidence to indicate that offering PACs would increase the number of bidders or decrease the dispersion of the submitted bid prices for asphalt line items.

The primary contributions of this study to the existing body of knowledge are as follows: (1) creation of univariate time series forecasting models for asphalt cement price indexes, (2) creation of ARCH/GARCH models to measure and forecast the volatility of asphalt cement price index, (3) creation of multivariate regression models to explain variation in highway contractors' submitted bid prices for major asphalt line items, (4) empirical assessment of whether offering PACs contributes to variation in contractors' submitted bid prices for major asphalt line items in highway projects, and (5) empirical assessment of whether offering PACs affects the number of bidders and the dispersion of bid prices.

The primary contributions of this study to the state of practice are as follows: (1) helping contractors and state DOTs prepare more accurate cost estimates, bids, and budgets for highway construction projects; (2) helping contractors and state DOTs to analyze the uncertainty in the price of asphalt cement and to develop proper risk management strategies; (3) enhancing the understanding that capital planners of transportation agencies have of important variables affecting submitted bid prices in transportation projects and the effects that offering PACs has on bid prices; (4) helping contractors price PACs, develop their risk profiles, and determine their bid price; and (5) helping state DOTs assess the received bids more accurately.

CHAPTER 1: INTRODUCTION

The United States has more than 2.6 million miles of paved roads and highways (FHWA 2013), and 93% of this infrastructure is surfaced with asphalt. Maintenance of paved roads and highways, in addition to new projects, requires a significant amount of asphalt. Each year, more than 500 million tons of asphalt mixture is produced in the United States (NAPA 2015), and the demand is forecasted to increase 3.3% annually (Freedonia 2015).

1.1. Uncertainty in Price of Asphalt Cement

Significant volatility and unprecedented uncertainty in the price of asphalt cement is a serious challenge for both contractors and state departments of transportation (DOTs) with regard to proper cost estimation and budgeting of transportation projects (Damnjanovic et al. 2009). The volatility in the price of asphalt cement may lead to uncertainty about project cost. Cost uncertainty in turn may increase risk for contractors in fixed-price contracts and, consequently, may lead to price speculation and inflated bid prices being submitted by contractors to secure their profits against possible price increases (Damnjanovic et al. 2009). Therefore, owner organizations may face price speculation, inflated bids, very short-term price guarantees, and too few bidders for a project. Contractors may lose bids due to cost overestimation or lose profits due to cost underestimation (Ashuri and Lu 2010).

The price of crude oil and its byproducts, such as asphalt cement, have been more volatile than the price of many other commodities since the 1973 oil crisis (Fleming and Ostdiek 1999; Verleger 1994). This problem has worsened in the last decade. From 2003 through 2005, asphalt cement prices increased roughly 4% per year, but between August 2005 and August 2006, asphalt cement prices spiked by 38% (Gallagher and Riggs 2006). Figure 1-1 shows the considerable fluctuations in the average price of asphalt cement in the state of Georgia from September 1995 to July 2015.

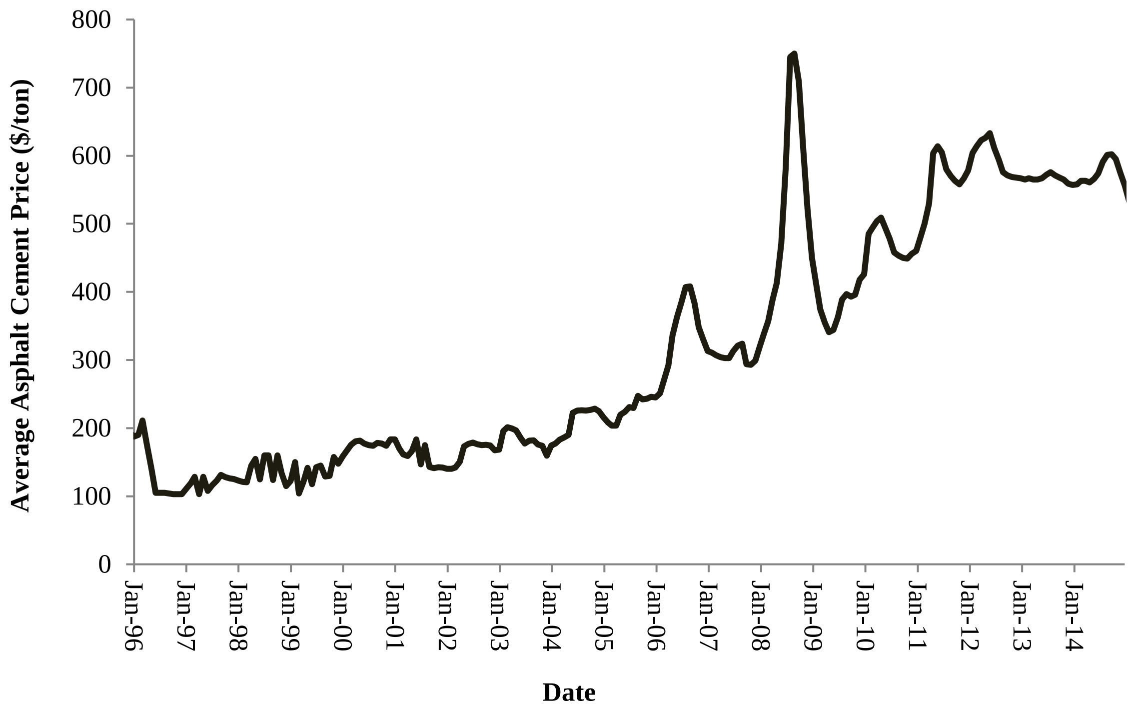

Figure 1-1: Average price of asphalt cement in the state of Georgia

1.2. Price Adjustment Clauses

Several DOTs share the concern that they often overpay for projects under fixed-price contracts, which transfer the material price risk to contractors due to increased risk premiums and hidden contingencies in contractors' submitted bid prices (Eckert and Eger 2005). For example, transportation officials in Kentucky, New Hampshire, Pennsylvania, and Washington state DOTs believed that they may have paid more money to contractors than actual added costs, due to increased material prices (Holmgren et al. 2010).

A common method that state DOTs widely use to handle the issue of extra risk premiums in submitted bid prices and to avoid overpaying contractors is to offer price adjustment clauses (PACs) in contracts. PACs are risk-sharing strategies to divide the risk of upward and downward movements of material prices between owners and contractors. In other words, a PAC is a risk-sharing contractual mechanism that guarantees an adjustment in payment to contractors based on the size and direction of the material price change. In a contract with a PAC, a state DOT accepts at least part of the risk of price escalation and pays the contractor for any increases above an agreed-upon threshold. Furthermore, if the price decreases below the threshold, the state DOT benefits from the savings. This risk-sharing strategy protects contractors against future material price escalation and encourages them to exclude extra risk premiums from their submitted bid prices. State DOTs may benefit from this shift in risk allocation through contractors' willingness to submit lower bids (Skolnik 2011). Currently, offering PACs is the most common risk-management strategy for handling the consequences of material price uncertainty. Results from a Delphi survey of transportation experts show that PACs are among the top ten programs widely used as cost reduction methods (Damnjanovic et al. 2009).

1.3. History of Price Adjustment Clauses

PACs were used for the first time in the United States during World War I to manage the rapidly increasing price of coal (Baron and De Bondt 1979). In the 1970s, electric utilities faced significant increases in the price of fuel inputs, which resulted in many utility investors having to absorb unexpected increases in fuel costs. Motivated by the concern that these costs ultimately would be borne by consumers, 43 out of 50 states either adopted or expanded existing fuel adjustment clauses (FACs) by 1974 (Golec 1990). PACs can be divided into two categories: redetermination processes, which adjust prices by a predetermined formula, and renegotiation processes, which establish prices through agreement by both parties. Redetermination processes are more frequently used compared to renegotiation process (Crocker and Masten 1991). The literature indicates that redetermination processes are more efficient and more frequently used due to the higher cost of implementing negotiated price changes (Carrol et al. 2006).

Contrary to the widespread application of adjustment clauses in the electric utility industry, the impact of this clause was controversial, and in the late 1970s and during the 1980s, poor efficiency resulting from the PAC program was a hot topic. Baron and De Bondt (1979) observed that FACs can lead to inefficiency problems related to the choice of technology and the selection of fuel supply sources because if utilities can shift all fuel cost increases to consumers, then there is no incentive to select the lowest-cost fuel supply.

Kaserman and Tepel (1982) found that FACs can lead to unnecessarily high utility company costs because of an adverse aggregate input price effect. They examined the influence of automatic FACs on the prices paid by electric utilities for aggregate fuel input. They asserted that the direct correlation between output price and aggregate fuel cost might lead to prices that are higher for aggregate fuel inputs than they would be in the absence of adjustment clauses.

Gollop and Karlson (1978) empirically analyzed the effects of the electric utility's ability to recover costs through an automatic fuel adjustment mechanism on the average cost. The authors found that the adjustment clause might lead to higher fuel costs because of inefficiency. They suggested that frequent monitoring of FAC provisions can prevent inefficient behavior while allowing utilities to recover quickly increasing input costs during times of high inflation. Later, in 1982, Isaac examined the effects of the FAC on the input choice of electric utilities and confirmed that adjustment mechanisms can lead to inefficiencies in input choices. However, these mechanisms also can help to preserve the financial integrity of electric utilities. Kendrick (1975) examined the impact of adjustments clauses on the telecommunications industry and concluded that the mechanism should consist of efficiency incentives to ensure good productivity.

Since 1974, other industries, such as building and highway construction, have gradually begun offering PAC for selected commodities to handle the problem of inflated bids (Holmgren et al 2010). In 1974, the American Association of State Highway and Transportation Officials (AASHTO) suggested implementing PACs in transportation projects (AASHTO 1974). In 2009, a survey by the AASHTO Subcommittee on Construction, Contract Administration Section showed that only 3 agencies—Arkansas, Michigan, and Texas DOTs—do not employ PACs in their contracts. Furthermore, 40 state DOTs offer the PAC for asphalt cement, and 42 state DOTs offer the PAC for fuel (AASHTO 2009).

1.4. Design of Price Adjustment Clauses

Although the primary purpose of all PAC programs across the United States is to shift the risk of material price fluctuations from contractor to state DOTs and, consequently, eliminate the possibility of risk premiums in contractors' submitted bids, different transportation agencies use various design elements in their PAC programs. The most important design elements are the type of eligible materials, calculation of the index, trigger points, the presence of opt-in or opt-out, and formulas to calculate the price adjustment. Figure 1-2 shows the distribution of the PAC programs based on the eligible materials.

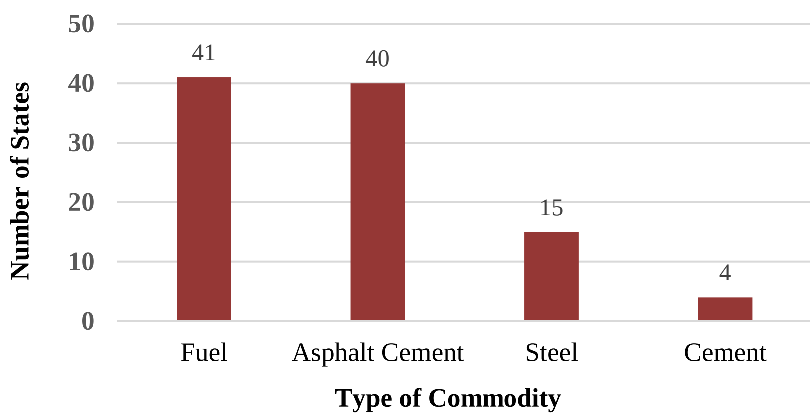

Figure 1-2: Number of states that offer PAC (Source: Skolnik 2011)

Trigger points refer to the percent changes in material prices that initiate the application of relevant adjustment clauses. The distribution of the trigger point is broad. A large group of state DOTs uses 5-7.5% as the trigger value. Skolnik (2011) surveyed the AASHTO members to develop Figure 1-3, which depicts the distribution of the trigger point for various eligible line items.

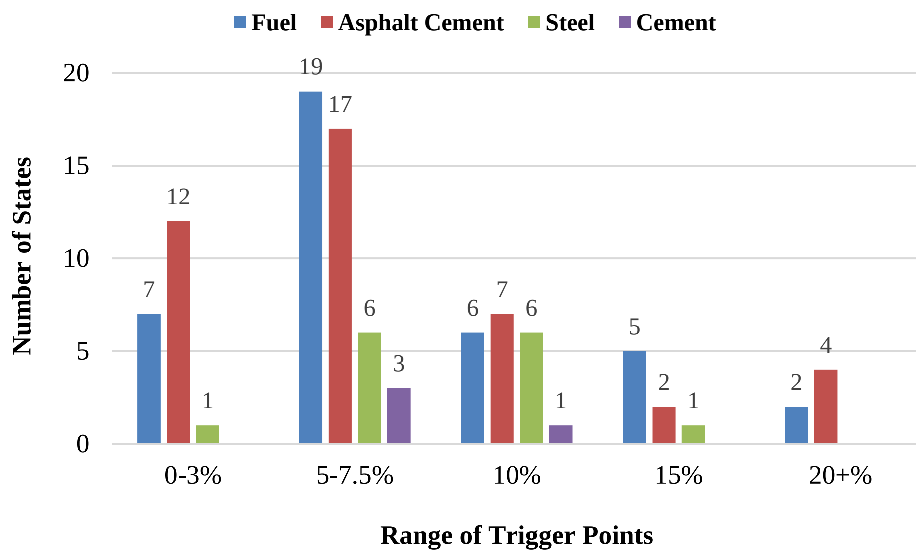

Figure 1-3: Trigger points for price adjustment (Source: Skolnik 2011)

Opt-in or opt-out indicates whether the contractor has the right to accept or decline the PAC after the contract is awarded. The results of the AASHTO members survey (2009) indicate that only a small percentage of states with PACs also have opt-in clauses, which give contractors the right to decide whether to accept the PAC. Figure 1-4 shows the number of state DOTs that has an opt-in policy.

Furthermore, some state DOTs, such as New York State, Iowa, and Montana, apply a dollar value rather than a percent as the trigger values. For example, New York State

DOT applies adjustment for fuel when the fuel price changes by at least 10 cents (Holmgren et al. 2010).

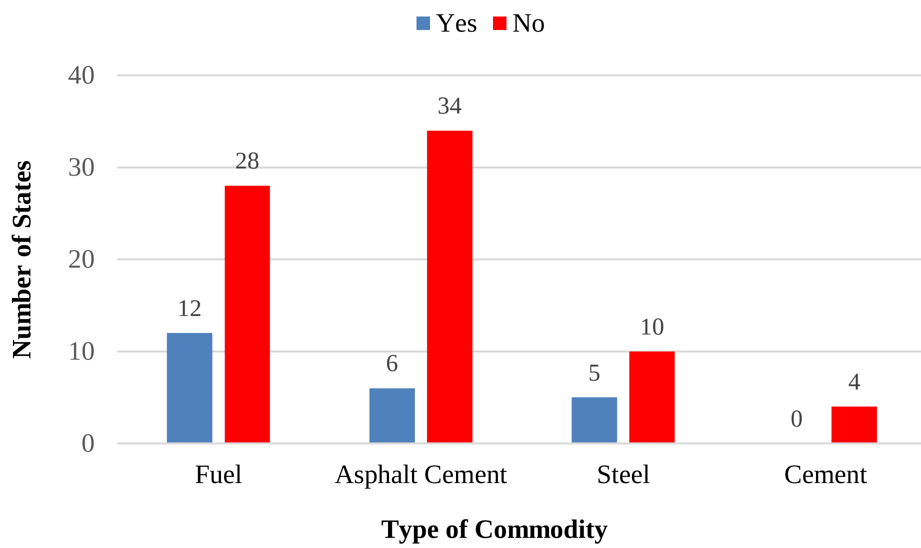

Figure 1-4: Number of states that has an opt-in policy for various line items (Source: Skolnik 2011)

Some state DOTs always offer PACs for all projects, whereas some state DOTs offer PACs under specific conditions for some projects. Figure 1-5 shows the percentages of different contract conditions for PAC exclusion in the state DOTs that offer PACs. It can be seen that just over half of state DOTs exclude projects from these clauses for specific pay items, 38% of state DOTs exclude projects based on minimum pay item quantities, 23% of state DOTs exclude projects by dollar amount, 17% of state DOTs exclude projects by project duration, and 17% of state DOTs exclude only designated projects. No state DOT was reported to exclude projects because they are funded solely at the state level. It can be concluded that projects are generally excluded from the PAC due to the type of specific pay item or because they are small in dollar amount, pay item quantity, or duration.

Specific pay items are most likely not included due to small amounts of fuel or construction inputs consumed or a lack of reliable data at the level of usage for those pay items. Moreover, based on the contract conditions for PAC exclusion, around 25% of projects in the states with the PAC are not eligible for this clause (Skolnik 2011).

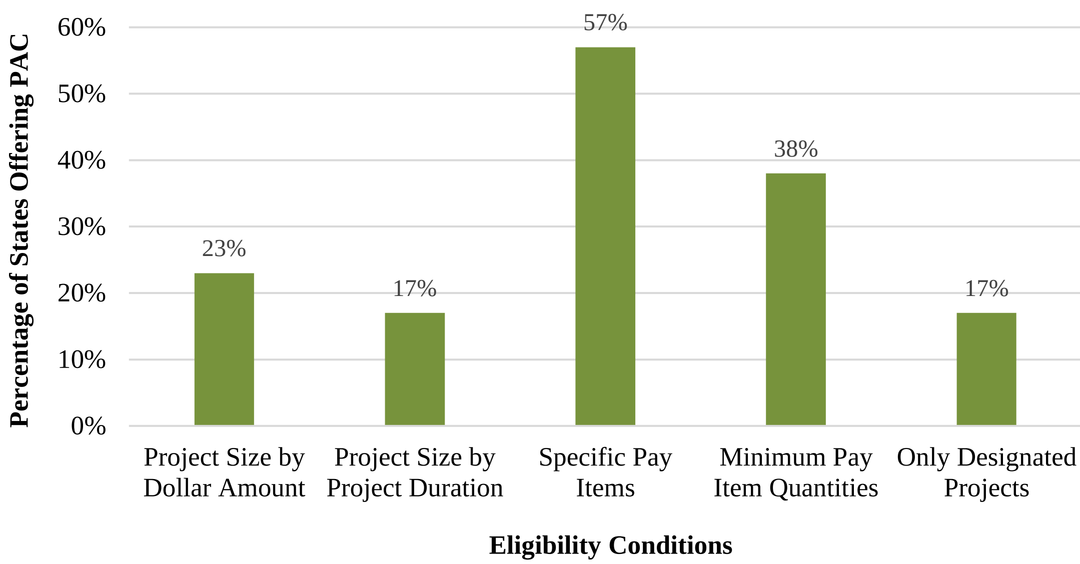

Figure 1-5: Distribution of contract conditions among state DOTs for PAC exclusion (Source: Skolnik 2011)

1.5. Price Adjustment Clause in Georgia

The Georgia Department of Transportation (GDOT) has offered PAC for asphalt cement in transportation projects since September 2005. GDOT changed the provision of PAC for asphalt cement two times, in 2009 and 2011. The main objectives of all three provisions of PAC for asphalt cement are the same; however, they are different in design elements, trigger points, and restrictions.

1.5.1. PAC Provision of 2005

GDOT first developed the PAC provision for asphalt cement on September 15, 2005. Based on this provision, if the asphalt cement price for the current month is greater than the asphalt cement price for the month in which the project was let to contract, the contractor will be paid an amount calculated in accordance with the following formula (GDOT 2016):

$$\mathrm{PA} = (\frac{\mathrm{APM} - \mathrm{APL}}{\mathrm{APL}} - 0.05)\times\mathrm{TMT}\times\mathrm{APL}$$

where:

PA = price adjustment;

APM = the monthly asphalt cement price (Georgia base asphalt price [GBAP]) for the month the hot mix asphalt/bituminous tack/bituminous surface treatment is placed;

APL = the monthly asphalt cement price (GBAP)" for the month that the project was let;

TMT = total monthly tonnage of asphalt cement computed by the engineer based on the hot mix asphaltic concrete of the various types per ton.

On the other hand, if the asphalt cement price for the current month is less than the asphalt cement price for the month in which the project was let to contract, GDOT will deduct an amount calculated in accordance with the following formula (GDOT 2016):

$$\mathrm{PA} = (\frac{\mathrm{APM} - \mathrm{APL}}{\mathrm{APL}} + 0.05)\times\mathrm{TMT}\times\mathrm{APL}$$

According to the above formulas, no price adjustment shall be made until the APM is greater than 5% above or below the APL. This 5% trigger point is one of the most important design elements of the PAC program.

Based on this provision of the PAC, the monthly asphalt cement price index is determined based on both national base asphalt price (NBAP) and local base asphalt price (LBAP). NBAP is calculated based on the arithmetic average of the previous four weeks' Posted Price Asphalt Cement for the East Coast market-GA/FL as listed in the *Asphalt Weekly Monitor*, published by Poten and Partners. However, LBAP is calculated based on the arithmetic average posted price of PG asphalt cement from GDOT's monthly survey, obtained from approved asphalt cement suppliers of bituminous materials to GDOT projects and the suppliers terminal after removing the highest and the lowest price.

The other important characteristics of the PAC are the eligibility criteria and restrictions. The restrictions of this provision are as follows:

- A price adjustment shall not be made on any hot mix asphalt placed between the letting date and 180 days after the letting date.
- Cut-back, tack-coat, and treatment projects are not eligible for price adjustment.
- There is a cap of 50% above the APL for any price adjustment.
- After the original contract time has expired, no further asphalt cement price adjustment will be made. The asphalt cement price adjustment for any hot mix asphalt placed after the original contract time expires will be computed based on the monthly asphalt cement price at the time of contract expiration or the monthly asphalt cement price at the time the contract was let, whichever is less.

1.5.2. PAC Provision of 2009

GDOT established a new provision for price adjustment on August 21, 2009. The most important differences between the second version and the first are the cap on the price adjustment and the eligibility criteria for the projects. In the second version, GDOT increased the cap from 50% to 125%. Thus, after August 21, 2009, any volatility of the asphalt cement price index, from 5% to 125%, is covered by the PAC program. Furthermore, according to the second version, no price adjustment will be made on any project with fewer than 366 calendar days between the contract letting date and the specified completion date. The duration between the original completion date and the letting date was not a criterion for eligibility under the 2005 version of the PAC program. However, for all eligible projects based on the provision of 2005, a price adjustment was not made between the letting date and 180 days after the letting date.

1.5.3. PAC Provision of 2011

Two years after the 2009 provision, on August 19, 2011, GDOT revised the PAC program and established the third provision. The 5% trigger point was canceled in the third version. Thus, the price adjustment is determined as follows (GDOT 2016):

$$\mathrm{PA} = \left(\frac{\mathrm{APM} - \mathrm{APL}}{\mathrm{APL}}\right) \times \mathrm{TMT} \times \mathrm{APL}$$

Another change in the third version compared to the second is the reduction of the cap from 125% to 60%. Furthermore, the calculation of the asphalt cement price index is only based on the GBAP, which is determined based on the arithmetic average of posted prices of PG asphalt cement from GDOT’s monthly survey, obtained from approved asphalt cement suppliers of bituminous materials to GDOT projects and the suppliers terminal.

1.6. Potential Benefits of Price Adjustment Clauses

Owner organizations may benefit from a PAC in two main ways. First, offering PACs encourages contractors to exclude extra risk premiums from their bid prices and consequently submit lower bid prices. Second, offering PACs can potentially boost competition among bidders and result in a higher number of bidders and less dispersion in the bid prices received for a project. Skolnik (2011) conducted a survey of 50 state DOTs and 400 highway construction contractors to identify the possible benefits and beneficiaries of and barriers to the successful implementation of the PAC. The results indicate that the most important benefits of the PAC from the viewpoint of state DOTs are:

- Better bid prices (78% of respondents noted this benefit)
- Contractor stability (56% of respondents noted this benefit)
- Increased number of bidders (24% of respondents noted this benefit)
- Fewer bid retractions (2% of respondents noted this benefit)

In addition, a percentage of state DOT respondents reported perceived benefits of offering the PAC for various commodities:

- Fuel (60%)
- Liquid asphalt (63%)
- Cement (most state DOTs do not offer the PAC for cement; of the 10% that do, half perceived significant benefits)

- Steel (a large number of state DOTs do not offer the PAC for steel; of the 39% that do, 13% perceived significant benefits)

Moreover, a percentage of state DOT respondents reported perceived benefits of offering the PAC for various industry stakeholders:

- Prime contractors (81%)
- Subcontractors (70%)
- State DOTs (61%)
- Suppliers (60%)
- Others (2% of the respondents perceived a significant benefit for taxpayers)

On the other hand, a percentage of contractor respondents reported perceived benefits of offering the PAC for various commodities:

- Liquid asphalt (91%)
- Fuel (72%)
- Steel (72%)
- Cement (58%)

Furthermore, a percentage of contractor respondents reported perceived benefits of offering the PAC for various industry stakeholders:

- State DOTs (82%)
- Prime contractors (83%)
- Subcontractors (84%)

- Suppliers (78%)

Identification of the most important barriers to successful implementation of the PAC is critical. The results of the survey by Skolnik (2011) indicate that the most important barriers to successfully implementing the PAC from the viewpoint of state DOTs are

- Administrative cost
- Contractor resistance
- Process of creating the policy
- Updated fuel usage factors
- Costs of the programs do not justify the benefits

However, the barriers most cited by contractors are

- Timing on invoices versus the index payment calculations—this problem involves a discrepancy between the date the materials are purchased and the index date used by state DOTs
- A high trigger value for index payments
- Incorrect index values, either due to outdated indexes or incorrect calculations

Eckert and Eger (2005) gave a list of possible barriers to successful implementation of the PAC:

- Contracts must have set-aside contingency funding to be able to address indexed adjustments. These funds, whether used or not, are tied to a contract (i.e., are not available for other work) until the contract is closed.

- Risk management is not well understood by most, and therefore the long-run benefits may not be understood.
- Suppliers could be artificially raising prices, which will affect the index without the state DOT’s knowledge.
- It is extremely difficult to track payments under the index process over the years. Adjustments increase the complexity of the tracking process.
- It is difficult to ensure that the prices quoted by suppliers for the index are true monthly prices for liquid asphalt concrete.

CHAPTER 2: PROBLEM STATEMENT AND RESEARCH OBJECTIVES

2.1. Motivation and Gaps in Knowledge

Although uncertainty in the price of asphalt cement is a serious challenge for both contractors and state DOTs and many transportation agencies use PACs to control the consequences of material price volatility, there is little knowledge about analyzing uncertainties in the price of asphalt cement and the actual performance of PACs. These gaps in the current state of knowledge may result in significant financial risks and inefficient investments in risk management strategies.

2.1.1. Gap in Knowledge 1: Modeling and Forecasting Fluctuations in the Price of Asphalt Cement

Although fluctuations in the price of asphalt cement are a critical source of risk in highway construction projects with regard to cost estimations and budgeting, there is little knowledge about how asphalt cement price fluctuates over time. The ability to forecast asphalt cement price could result in more accurate cost estimations and budgeting.

In the current state of practice, a simple escalation approach is typically used to take into account the rise in asphalt cement price. For example, cost estimators inflate the estimated cost of materials to the expected midpoint of the construction date to capture possible changes in the future prices of materials in their estimates (Anderson et al. 2006). Another approach often used by cost estimators is to add a fixed percentage of the total estimated cost as the risk premium to cover possible escalation in material prices, including the price of asphalt cement (Laryea and Hughes 2009). These simple methods do not take into account the fact that the price of asphalt cement is subject to significant variations, even over a short period of time. These approaches are limited in characterizing the variations of asphalt cement price over time and, hence, are problematic for distributing the project budget over the project duration (Walls and Smith 1998).

Currently, a more advanced approach to modeling variations in material prices over time is the Monte Carlo simulation. Considering the uncertainty about the rate of escalation for the price of asphalt cement, a probabilistic approach based on Monte Carlo simulation has been used to quantify the range and the likelihood of the project cost (Back et al. 2000). Monte Carlo simulation has been used to draw random values for the escalation rate of material price in order to characterize uncertainty about total project cost. An approach based on Monte Carlo simulation can be used to characterize uncertainty about future prices of asphalt cement, but the major limitation of this approach is that Monte Carlo simulation does not address the effects of autocorrelation in historical prices of asphalt cement (note that autocorrelation represents the relationship between a time series variable and itself over various time intervals). At any point in time, a Monte Carlo simulation randomly generates an escalation rate independent of the previous rates (Ibbotson 2005)—for example, the randomly generated escalation rate of asphalt cement price could be –10% in one period and +60% in the next. In this study, we show that actual historical records of asphalt cement price are autocorrelated time series data. Variations in the escalation rate of asphalt cement price are not completely random. Past values of asphalt cement are statistically significant in determining its current and future values. Using historical records of asphalt cement prices to develop proper forecasting models is a motivation for the third chapter of this dissertation.

2.1.2. Gap in Knowledge 2: Quantifying and Forecasting Uncertainties in the Price of Asphalt Cement

Transportation agencies apply various risk management strategies, such as offering PACs, to control the consequences of material price uncertainty. Before using any risk management strategy, it is necessary to measure, analyze, and forecast material price uncertainty and ensure that the strategy is employed at the proper time. This issue is more critical for asphalt cement because the level of volatility and uncertainty in its price is not constant over time and may change significantly even over a short period of time. Transportation agencies need to constantly track the level of uncertainty in the price of asphalt cement to keep decisions about implementing their risk management strategies current. However, there is little knowledge about measuring, analyzing, and forecasting uncertainty in the price of asphalt cement. Typically, cost estimators and risk managers consider the uncertainty in the price of materials such as asphalt cement solely based on their fluctuations (Gallagher and Riggs 2006). However, fluctuations do not necessarily indicate uncertainty: A variable might be fluctuating but predictable. Therefore, the uncertainty of a variable such as the price of asphalt cement should be defined based on its unpredictability, which is a latent variable and is not directly observable (Engle and Patton 2001). This gap in knowledge makes it difficult for transportation agencies to recognize the proper time to implement their risk management strategies and adequately control the consequences of volatility in the price of asphalt cement. Quantifying and forecasting uncertainties in the price of asphalt cement is a motivation for the fourth chapter of this dissertation.

2.1.3. Gap in Knowledge 3: Empirically Analyzing Effects of PACs on Submitted Bid Prices

State DOTs may benefit from PACs through contractors' willingness to submit lower bids (Skolnik 2011). Most state DOTs in the United States have employed PACs in their transportation contracts. In 2009, a survey done by the AASHTO Subcommittee on Construction, Contract Administration Section, indicates that 40 state DOTs offer PACs for asphalt cement. The results from a Delphi study of transportation experts show that PAC is among the top ten program-wide cost reduction methods (Damnjanovic et al. 2009). However, most of the findings of previous studies of PACs derived from surveys of state DOT officials and other transportation experts and the actual impacts that offering PACs has on bid prices are not clear. For example, a survey of 50 state DOT officials and 400 highway contractors conducted by Skolnik (2011) revealed that 78% of state DOTs perceived reduced bid prices as one of the most important benefits of offering PAC. Additionally, nearly all responding contractors mentioned that they would add contingencies to their bids in the absence of PACs. In other words, most survey respondents perceived reduction in bid prices as one of the most significant benefits of offering PAC in transportation contracts. However, none of the respondents to Skolnik's survey provided any empirical evidence to support their perception.

In another study conducted by Eckert and Eger (2005), several state DOT officials were surveyed about the risk of asphalt price volatility and their current price adjustments. The authors recognized a concern shared by several state DOT officials that state DOTs often overpay for projects under fixed-price contracts that transfer the asphalt price risk to contractors. Interviewees argued that highway contractors add hidden contingencies to their submitted bid prices if the asphalt price risk is transferred to them in highway projects. However, no empirical evidence was provided by the interviewees, and no comparison was made between contractors' submitted bid prices in projects with PACs and those without PACs.

In a similar study of fuel PACs, Holmgren et al. (2010) surveyed DOT officials from all fifty states. Thirty-eight state DOT officials believed that PACs can share the risks of price volatility appropriately and that their fuel price adjustments are fair. However, they did not provide any empirical evidence to justify their beliefs.

A review of the literature revealed a gap in the current state of knowledge in empirical assessment of PACs. Furthermore, the considerable financial burden PACs impose on state DOTs (e.g., GDOT's net payment to contractors as a PAC only for asphalt cement exceeded 69 million dollars between 2007 and 2012) emphasizes the importance of analyzing the actual effects that offering PACs has on submitted bid prices.

2.1.4. Gap in Knowledge 4: Empirically Analyzing Effects of PACs on Competition

In addition to excluding extra risk premiums from submitted bid prices, transportation agencies may benefit from PACs through increased competition among bidders. Offering PACs may boost competition among bidders and result in a greater number of bidders and less dispersion in the bid prices received for a project. Lack of competition would harm economic efficiency (Cheung and Shen 2016). Theoretically, offering PACs in contracts can stabilize the construction market and support all contractors regardless of their size and access to sources of critical materials such as asphalt cement.

Therefore, offering PACs in construction contracts may encourage greater competition and result in more bidders and less dispersion in the bid prices received for a project. Most findings from previous studies of PACs, derived from surveys of state DOT officials and other transportation experts, are not clear when assessing the actual impact of offering PACs. For example, a survey of 50 state DOT officials and 400 highway contractors conducted by Skolnik (2011) revealed that 61% of the respondents believed that PACs offer significant benefits for DOTs and lead to contractor stability and a greater number of bidders. However, none of the respondents to Skolnik's survey provided any empirical evidence to support their perception. In another study conducted by Eckert and Eger (2005), several state DOT officials were surveyed about the risk of asphalt price volatility and their current price adjustments. Most of the officials believed that offering PACs establishes parity between bidders and increases competition. However, no empirical evidence was provided by the interviewees. In a similar study of fuel PACs, Holmgren et al. (2010) surveyed officials from the DOTs of all fifty states; thirty-eight state DOT officials believed that PACs can allocate the risks of price volatility appropriately and that their fuel price adjustments are fair. However, they did not provide any empirical evidence to justify their beliefs. The actual impact of PACs on competition has not been analyzed, and a review of the literature indicates a gap in the current state of knowledge in empirical assessment of PACs.

2.2. Research Objectives

Due to the aforementioned gaps in the current state of knowledge, this dissertation aims to analyze uncertainty in the price of asphalt cement and examine the performance of

PACs in highway construction projects. This overall research objective is broken down into four sub-objectives.

2.2.1. Research Objective I: Modeling and Forecasting Asphalt Cement Price

Due to the first gap in knowledge, the first research objective of this study is to identify and characterize variations observed in the actual price of asphalt cement over time. This knowledge then will be used to create time series forecasting models for asphalt cement price and examine whether and how time series forecasting models can predict the future price of asphalt cement with greater accuracy than the existing approaches.

The results of this part of the study help both state DOTs and contractors improve their cost estimations, prepare more accurate budgets, and consequently reduce the risk of asphalt cement price volatility in highway construction projects.

2.2.2. Research Objective II: Quantifying and Forecasting Uncertainty in Asphalt Cement Price

Due to the second gap in knowledge, the second research objective of this study is to measure, model, and forecast asphalt cement price uncertainty. The results of this part of the study can help contractors and state DOTs measure and forecast volatility in the price of asphalt cement and subsequently develop more proper risk management strategies to address the risk of material price uncertainty in highway construction projects.

2.2.3. Research Objective III: Examining Effects of PACs on Bid Prices

Due to the third identified gap in the current state of knowledge, the third research objective of this dissertation is to empirically examine the effect that offering PACs has on variation in submitted bid prices for major asphalt line items in transportation projects and to check whether PACs successfully exclude extra risk premiums. The outcomes of this objective enhance transport agencies' understanding of the actual effects of offering PACs in reducing bid prices.

2.2.4. Research Objective IV: Examining Effects of PACs on Competition

Due to the fourth gap in knowledge, the fourth research objective of this study is to empirically analyze the effects that offering PACs has on competition among bidders for transportation projects. This can help capital planners and transportation agencies systematically evaluate the actual effects that offering PACs has on competition among bidders.

2.3. Research Methodology

This dissertation aims to address the four presented research objectives in four separate sections. The research methodology for each research objective is presented in this section briefly and will be discussed in full detail in the corresponding chapters.

To address the first research objective, modeling and forecasting of fluctuations in asphalt cement price, a univariate time series analysis is conducted. First, historical records of asphalt cement price are collected. Second, variations in asphalt cement price over time are identified and characterized. Then, based on the identified time series characteristics, univariate time series forecasting models, such as Holt Exponential Smoothing (ES), Holt-Winters ES, autoregressive integrated moving average (ARIMA), and seasonal ARIMA, are created to take into account the short-term variation in asphalt cement price in forecasting its future values. Next, diagnostics tests including residual analysis are conducted to validate the applicability of the models. Finally, out-of-sample forecasting is performed to measure the predictability of the developed forecasting models.

The second research objective, quantifying and forecasting uncertainties in the price of asphalt cement, is addressed using autoregressive conditional heteroscedasticity (ARCH) and generalized autoregressive conditional heteroscedasticity (GARCH) time series volatility models. In the first step, the univariate time series models developed for the first research objective are fitted to the time series of asphalt cement price to capture the conditional mean of asphalt cement price over time. Next, the residuals of the model are examined using a heteroscedasticity test to check if the volatility in the price of asphalt cement is statistically significant. If heteroscedasticity exists, ARCH/GARCH models are created, and the conditional volatility of asphalt cement price is measured and modeled over time. The conditional volatility models then are validated and their predictability is evaluated.

Contractors' submitted bid data from 841 highway projects awarded in the state of Georgia were collected and used to investigate the third research objective, empirical assessment of the effects of PACs on submitted bid prices. A literature review and interviews with transportation cost professionals are conducted to identify a potential list of explanatory variables for modeling the variation in contractors' submitted bid prices. The dataset and identified potential explanatory variables, including a binary variable for the availability of PAC for a project, are used to create multivariate linear regression models to explain variations in submitted bid prices for major asphalt line items in transportation projects. Diagnostic tests such as analysis of variance (ANOVA) and residual analysis are conducted to check the validity of the models. Finally, the binary variable showing the availability of PAC for a project is checked for statistical significance in the models.

To address the fourth research objective, empirical assessment of the effect of PACs on competition among bidders, historical records of the average number of bidders and dispersion of submitted bid prices are monitored over time using system monitoring processes to check whether their variations statistically changed after the introduction of the PAC program. To analyze the effects of PACs on the number of bidders, two variables are investigated: 1) the average number of bidders per project; and 2) the number of unique contractors divided by the number of projects for each month. The cumulative sum (CUSUM) system monitoring method combined with time series analysis is used to check whether these two variables statistically changed after the introduction of the PAC program. Furthermore, a standard deviation control chart with variable sample size is used to check whether the dispersion of the submitted bid prices changed after PACs were offered.

Figure 2-1 shows the overall research methodology used to achieve the research objectives in this dissertation.

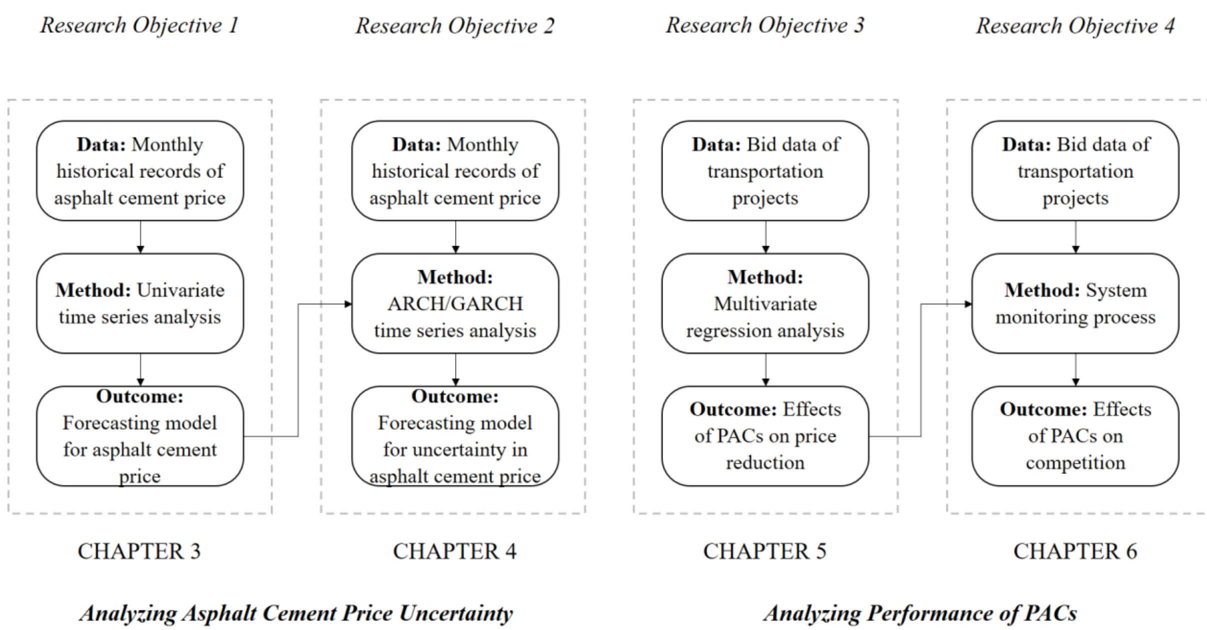

Figure 2-1: Overall research methodology

2.4. Dissertation Organization

To achieve these research objectives, the remainder of this dissertation is structured as follows. Chapter three addresses the first objective. Historical records of asphalt cement price are analyzed and characterized to develop univariate time series forecasting models to predict the future price of asphalt cement.

The second research objective of this dissertation is addressed in the fourth chapter. Volatility and level of uncertainty in the price of asphalt cement is measured, modeled, and predicted using ARCH and GARCH time series models.

Empirical analysis of the impact that offering PACs has on submitted bid prices is presented in chapter five. Multivariate regression analysis was used to explain variations in submitted bid prices for major asphalt line items in transportation projects and to identify statistically significant explanatory variables (including the availability of PACs) that affect submitted bid prices.

Chapter six presents the empirical analysis, using system monitoring processes, of the effects that offering PACs has on the level of competition. Finally, chapter seven concludes the research work presented in this dissertation and suggests possible future work and extensions of the proposed analysis.

CHAPTER 3: MODELING AND FORECASTING ASPHALT CEMENT PRICE

3.1. Introduction

The ability to properly forecast asphalt cement price results in more accurate cost estimations and a decreased level of uncertainty and financial risks. This study departs from the existing body of knowledge and challenges the lack of proper treatment of short-term variations in predicting asphalt cement price. The price of asphalt cement over time is autocorrelated time series data that can be analyzed, and its major characteristics can be identified for use in forecasting its future values. The research objectives of this chapter are to (a) identify and characterize the variations observed in the actual price of asphalt cement over time; and (b) use this knowledge to create time series forecasting models for asphalt cement price and check if time series forecasting models can predict future values of asphalt cement more accurately than existing approaches. To achieve these research objectives, the remainder of this chapter is structured as follows. After a brief literature review of forecasting models, the proposed research approach and steps conducted in this study are described. Then the time series dataset of the asphalt cement price index is introduced, and its major characteristics (i.e., autocorrelation, stationarity, and seasonality) are investigated. Based on the identified characteristics, four univariate time series forecasting models, Holt ES, Holt-Winters ES, ARIMA, and seasonal ARIMA, are created to take into account the short-term variations in asphalt cement price when forecasting its future values. Diagnostic tests, such as goodness of fit and residual analysis, are conducted to measure the accuracy and verify that the underlying conditions hold true for each developed model. The predictability of each time series model is evaluated and compared to previously existing methods using an out-of-sample forecasting process. Finally, conclusions and future work are presented.

3.2. Forecasting Models

Forecasting models can be classified into the two categories of causal models and time series models (Taylor and Bowen 1987). Casual models, such as linear regression models, forecast a variable using independent explanatory variables. These models are widely applied in the construction area. For example, Persad et al. (1995) used regression models to forecast engineering manpower requirements for highway preconstruction activities. Christian and Pandeya (1997) predicted the operation and maintenance costs of facilities using regression models. Lowe et al. (2006) developed linear regression models to predict the construction cost of buildings in the United Kingdom; they considered forty-one potential explanatory variables to predict the cost. Sonmez et al. (2007) used regression analysis to develop a model to predict cost contingency in international projects using fourteen potential independent factors. Abu Hammad et al. (2010) created a probabilistic regression model to predict the cost of public building projects using several explanatory factors, such as project area and project duration. Heravi and Ilbeigi (2012) developed a multivariate model to quantify and forecast project success using eleven explanatory variables. Behmardi et al. (2013) developed and compared the performance of a linear mixture model and a Bayesian model to predict the cost of bridge replacement in Oregon using the structural characteristics of the bridges. Ilbeigi et al. (2015a) identified and considered fifteen potential explanatory variables to model and forecast variations in submitted bid prices for pavement line items in highway construction projects.

Contrary to the widespread application of causal models, in some cases, it may be very difficult to identify, quantify, and predict the explanatory variables, especially when the model requires economic-related explanatory variables (Ashuri and Lu 2010). Because asphalt cement is a petroleum product, too many factors related to different areas, such as market conditions, social and political issues, technology, and economic growth, may affect its price. Accurately identifying, quantifying, and predicting future values of all explanatory variables to model and forecast the future price of asphalt cement may not be a feasible solution in the real world. In this situation, univariate time series forecasting models are a powerful alternative to causal models.

Univariate time series models determine the future values of a variable based only on its previous records and observations. A time series forecasting model identifies meaningful characteristics in the history of the variable and predicts future values based on those characteristics and prior observations. A univariate time series forecasting model only requires one input for creating and calibrating the model, an important feature that has resulted in widespread application of these models. For example, Hwang and Liu (2009) used time series forecasting models to predict short-term productivity in construction operations. Ashuri and Lu (2010) created univariate time series forecasting models to predict the Engineering News Records (ENR) Construction Cost Index (CCI). Xu and Moon (2011) used a cointegrated vector autoregression (VAR) time series model to forecast the trend of the construction cost index. Shahandashti and Ashuri (2015) forecasted the highway construction cost index using vector error correction time series models.

Considering the significant capabilities of time series forecasting models to predict the future values of a variable based only on its historical records, in this study, univariate time series forecasting models are used to model the variations in asphalt cement price over time and predict its future values.

3.3. Research Methodology

The historical prices of asphalt cement are time series in nature. Time series are subject to specific properties, such as autocorrelation, stationarity, and seasonality. Statistical time series methods are used to identify and characterize the main properties of historical asphalt cement prices. After identifying the main characteristics of the asphalt cement time series data, in-sample model fitting is conducted to create four time series models for predicting asphalt cement price. Residual analysis tests are conducted to verify whether the underlying conditions of the created time series models hold true. Goodness-of-fit tests are performed to determine the applicability of the created time series models for forecasting asphalt cement price. Finally, out-of-sample forecasting is conducted to evaluate the predictability of the developed models compared to the previously existing models. Figure 3-1 shows the process of time series analysis, model development, and predictability evaluation.

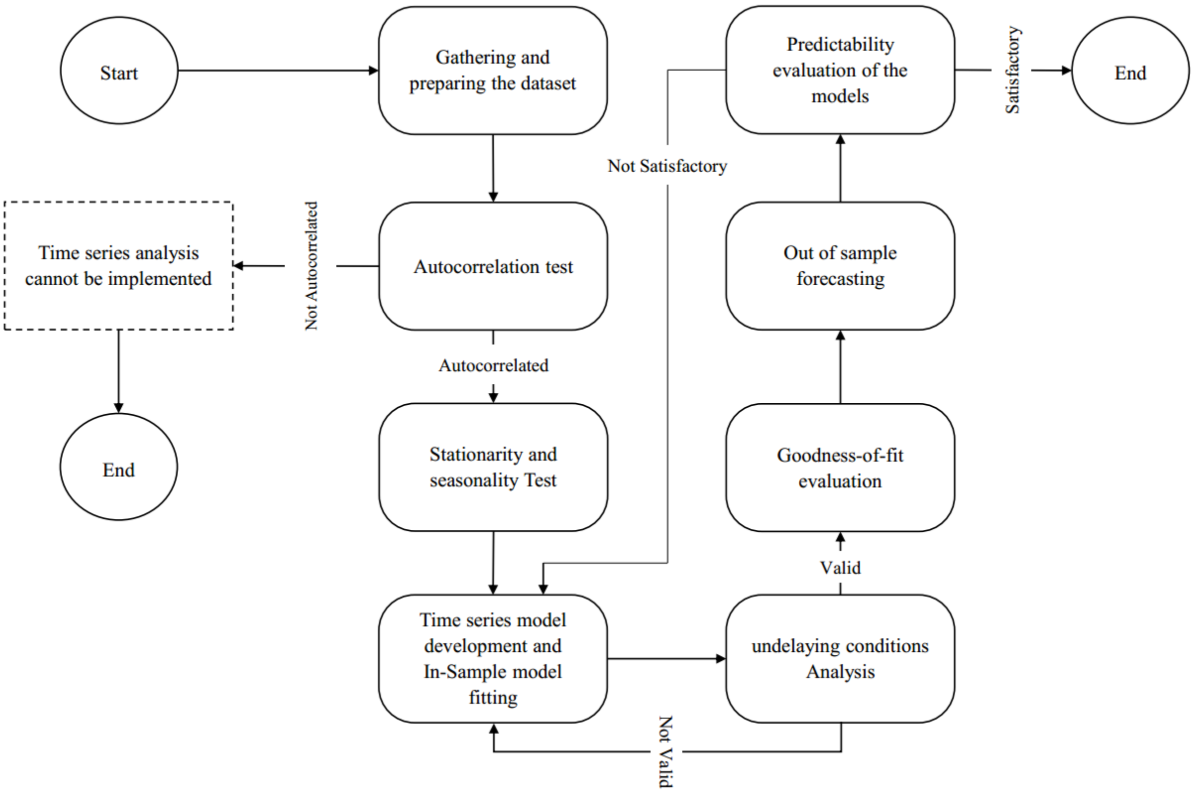

Figure 3-1: Process of time series analysis, model development, and predictability evaluation

3.4. Dataset

In this study, the monthly asphalt cement price index in the state of Georgia is analyzed and used to develop the forecasting model. GDOT determines the asphalt cement price index based on the average price of asphalt cement from the department’s monthly survey of approved asphalt cement suppliers. The maximum and minimum prices are excluded from the calculation of the index. The dataset consists of 228 observations of the asphalt cement price index in Georgia from January 1996 to December 2014 (Figure 1-1). Observations from January 1996 to December 2013 are considered for in-sample model fitting and parameter estimation. The last twelve observations (i.e., from January 2014 to December 2014) are used for out-of-sample forecasting and predictability evaluation.

3.5. Time Series Analysis

The results of the Ljung-Box Q test (Ljung and Box 1978) (

Table 3-1) specify that the time series of the asphalt cement price index is autocorrelated (i.e., the correlations between the values of the series at different time lags are statistically significant), indicating that variations in the asphalt cement price index are not random and depend on the index's past values. Therefore, use of time series analysis to explain variations in the asphalt cement price index is meaningful, and time series forecasting models for the asphalt cement price index can be created.

One of the most important characteristics of a time series is stationarity. Although the graph of the asphalt cement price index (Figure 1-1) shows an upward trend, indicating the potential for a non-stationary time series, an Augmented Dickey-Fuller (ADF) (Fuller 1976) test is conducted to investigate the non-stationary property of the price index more rigorously. The resulting ADF test statistic is *–0.1424* with a p-value of *0.63,* indicating that the null hypothesis that the time series of asphalt cement price index is non-stationary cannot be rejected.

Another important characteristic of a time series is seasonality. Figure 3-2 shows the box plot of the monthly asphalt cement price index. The plot does not show a very strong difference between the average asphalt cement price index for each month.

Table 3-1: Results of the Ljung-Box Q test

Lag	Autocorrelation	Q-Statistic	P-Value
1	0.985	219.20	0.000
2	0.961	428.97	0.000
3	0.933	627.60	0.000
4	0.904	814.67	0.000
5	0.876	991.32	0.000
6	0.852	1159.3	0.000
7	0.831	1319.8	0.000
8	0.814	1474.5	0.000
9	0.802	1625.1	0.000
10	0.791	1772.6	0.000
11	0.784	1917.9	0.000
12	0.776	2061.2	0.000
13	0.768	2202.2	0.000
14	0.760	2341.0	0.000
15	0.753	2477.8	0.000
16	0.746	2612.7	0.000
17	0.740	2746.2	0.000
18	0.734	2878.2	0.000
19	0.727	3008.2	0.000
20	0.719	3136.2	0.000

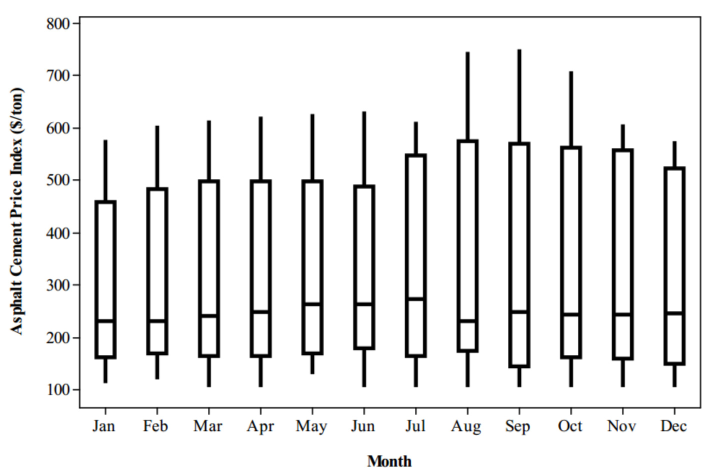

Figure 3-2: Box plot of monthly asphalt cement price index

Furthermore, Figure 3-3 (a) and (b) show autocorrelation function (ACF) plots of the original time series of the asphalt cement price index and the ACF of the time series after removing the trend. The ACF plots do not display any apparent cyclical behaviors.

Thus, no seasonal pattern in the asphalt cement price index is evident. However, during the creation of the models, we will check whether considering seasonal factors improves the forecasting models.

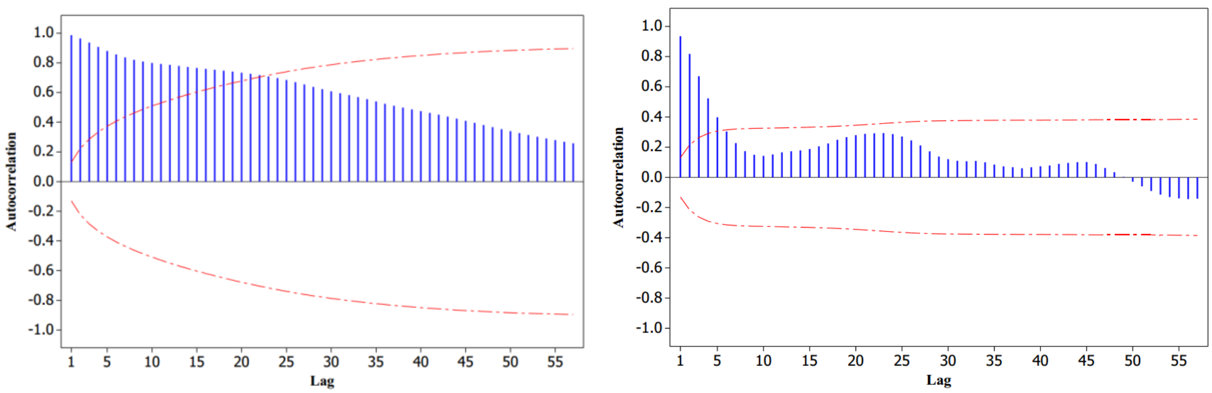

Figure 3-3: (a) ACF plot of the original time series of asphalt cement price index; (b) ACF plot of the time series after removing the trend

3.5.1. In-Sample Model Fitting

Considering the identified characteristics, Holt ES, Holt-Winters ES, ARIMA, and seasonal ARIMA models are applied to the asphalt cement price index. After estimating the parameters and fitting the models, mean absolute percentage error (MAPE), mean square error (MSE), and mean absolute error (MAE) are used to measure and compare the goodness-of-fit of the models.

3.5.1.1. Holt ES

Holt ES is designed for modeling non-stationary time series (Holt 2004). The Holt ES model consists of two parameters: mean smoothing parameters (α) and trend smoothing parameters (β). Parameter α estimates the monthly mean of the variable, and parameter β

estimates the monthly trend factor or growth rate of the variable (Gardner 1985). These parameters are estimated using a recursive approach to minimize the sum of squared errors. The optimal value of α and β are estimated at *1* and *0.64*, respectively. The sum of squared errors is *124245.6*. The three error measures of the Holt ES model are calculated as follows: *MAPE=5.68%*, *MSE=557.88*, and *MAE=14.11*.

3.5.1.2. Holt-Winters ES

Winters (1960) developed the Holt-Winters ES model based on the Holt ES method. The Holt-Winters ES model is recommended for time series data that display trend and seasonality. Holt-Winters ES has a seasonal smoothing parameter (γ) in addition to mean and trend smoothing parameters (i.e., α and β). Although there is no strong evidence for seasonality in the time series of the asphalt cement price index, the Holt-Winters ES method is applied to check whether including the seasonality parameter could improve the model. Similar to the Holt ES model, the parameters are estimated using a recursive approach. The optimal values of the parameters are $\alpha=0.9515$, $\beta=0.00457$, and $\gamma=1$. The sum of squared errors is *151074.9*, which is considerably larger than the sum of squared errors with the Holt ES model. The three error measures to check the goodness-of-fit for the Holt-Winters ES are as follows: *MAPE=6.44%*, *MSE=736.95*, and *MAE=16.70*. All of the error measures are larger than those of the Holt ES model.

3.5.1.3. ARIMA

ARIMA models are designed based on the combination of autoregressive (AR) and moving average (MA). An ARIMA model consists of three parameters: p, q, and d. Parameters p and q are integers that describe the order of AR and MA in the model. Parameter d represents the difference order required to transform the original dataset to a stationary time series. Because the original time series of the asphalt cement price index is non-stationary, the first step to create the ARIMA model is to transfer the original dataset to a stationary time series. In this manner, the differencing operator of order one can be applied to the original dataset. However, some useful information and some data points might be lost during the differencing process (Diebold 1998). A better alternative to differencing is to include the trend variable in the model. The trend is captured using an integer variable that starts at one for the first month and increases incrementally by one unit afterward. The ADF test is conducted to check if capturing the trend makes the series stationary. The t-statistic of the ADF test after capturing the trend is *–4.685167* with a p-value of *0.0010,* indicating that the null hypothesis of the index being non-stationary is strongly rejected; the series is stationary if the trend is included in the model. Furthermore, to capture any possible seasonal pattern, twelve dummy variables representing each month are added into the model. Thus, the equation of the ARIMA model for the time series of the asphalt cement price index is as follows:

$$ARIMA(p,d,q) = c + \alpha(trend) + \sum_{i=1}^{p} \varphi_i AR(i) + \sum_{j=1}^{q} \theta_j MA(j) + \sum_{k=1}^{12} \beta_k M_k$$

Where:

p is the order of the AR operator

q is the order of the MA operator

d is the differencing order, which is equal to 0 in our case

c is the intercept

α is the coefficient of the trend

φ_i is the coefficient of the i^{th} AR operator

θ_j is the coefficient of the j^{th} MA operator

M_k is a dummy variable that is 1 if the observation belongs to month k and 0 otherwise

β_k is the coefficient of the binary variable of month k

The optimal values of p and q are determined based on the Akaike information criterion (AIC) (Akaike 1998) and the Bayesian information criterion (BIC) (Schwarz 1978). To select the proper model, different models with various combinations of p and q were studied. The coefficients of the model are determined using maximum likelihood estimation (MLE). The results indicate that the *ARIMA(2,0,2)* produces the lowest AIC and BIC, equal to *8.81* and *8.91*, respectively. In this study, the significance level is considered equal to *5%*. Because the p-values of the intercept, *MA(1)*, and all monthly binary variables except the variables for May and August are considerably higher than the significance level, they are not statistically significant and can be removed from the model. Table 3-2 shows the results of the model.

Table 3-2: Results of the ARIMA(2,0,2) model

Variable	Coefficient	t-Statistic	P-Value
Trend	2.6928	22.4296	0.0000
AR(1)	1.3799	22.8986	0.0000
AR(2)	–0.4840	–8.1334	0.0000
MA(2)	0.2060	2936.12	0.0000
M_5	5.8911	2.2167	0.0277
M_8	5.5038	2.0729	0.0394

The final equation of the ARIMA model can be represented as follows:

$$\widehat{ACPI}_t = 2.6928 \times Trend + 1.3799 \times AR(1) - 0.4840 \times AR(2) + 0.2060 \times MA(2) + 5.8911 \times M_5 + 5.5038 \times M_8$$

The three error measures of the ARIMA model are *MAPE=5.96%*, *MSE=373.71*, and *MAE=12.82*. All the error measures are lower than the error measures of the Holt ES and the Holt-Winters ES models, indicating that the ARIMA model has better goodness-of-fit than the Holt family models. Figure 3-4 shows the graph of the actual, fitted, and residuals of the ARIMA model.

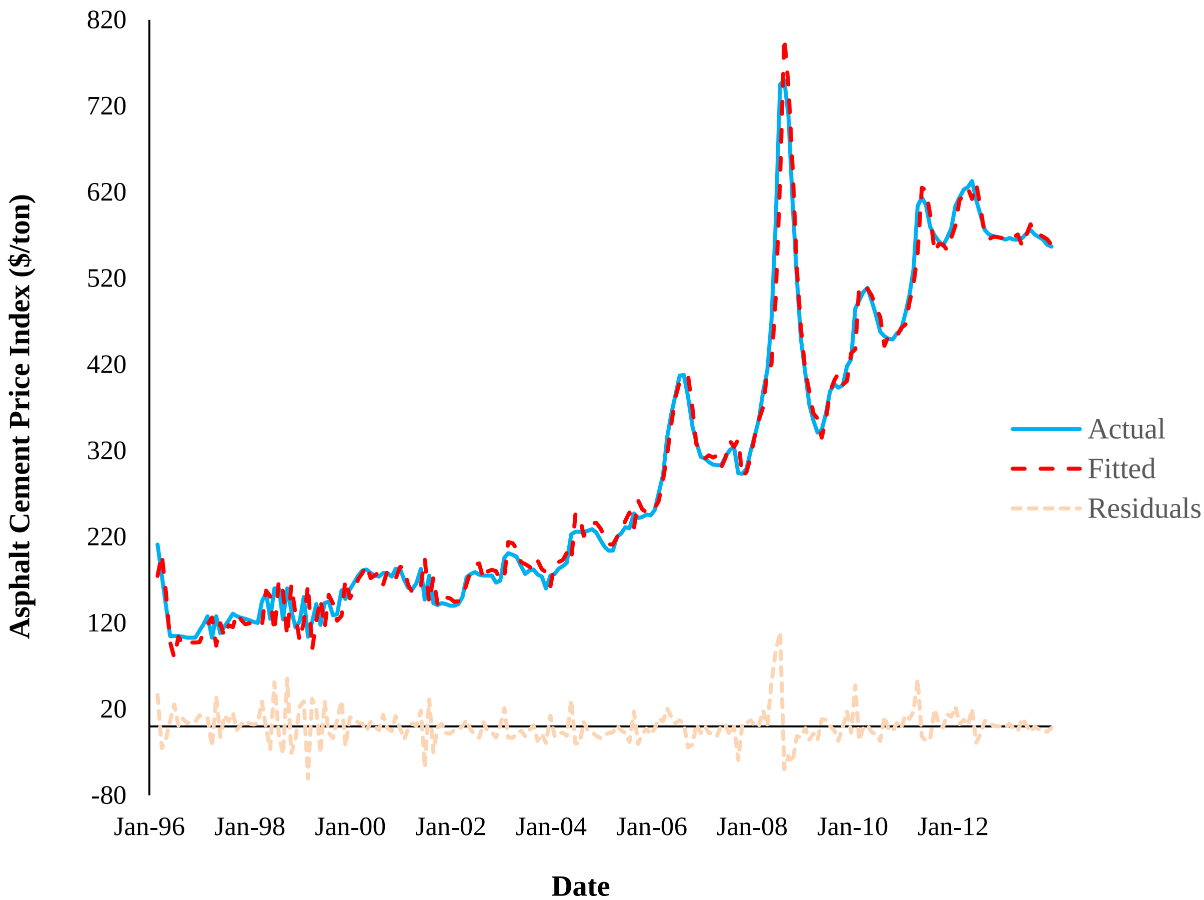

Figure 3-4: Actual, fitted, and residuals of the ARIMA(2,0,2) model

The key underlying condition of the ARIMA models is that the residual must follow a white noise process with a mean of *0* and finite variance. Figure 3-5 shows the correlogram of the residuals, and Table 3-3 shows the results of the Ljung-Box Q test. Because the p-values for all lag levels are higher than the significance level of *5%*, the null hypothesis that the data are independently distributed cannot be rejected. Thus, the residuals do not show any serial correlation and can be considered a white noise process.

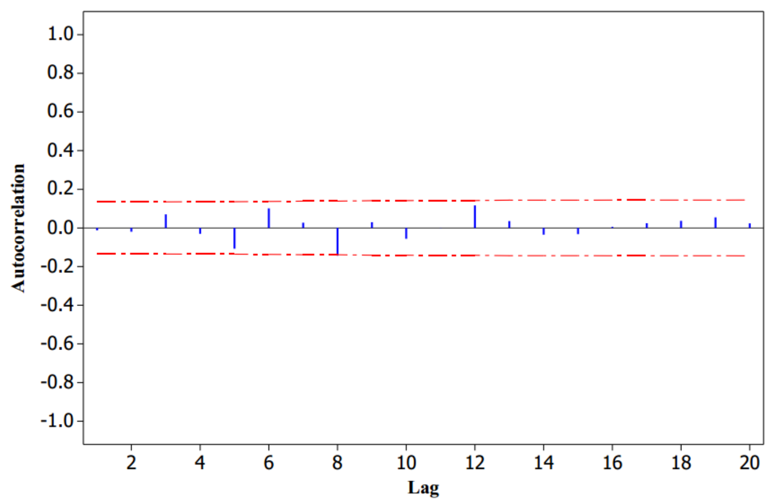

Figure 3-5: Correlogram of the residuals of the ARIMA(2,0,2) model

3.5.1.4. Seasonal ARIMA

Although the potential seasonality pattern was captured using dummy variables in the ARIMA model, another approach is to use a seasonal ARIMA model, which is an extended version of the ARIMA model. In addition to the parameters *p*, *q*, and *d*, which are required to create a regular ARIMA model, a seasonal ARIMA model uses parameters *P*, *Q*, and *D* to capture potential seasonality. Parameters *P* and *Q* describe the orders of the

Table 3-3: Results of the Ljung-Box Q test for the residuals of the ARIMA(2,0,2) model

Lag	Autocorrelation	Q-Statistic	P-Value
1	–0.012	0.0330	
2	–0.021	0.1283	
3	0.071	1.2763	
4	–0.030	1.4812	0.224
5	–0.106	4.0581	0.131
6	0.100	6.3503	0.096
7	0.026	6.5089	0.164
8	–0.144	11.283	0.046
9	0.031	11.510	0.074
10	–0.058	12.308	0.091
11	–0.002	12.309	0.138
12	0.119	15.620	0.075
13	0.034	15.900	0.103
14	–0.036	16.208	0.134
15	–0.030	16.428	0.172
16	0.005	16.433	0.227
17	0.024	16.575	0.280
18	0.036	16.888	0.326
19	0.053	17.562	0.350
20	0.023	17.691	0.409

seasonal autoregressive (SAR) and the seasonal moving average (SMA) in the model, respectively. Parameter D is the difference order required to remove the seasonality of the transformed stationary dataset. Because the seasonality pattern was not obvious in the box plot diagram, various seasonal ARIMA models with different values for parameter D are tested. Parameter d is set to 0 because, similar to the ARIMA model, the original dataset is transferred to a stationary time series by including a trend variable in the model. The equation of the seasonal ARIMA model for the time series of the asphalt cement price index is as follows:

$$ARIMA(p,d,q)(P,D,Q) = c + \alpha(trend) + \sum_{i=1}^{p} \varphi_i AR(i) + \sum_{j=1}^{q} \theta_j MA(j) + \sum_{k=1}^{P} \lambda_k SAR(k) + \sum_{l=1}^{Q} \delta_l SMA(l)$$

Where:

P is the order of the SAR operator

Q is the order of the SMA operator

D is the differencing order required to remove the seasonality

λ_k is the coefficient of the k^{th} SAR operator

δ_l is the coefficient of the l^{th} SMA operator

The initial values of the parameters p, q, P, and Q are determined based on the AIC and BIC values. Various combinations of the parameters are considered to identify the proper models. The coefficients of the model are determined using MLE.

Similar to ARIMA models, the key underlying condition of the seasonal ARIMA models is that the residual must follow a white noise process with a mean of *0* and finite variance. Analyzing various combinations of the parameters indicates that several models, such as seasonal *ARIMA(1,0,12)(1,1,0)*, produce relatively low AIC and BIC. However, the simplest model with low AIC and BIC that satisfies the underlying condition of the residuals following a white noise process is the seasonal *ARIMA(2,0,2)(8,0,5)*. The AIC and BIC of this model are *8.78* and *8.88*, respectively. Table 3-4 shows the results of the seasonal *ARIMA(2,0,2)(8,0,5)*. In Table 3-4, those variables that are not statistically significant within the *5%* significance level are removed from the results. Figure 3-6 shows the graph of the actual, fitted, and residuals of the seasonal ARIMA(2,0,2)(8,0,5) model.

Table 3-4: Results of the seasonal ARIMA(2,0,2)(8,0,5)

Variable	Coefficient	t-Statistic	P-Value
Trend	2.6960	22.0585	0.0000
AR(1)	1.3470	19.2658	0.0000
AR(2)	–0.4123	–5.9075	0.0000
SAR(8)	–0.1869	–2.6558	0.0085
MA(2)	0.1887	2.4773	0.0141
SMA(5)	–0.2215	–2.9086	0.0040

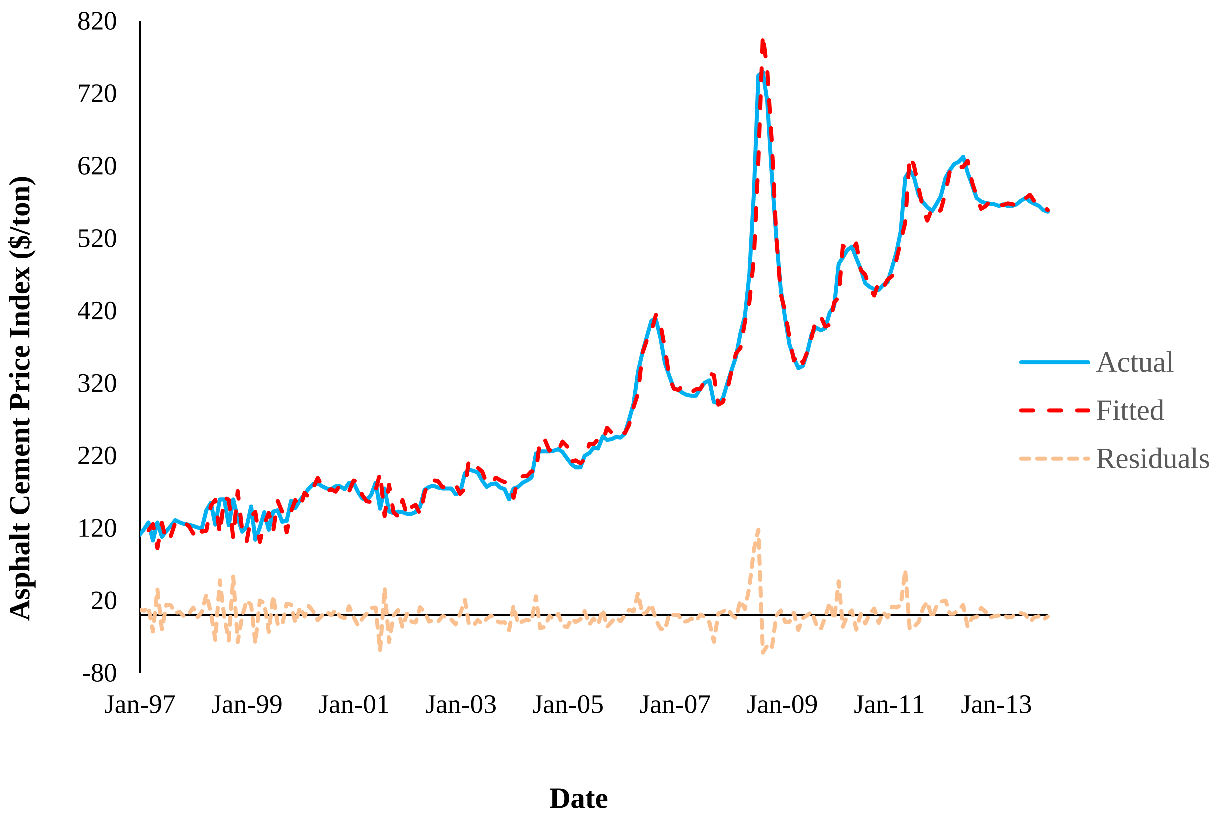

Figure 3-6: Actual, fitted, and residuals of the seasonal ARIMA(2,0,2)(8,0,5) model

Figure 3-7 shows the correlogram and Table 3-5 shows the results of the Ljung-Box Q test for the residuals of the *ARIMA(2,0,2)(8,0,5)* model and indicate that the null hypothesis that the data are independently distributed cannot be rejected. Thus, the residuals can be considered a white noise process.

Table 3-5: Results of the Ljung-Box Q test for the residuals of the seasonal ARIMA(2,0,2)(8,0,5) model

Lag	Autocorrelation	Q-Statistic	P-Value
1	0.013	0.0351	
2	–0.023	0.1501	
3	0.029	0.3310	
4	–0.111	2.9613	
5	0.023	3.0713	
6	0.065	3.9738	0.046
7	–0.023	4.0842	0.130
8	–0.013	4.1211	0.249
9	0.006	4.1280	0.389
10	–0.101	6.3819	0.271
11	–0.014	6.4231	0.377
12	0.127	9.9949	0.189
13	0.013	10.030	0.263
14	–0.075	11.288	0.257
15	–0.005	11.293	0.335
16	–0.062	12.165	0.351
17	0.024	12.294	0.422
18	0.066	13.298	0.425
19	0.017	13.363	0.498
20	0.030	13.569	0.558

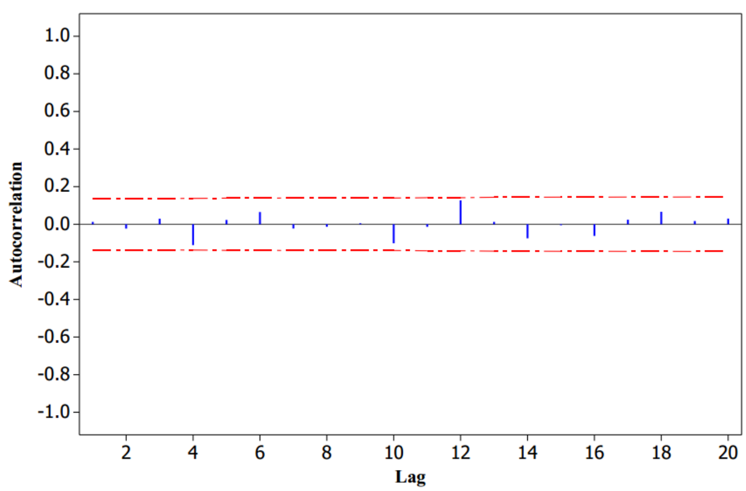

Figure 3-7: Correlogram of the residuals of the seasonal ARIMA(2,0,2)(8,0,5) model

The three error measures of the seasonal ARIMA model are *MAPE=5.52%*, *MSE=371.21*, and *MAE=12.41*. All the error measures are slightly lower than those of the *ARIMA(2,0,2)* model.

3.5.2. Validation: Out-of-Sample Forecasting

After creating the time series forecasting models and evaluating their goodness-of-fit, out-of-sample forecasting can be conducted to evaluate the predictability of the models and validate the results. As noted earlier, a subset of the first 216 observations from January 1996 to December 2013 was used to create and calibrate the models. Now, using the time series forecasting models, the asphalt cement price index from January 2014 to December 2014 is forecasted. By comparing the forecast values with the actual values, the predictability of the models is evaluated.

The three error measures (i.e., MAPE, MSE, and MAE) are used to analyze the predictability of the models more rigorously. Table 3-6 shows the out-of-sample forecasting error measures of the time series models. The results indicate that all developed time series models can predict the price of asphalt cement properly with errors of less than 4%. Among the four models, the Holt ES and ARIMA models are the most accurate, with less than 2% error.

Table 3-6: Out-of-sample forecasting error measures

Model	MAPE	MSE	MAE
Holt ES	1.62%	147.67	9.50
ARIMA	1.94%	222.92	11.11
Seasonal ARIMA	2.15%	253.68	12.34
Holt-Winters ES	3.62%	564.29	20.99

Figure 3-8 shows the results of the out-of-sample forecasting analysis. Because the out-of-sample forecasting process uses the forecast values of the lagged data points, the forecast errors tend to compound over time and result in larger errors (cumulative error).

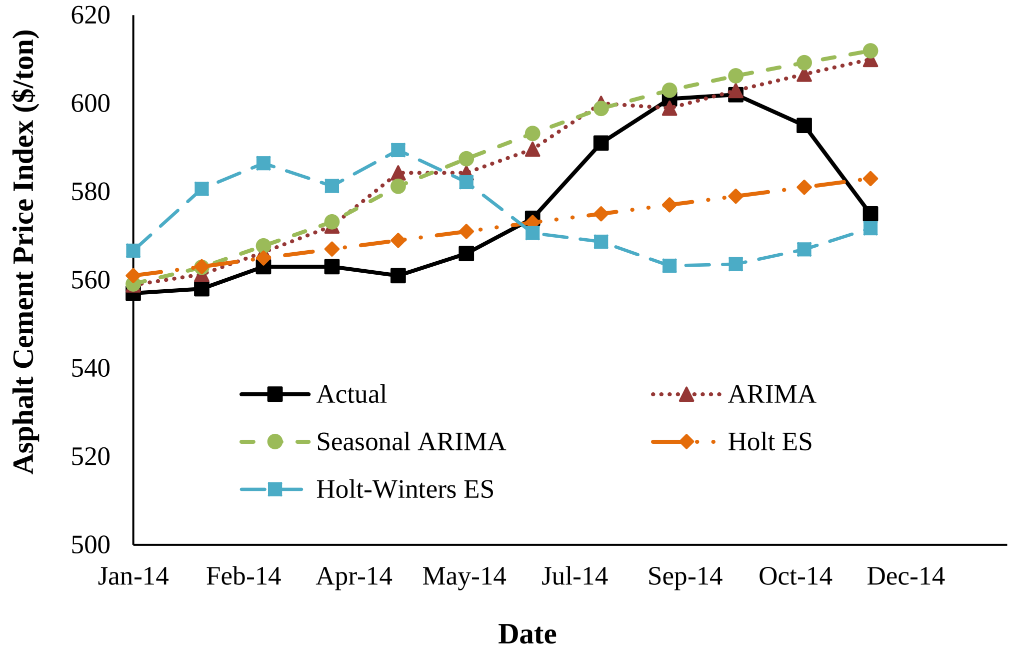

Figure 3-8: Out-of-sample forecast of asphalt cement price index

Overall, Figure 3-8 shows that the forecast values are closer to the actual values for the early points in the out-of-sample period and gradually depart from the actual values due to the cumulative error. Therefore, all models have better predictability for early points in the out-of-sample forecasting period. The results of the out-of-sample forecasting validate the applicability of the developed time series models for predicting the future values of asphalt cement price.

3.6. Predictability of Time Series Models versus Monte Carlo Simulation

As noted in the introduction section, Monte Carlo simulation has been widely used to predict the cost of projects. Among the existing approaches, such as adding a fixed percentage of the total cost as a risk premium or inflating the estimated cost of materials to the expected midpoint of the construction period, the Monte Carlo approach is the only method capable of modeling short-term variations in asphalt cement price. However, the predictability of this method depends significantly on the accuracy of the input distributions; furthermore, this method does not consider the effects of autocorrelation in the historical records of asphalt cement price. Conversely, time series forecasting models are independent of any assumption or fitted distributions, and their only input is the actual historical price of asphalt cement. Furthermore, time series models can capture the effects of autocorrelation in the price of asphalt cement appropriately. In this section, a Monte Carlo simulation model is developed to forecast the future values of asphalt cement price, and the results are compared to those of the developed time series forecasting models.

Figure 3-9 shows the histogram of the escalation rates in the history of asphalt cement price. In the current state of practice, fitting a triangular distribution to the histogram is recommended (Back et al. 2000). The mode parameter, lower boundary, and upper boundary parameters of the fitted triangular distribution are estimated to equal *0.00355*, *–0.31063*, and *0.29873*, respectively. The primary value of asphalt cement price is set to the actual price in December 2013 (i.e., *$575*).

A simulation process is conducted to generate future random paths of the price of asphalt cement from January 2014 to December 2014; Figure 3-10 shows the generated random paths. Each path is a possible scenario for the future value of asphalt cement during the out-of-sample forecasting period.

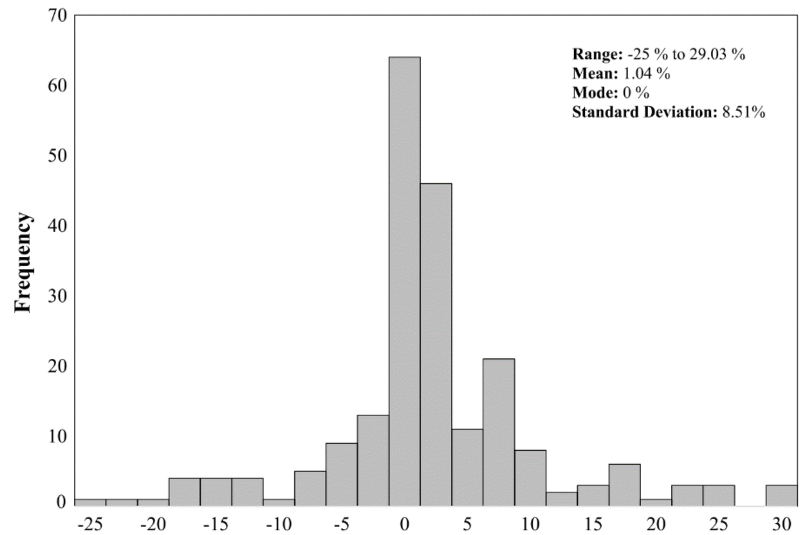

Figure 3-9: Histogram of escalation rates in the history of asphalt cement price

More than 100,000 random paths are generated during the simulation process, and the means of the simulated future values of asphalt cement at each time point during the out-of-sample period are calculated. Figure 3-11 shows the expected values of future asphalt cement price as calculated by Monte Carlo simulation and compares them to the actual values.

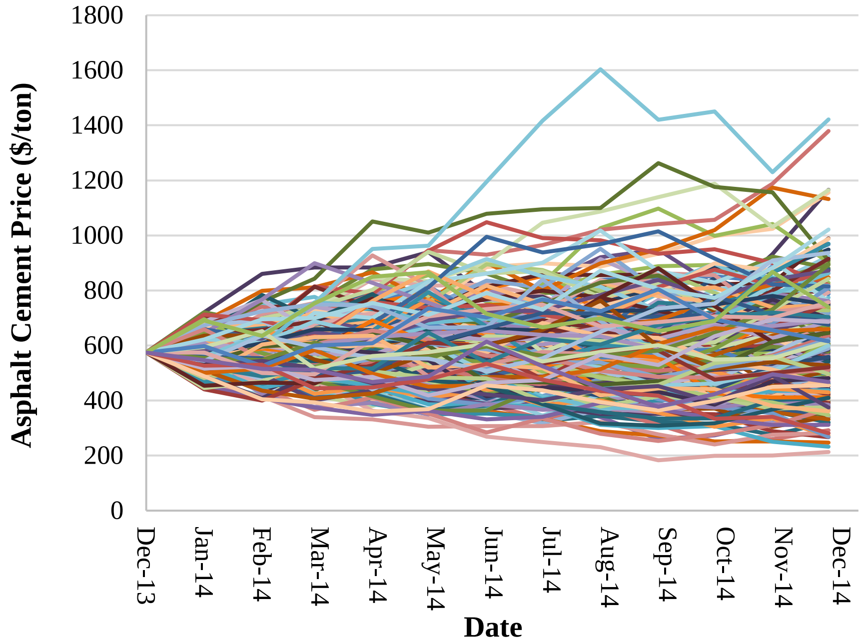

Figure 3-10: Random paths of future values of asphalt cement price generated by Monte Carlo simulation

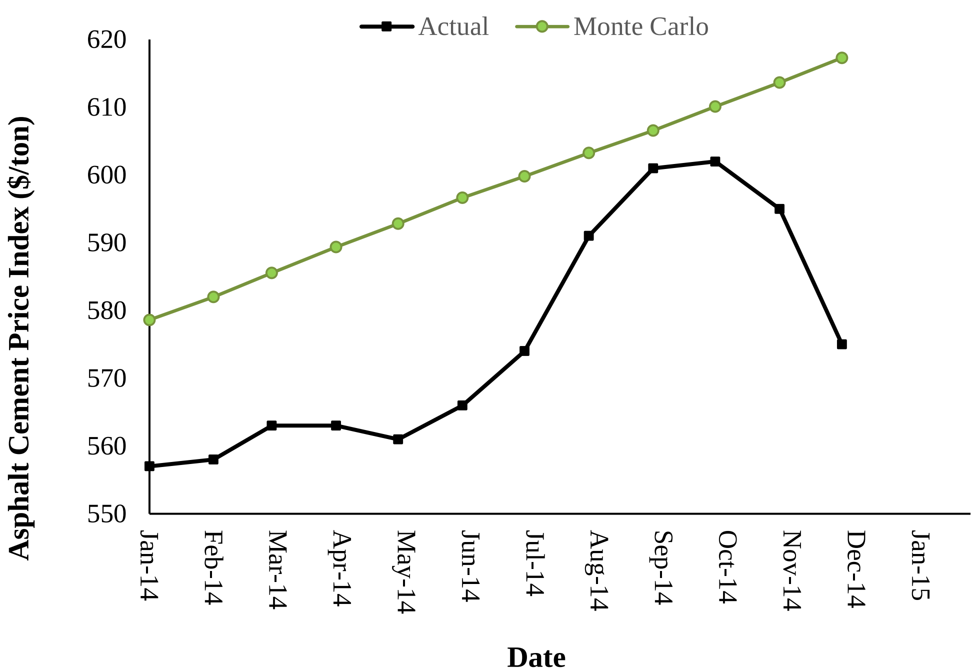

Figure 3-11: Results of the Monte Carlo simulation compared to the actual prices of asphalt cement

The results of the simulation process indicate that the MAPE, MSE, and MAE of the Monte Carlo model are *3.64%*, *827.89*, and *21.47*, respectively. All three error measures are higher for the Monte Carlo simulation than for all of the developed time series models. To analyze the predictability of the Monte Carlo simulation for asphalt cement price more rigorously, thirty-four other distributions, including normal, log normal, gamma, beta, Cauchy, and Weibull distribution, were fitted to the histogram of the price escalation rates. The results show that a Cauchy distribution with mean of 0 and a standard deviation of 0.02563 has the best goodness-of-fit. Using the Cauchy distribution instead of the triangular distribution improves the predictability of the Monte Carlo simulation with a MAPE of *2.26%*. However, three out of the four developed time series models, Holt ES, ARIMA, and seasonal ARIMA, still have better predictability compared to the Monte Carlo simulation using the Cauchy distribution. It should be noted that time series forecasting models are faster and computationally less expensive than the Monte Carlo simulation as well.

3.7. Summary

The typical existing methods for modeling asphalt cement price (i.e., adding a fixed percentage of the total estimated cost as the risk premium or inflating the estimated cost of materials to the expected midpoint of the construction period) do not explicitly take into account that the price of asphalt cement is subject to significant variations, even over a short period of time. A more advanced alternative, Monte Carlo simulation, has been widely used to quantify the range and likelihood of project cost. However, Monte Carlo simulation cannot consider the effects of autocorrelation in the price of asphalt cement when forecasting its future values, and the simulation's predictability depends heavily on the accuracy of the input distributions.

On the contrary, univariate time series forecasting models forecast a variable using only its historical observations and can properly capture the effects of autocorrelation in the time series of a variable to predict its future values. In this empirical study, the time series of asphalt cement price is analyzed, and its major characteristics are identified. The results of this empirical study show that the time series data of asphalt cement price is autocorrelated, non-stationary, and does not have a very strong seasonal pattern. Based on the identified time series characteristics, four univariate time series forecasting models, Holt ES, Holt-Winters ES, ARIMA, and seasonal ARIMA, were created to take into account the short-term variations in asphalt cement price in forecasting its future values. The results of in-sample model fitting show that all four models have proper goodness-of-fit. Residual analysis reveals that the underlying conditions of the models hold true, and, therefore, these time series models are usable. The results of the out-of-sample forecasting show that all four time series models can predict the future value of asphalt cement price with proper accuracy, but the ARIMA and Holt ES models are the most accurate among the four with less than 2% error. Furthermore, the results of this study show that time series forecasting models can predict the future values of asphalt cement more accurately compared to the previously existing methods, including Monte Carlo simulation.

This chapter makes two primary contributions to the existing body of knowledge: (1) a characterization of the variations in asphalt cement prices over time; and (2) the creation of univariate time series forecasting models to predict future values of asphalt cement prices. The results of this study can help both owners and contractors improve budgeting processes, prepare more accurate cost estimates, and reduce the risk of asphalt cement price variations in transportation projects. Although this study was conducted using the state of Georgia's asphalt cement price index, the proposed methodology can be used for similar datasets in other states and internationally.

As observed in the validation section, because the out-of-sample forecasting process uses the forecast values of the lagged data points, the forecast errors tend to compound over time, resulting in larger errors. Therefore, univariate time series forecasting models may not perform well for long-term predictions. A potential solution to this limitation of univariate time series forecasting models is to create multivariate time series models that use historical records of the price of asphalt cement in addition to the historical records of several other variables (i.e., leading indicators). Identifying the time series leading indicators of asphalt cement price and creating multivariate time series forecasting models for this price could be a basis for future works. Furthermore, developing and evaluating risk management strategies and hedging mechanisms to control the consequences of asphalt cement price volatility, such as PACs, are topics for future studies.

CHAPTER 4: QUANTIFYING AND FORECASTING UNCERTAINTY IN THE PRICE OF ASPHALT CEMENT

4.1. Introduction

Before using any risk management strategy, it is necessary to measure, analyze, and forecast material price uncertainty and ensure that it is the proper time to employ the strategy. This chapter addresses the second research objective of this dissertation: quantifying and forecasting uncertainties in the price of asphalt cement. To achieve this objective, the remainder of this chapter is structured as follows. After a brief introduction to ARCH and GARCH time series volatility models, the time series dataset of the asphalt cement price index is introduced. The proposed research approach and steps conducted in this study then are described. In the first step, a univariate time series model is fitted to the asphalt cement price index time series to capture the conditional mean of asphalt cement price over time. Next, the residuals of the model are examined by a heteroscedasticity test to check whether the volatility in the price of asphalt cement is statistically significant. If heteroscedasticity exists, ARCH/GARCH models are created, and the conditional volatility of asphalt cement price is measured and modeled over time. The conditional volatility models then are validated, and their predictability is evaluated. Finally, conclusions and suggestions for future work are presented. This study's primary contribution to the existing body of knowledge is systematically measuring and forecasting uncertainties in the price of asphalt cement over time. The results of this study can help transportation agencies properly analyze asphalt cement price uncertainty and subsequently wisely implement their risk management strategies at the proper time.

4.2. ARCH/GARCH Volatility Models

The uncertainty (i.e., unpredictability) of a variable can be quantified based on the concept of conditional volatility, which is defined by the variance of the error term (Engle 1982). Equation 1 shows a general regression model that can be used to estimate the price of asphalt cement.

$$ACP_t = m_t + e_t$$

Where:

ACP_t is asphalt cement at time t

m_t is the conditional mean function or the mean value of asphalt cement price at time t

e_t is the error term at time t and is distributed normally with a mean of 0 and variance of σ^2_t

Regular models simply assume that the variance of the error (i.e., σ^2_t) is constant over time (i.e., homogeneity of variance) and that the deviations of the actual observations from the conditional mean calculated by the model follow a white noise process. In other words, the unpredictability of the response variable (i.e., asphalt cement price) is constant through time. However, this assumption is not valid in many cases (Engle 1982; Enders 2008).

In 1982, Engle observed that even if the residuals of a model follow the white noise process, their squared values might be autocorrelated. Based on this interesting observation, he defined ARCH(L_1) to model conditional volatility (i.e., conditional variance), which depends upon the information available through time t as a function of the square of the residuals as follows:

$$\sigma_t^2 = \omega + \sum_{i=1}^{L_1} \alpha_i e_{t-i}^2$$

$$\forall i = 1, \ldots, L_1 \;\; \alpha_i, \omega > 0$$

Where:

ω is a constant

L_1 is the number of lags

α_i is the coefficient of the i^{th} observation in the window of L_1 lags

e_i is the residual of the regression model at time i

In some cases, the ARCH model requires long lag lengths to capture the impact of historical observations on current volatility (Danielsson 2011). To address this issue, Bollerslev (1986) introduced the generalized version of the ARCH model, GARCH(L_1,L_2), which incorporates the impact of historical conditional volatilities in addition to historical observations to estimate current volatility as follows:

$$\sigma_t^2 = \omega + \sum_{i=1}^{L_1} \alpha_i e_{t-i}^2 + \sum_{j=1}^{L_2} \beta_j \sigma_{t-j}^2$$

$$\forall i = 1, \ldots, L_1 \;\; and \; \forall j = 1, \ldots, L_2 \quad \alpha_i, \beta_j, and \; \omega > 0$$

Where:

L_2 is the number of lags for historical conditional volatilities

β_j is the coefficient of the j^{th} conditional volatility in the window of L_2 lags

σ_j is the conditional volatility at time j

If L_2 is equal to 0 in a GARCH model, it produces the same result as an ARCH model. The coefficients of the ARCH/GARCH models are estimated using MLE.

The majority of the volatility models applied to real world problems belong to the ARCH/GARCH family (Danielsson 2011). Vilasuso (2002) used GARCH models to forecast currency exchange rate volatility. Karmakar (2005) developed GARCH models to estimate the conditional volatility of Indian stock markets. Joukar and Nahmens (2015) modeled the volatility of the ENR construction cost index using ARCH/GARCH models. Ilbeigi et al. (2016c) used GARCH models to improve forecasting of asphalt cement price index.

4.3. Dataset

In this study, the monthly asphalt cement price index in the state of Georgia is used to measure, model, and forecast uncertainty in the price of asphalt cement. GDOT determines the asphalt cement price index based on the average of the asphalt cement prices from the department's monthly survey of approved asphalt cement suppliers. The maximum and minimum prices are excluded from the calculation of the index. The dataset consists of 229 observations from January 1996 to January 2015 (Figure 1-1). In this study, observations from January 1996 to December 2013 are considered for model creation, in-sample model fitting, and parameter estimation. The last twelve observations (i.e., from January 2014 to December 2014) are used for out-of-sample forecasting and predictability evaluation.

4.4. Research Methodology

In this study, ARCH/GARCH time series models are used to quantify and forecast uncertainties in the price of asphalt cement. As noted in the previous sections, uncertainty is defined as the variance of the error terms in a model that explains the variations in the mean of the historical observations (Engle 1982). Therefore, the first step of modeling uncertainties is to create the mean model, which is also called the conditional mean function. The conditional mean function can be any regular time series model, such as autoregressive moving average (ARMA), ARIMA, or seasonal ARIMA, that satisfies the underlying assumptions (e.g., the residuals of the model follow a white noise process) (Danielsson 2011). The error terms then are calculated, and the variation of their variances (i.e., volatility) is checked for statistical significance (i.e., heteroscedasticity). If heteroscedasticity exists (i.e., volatility is statistically significant), the ARCH/GARCH models are created and their parameters are estimated. Next, the ARCH/GARCH model is validated by conducting the heteroscedasticity test (ARCH test) on its residuals to make sure the model has captured the variations of the volatility properly. In other words, for the model to be acceptable, the variation of the variances of the residuals in the ARCH/GARCH model should not be statistically significant. Furthermore, the estimated volatilities using the ARCH/GARCH model are compared with the realized volatilities to evaluate the performance of the model more rigorously. Finally, out-of-sample forecasting is conducted to predict the future values of volatility and evaluate the predictability of the model.

In summary, the following steps are applied to measure, model, and forecast the volatility of the asphalt cement price index:

1- Creating conditional mean function

2- Heteroscedasticity testing on the residuals of the mean function to check whether the volatility is statistically significant

3- Creating ARCH/GARCH models if heteroscedasticity exists

4- Heteroscedasticity testing on the residuals of the ARCH/GARCH model to validate the model

5- Measuring conditional volatility using the created ARCH/GARCH model

6- Evaluating the model by comparing the estimated volatilities with realized volatilities

7- Conducting out-of-sample forecasting for conditional volatility

Figure 4-1 shows the process to quantify, model, and forecast uncertainties in asphalt cement price.

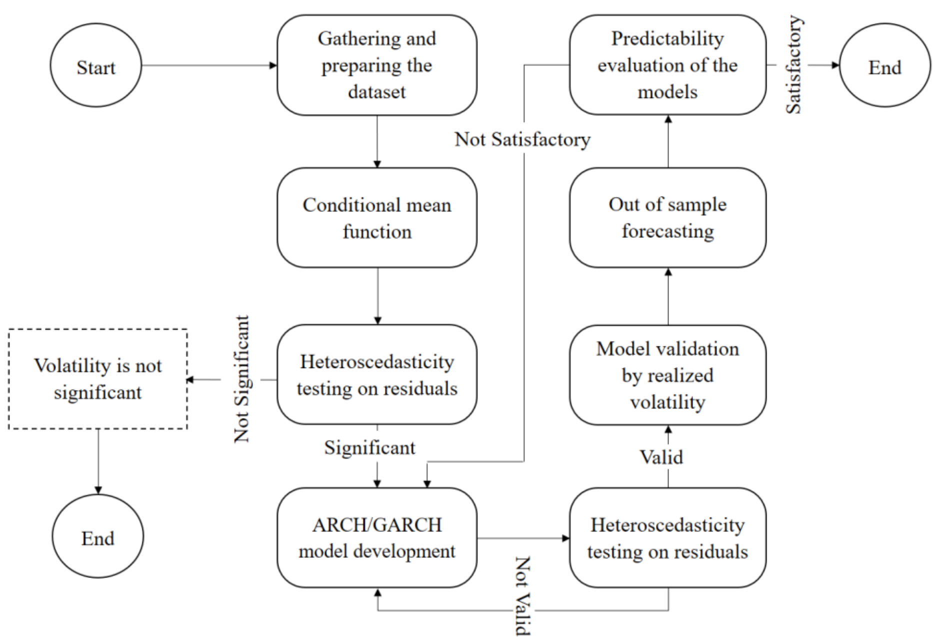

Figure 4-1: Process to quantify, model, and forecast uncertainties in asphalt cement price

4.5. Volatility Model Development

As noted before, the development of a volatility model consists of three major steps: (1) creating the conditional mean function, (2) conducting heteroscedasticity tests to check whether the volatility is statistically significant, and (3) creating ARCH/GARCH models.

4.5.1. Creating the Conditional Mean Function

Because the uncertainty of the asphalt cement price index is defined as the variance of the errors of the conditional mean function (m_t), the first step in analyzing volatility is to create the conditional mean function. Ilbeigi et al. (2016a) proposed different types of univariate time series models for the asphalt cement price index and showed that an Autoregressive Moving Average (ARMA) with a trend and an intercept variable can properly fit to the data and forecast future values of the asphalt cement price index.

The ARMA model consists of two parameters: p and q. These are integers that describe the order of AR and MA in the model. Because the original time series of the asphalt cement price index is non-stationary, its trend is captured in the model by using an integer variable that starts at 1 for the first month and increases incrementally by one unit afterward. Furthermore, to capture any possible seasonal pattern, twelve dummy variables representing each month are added into the model. Thus, the equation of the ARMA model for the time series of the asphalt cement price index is as follows:

$$ARMA(p,q) = c + \alpha(trend) + \sum_{i=1}^{p} \varphi_i AR(i) + \sum_{j=1}^{q} \theta_j MA(j) + \sum_{k=1}^{12} \beta_k M_k$$

Where:

p is the order of the AR operator

q is the order of the MA operator

c is the intercept

α is the coefficient of the trend

φ_i is the coefficient of the i^{th} AR operator

θ_j is the coefficient of the j^{th} MA operator

M_k is a dummy variable that is 1 if the observation belongs to month k and 0 otherwise

β_k is the coefficient of the binary variable of month k

Optimal values for p and q are determined based on the AIC (Akaike 1998) and the BIC (Schwarz 1978). To select the proper model, different models with various combinations of p and q are studied. Model coefficients are determined using MLE. Results indicate that the ARMA(2,2) produces the lowest AIC and BIC, equal to *8.81* and *8.91*, respectively. The significance level is considered equal to *5%*. Because the p-values of the intercept, MA(1), and all monthly binary variables except those for May and August are considerably higher than the significance level, they are not statistically significant and can be removed from the model. Table 4-1 shows the results of the model.

Table 4-1: Results of the ARMA(2,2) model

Variable	Coefficient	t-Statistic	P-Value
Trend	2.6928	22.4296	0.0000
AR(1)	1.3799	22.8986	0.0000
AR(2)	–0.4840	–8.1334	0.0000
MA(2)	0.2060	2936.12	0.0000
M_5	5.8911	2.2167	0.0277
M_8	5.5038	2.0729	0.0394

Note: The variables that were not statistically significant at the 5% level were excluded from the table

The final equation of the ARMA model can be represented as follows:

$$\widehat{ACPI}_t = 2.6928 \times Trend + 1.3799 \times AR(1) - 0.4840 \times AR(2) + 0.2060 \times MA(2) + 5.8911 \times M_5 + 5.5038 \times M_8$$

The key underlying assumption of the ARMA models is that the residual must follow a white noise process with a mean of 0 and finite variance. Figure 4-2 shows the correlogram of the residuals; because the residuals of the model depict a white noise process, the model is reliable and can properly capture the variations of the conditional mean of the time series. Figure 4-3 shows the graph of the actual, fitted, and residuals of the ARMA model.

Table 4-2 shows the results of the Ljung-Box Q test. Because the p-values for all lag levels are higher than the significance level of *5%*, the null hypothesis that the data are independently distributed cannot be rejected. Thus, the residuals do not show any serial correlation and can be considered a white noise process.

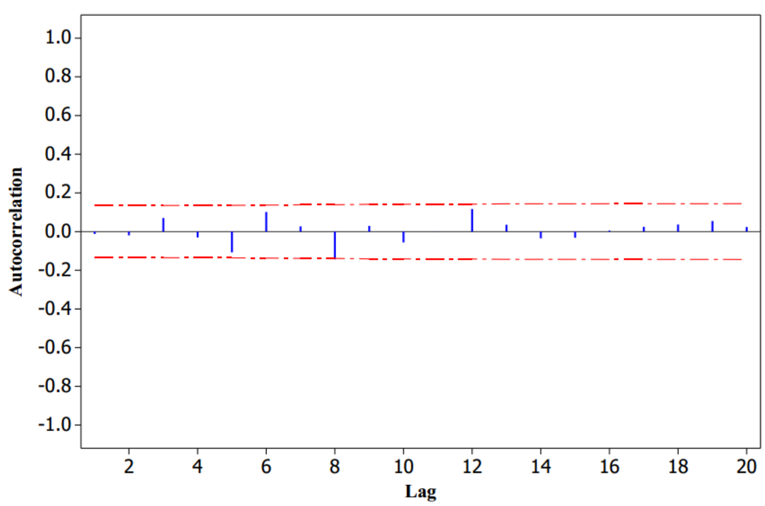

Figure 4-2: Correlogram of the residuals of the ARMA(2,2) model

Table 4-2: Results of the Ljung-Box Q test for the residuals of the ARMA(2,2) model

Lag	Autocorrelation	Q-Statistic	P-Value
1	–0.012	0.0330	
2	–0.021	0.1283	
3	0.071	1.2763	
4	–0.030	1.4812	0.224
5	–0.106	4.0581	0.131
6	0.100	6.3503	0.096
7	0.026	6.5089	0.164
8	–0.144	11.283	0.046
9	0.031	11.510	0.074
10	–0.058	12.308	0.091
11	–0.002	12.309	0.138
12	0.119	15.620	0.075
13	0.034	15.900	0.103
14	–0.036	16.208	0.134
15	–0.030	16.428	0.172
16	0.005	16.433	0.227
17	0.024	16.575	0.280
18	0.036	16.888	0.326
19	0.053	17.562	0.350
20	0.023	17.691	0.409

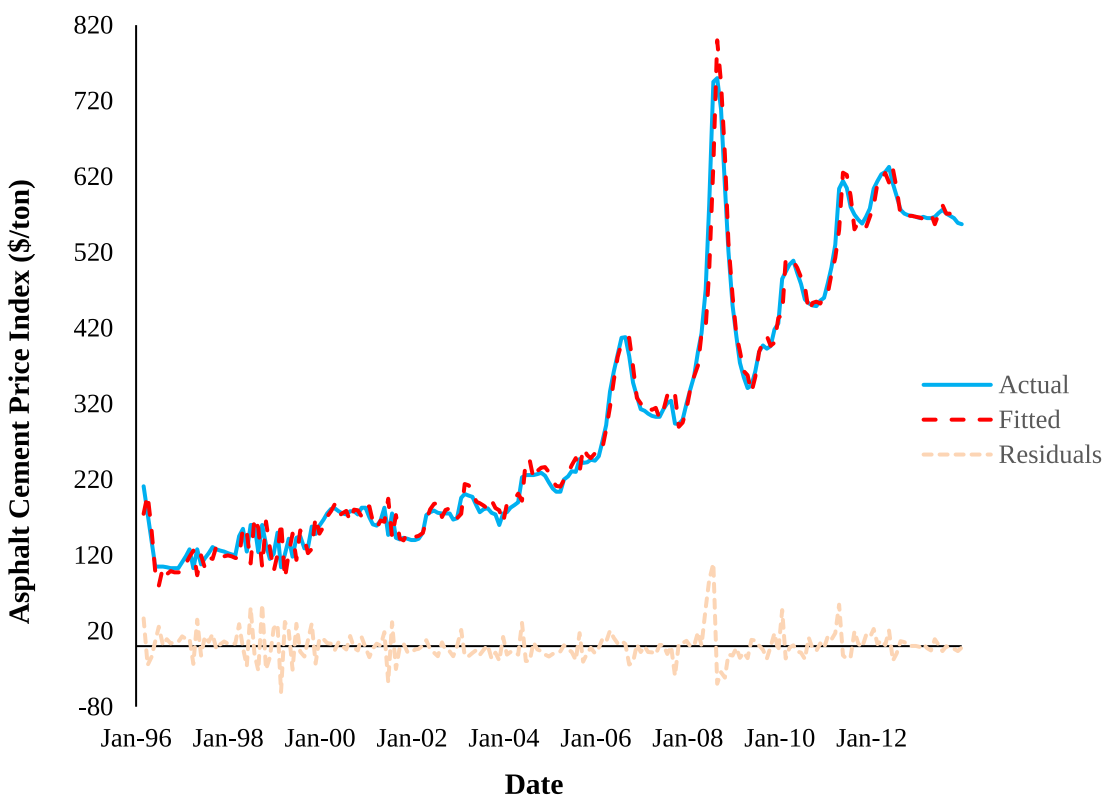

Figure 4-3: Actual, fitted, and residuals of the ARMA(2,2) model

4.5.2. Heteroscedasticity Test

After fitting the conditional mean function, the volatility of the asphalt cement price index should be checked for statistical significance. Although the residuals of the conditional mean function follow a white noise process, Engle (1982) found that the square of the residuals might not represent a white noise process, indicating the existence of heteroscedasticity. Heteroscedasticity indicates that the variability of the residuals of some subpopulations differs from that of other subpopulations. In other words, the unpredictability of asphalt cement, which is the source of material price volatility risk, differs over time. Engle (1982) introduced the ARCH test, which regresses the squared residuals on lagged squared residuals and a constant to test if the heteroscedasticity effect is statistically significant. The results of the ARCH test indicate that the F-statistic is *98.8731* with a p-value of *0.0000*, meaning that the null hypothesis of the absence of the ARCH components can be rejected strongly. In other words, the volatility is statistically significant.

4.5.3. Creating ARCH/GARCH Models

Because the results of the heteroscedasticity test indicate that the volatility of the asphalt cement price index is statistically significant, ARCH/GARCH models can be created to measure, model, and forecast the uncertainty (i.e., unpredictability) of asphalt cement price. The most important part of the modeling process is determining the proper number of lags in equations 2 and 3 (i.e., L_1 and L_2). Different models with various combinations of L_1 and L_2 are considered in order to select the proper model. Best model selection is conducted based on the AIC (Akaike 1998) and the BIC (Schwarz 1978).

The results indicate that the GARCH(2,1) model produces the lowest AIC and BIC, equal to *8.1821* and *8.3334*, respectively. Table 4-3 shows the estimated coefficients of the conditional volatility model.

Table 4-3: Coefficients of the conditional volatility model for the asphalt cement price index

Conditional Volatility Model (GARCH(2,1))			
Variable	**Coefficient**	**z-Statistic**	**P-Value**
ω	212.1689	9.7002	0.0000
α_1	0.776931	21.5847	0.0000
α_2	0.775087	22.5394	0.0000
β_1	–1.003282	–505.5455	0.0000

Note: The variables that were not statistically significant in 5% significant level were excluded from the table

After creation of the GARCH model, a heteroscedasticity test was conducted on the residuals of the GARCH model to check the effectiveness of the modeled volatility. The results of the ARCH test indicate that the F-statistic is *0.1695* with the p-value of *0.6810*, meaning that the null hypothesis of the absence of the ARCH components cannot be rejected. In other words, the GARCH(2,1) model can successfully capture variations in volatility, and the volatility of the residuals of the GARCH model is not statistically significant.

4.6. Measuring Conditional Volatility

After selecting the best GARCH model using AIC and BIC criteria, estimating the coefficients of the model using MLE, analyzing the capability of the model to capture variations in volatility using an ARCH test, and analyzing the residuals of the model for white noise processes, the created model can be used to measure conditional volatility through time. Figure 4-4 shows the calculated conditional volatility.

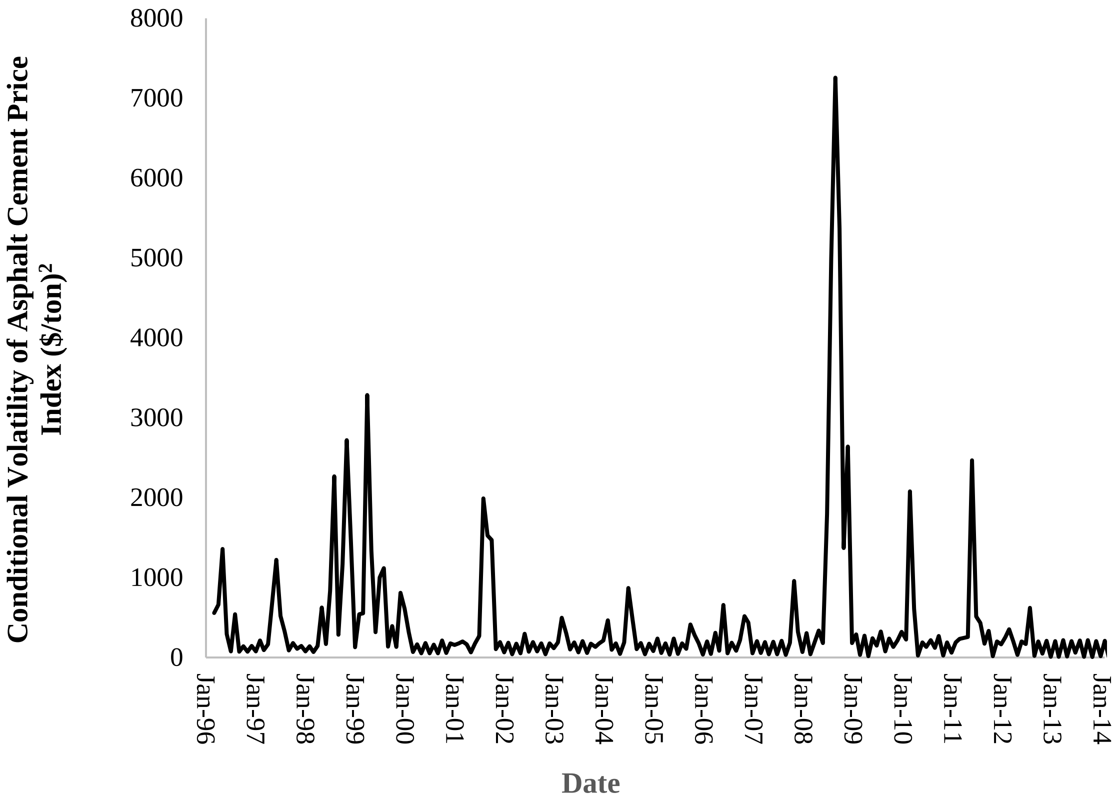

Figure 4-4: Calculated conditional volatility using GARCH(2,1)

Figure 4-4 indicates that between January 2002 and September 2007, volatility in the asphalt cement price index was lower (i.e., the price index was more predictable) relative to the period before January 2002. However, volatility increased suddenly in July 2008 and peaked in September 2008. This very large shock is followed by two other relatively large shocks in March 2010 and June 2011. Generally speaking, the volatility (i.e., unpredictability) of the asphalt cement price index was high between June 2008 and August 2012. However, volatility was much lower after August 2012 when compared with any other period of time since March 1996.

4.7. Validating the Model

As noted earlier, volatility is a latent variable and cannot be measured directly (Engle and Patton 2001). Therefore, model results cannot be compared with actual observed volatilities. Realized volatility is an alternative; it can provide a rough estimate of the actual volatilities (Andersen and Bollerslev 1998) and be used in place of actual volatility as a basis for evaluating the performance of the GARCH model (Danielsson 2011). The estimated and forecast volatilities of the GARCH model and the realized volatilities then can be checked for general consonance. Consonance is tested by the Granger Causality test (Granger 2001). The most common method of calculating realized volatility is calculating the square of the changes (Karmakar 2005). Vilasuso (2002) used this method to estimate the realized volatilities of currency exchange rates and subsequently evaluated the performance of his GARCH model. Figure 4-5 compares the estimated conditional volatilities of the asphalt cement price index using the GARCH(2,1) model and the realized volatilities derived from the square of monthly changes.

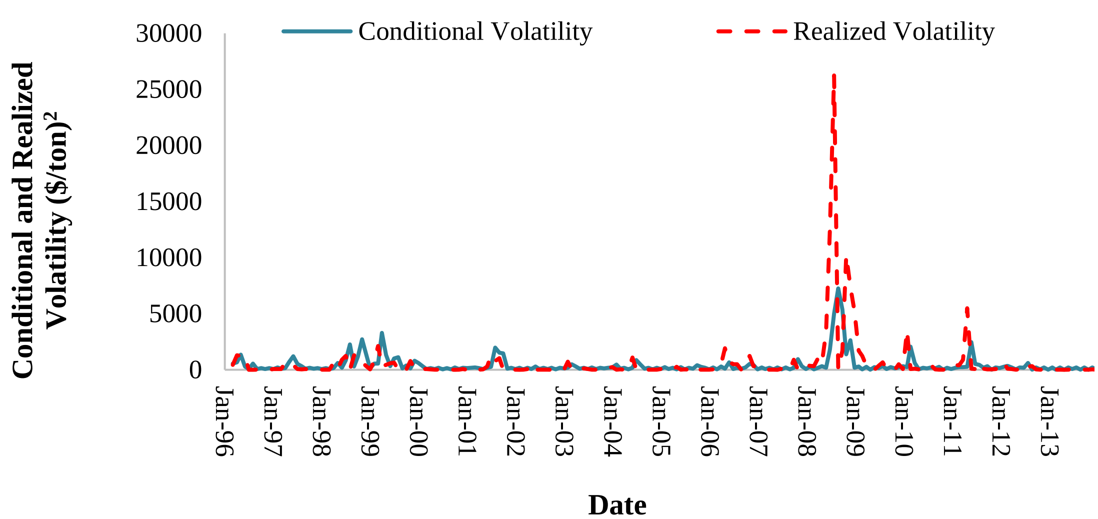

Figure 4-5: Comparison of estimated conditional volatilities and realized volatilities based on the square of the monthly changes

Balaban (2004) suggested calculating the average monthly volatility for daily observations such as currency exchange rates (i.e., calculating the sum of the daily volatilities using the Vilasuso (2002) method and dividing by the number of trading days). Applying this approach, Joukar and Nahmens (2015) measured the average realized volatility of the monthly CCI for 6-month periods and used the results to evaluate their volatility forecasting model. In this study, the average realized volatilities for 2-month, 4-month, and 6-month intervals are compared with the averages of the estimated and forecast volatilities over those time periods. Figure 4-6 to Figure 4-8 show the results.

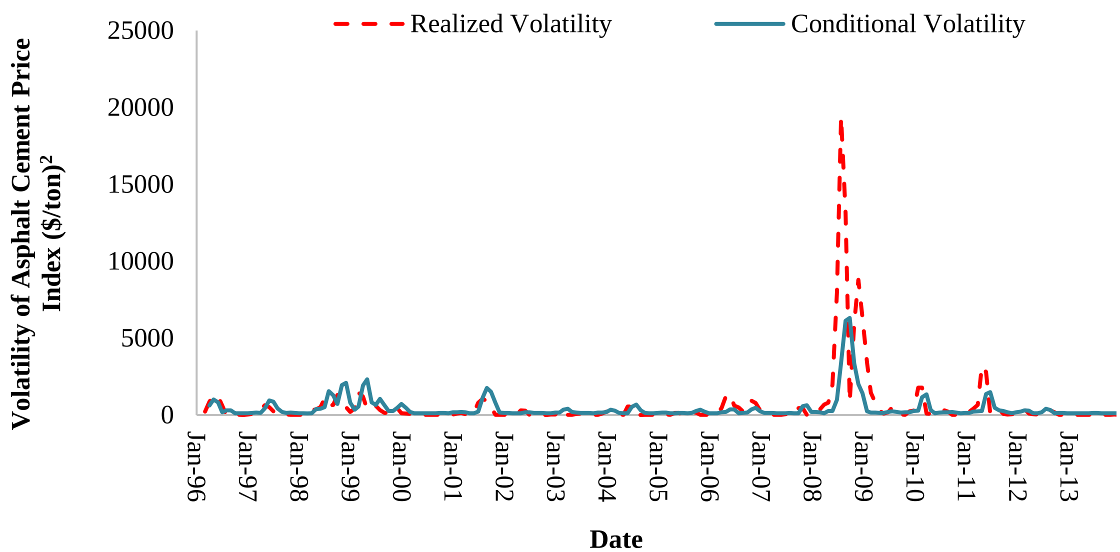

Figure 4-6: Comparison of conditional volatilities and average realized volatilities for 2-month intervals

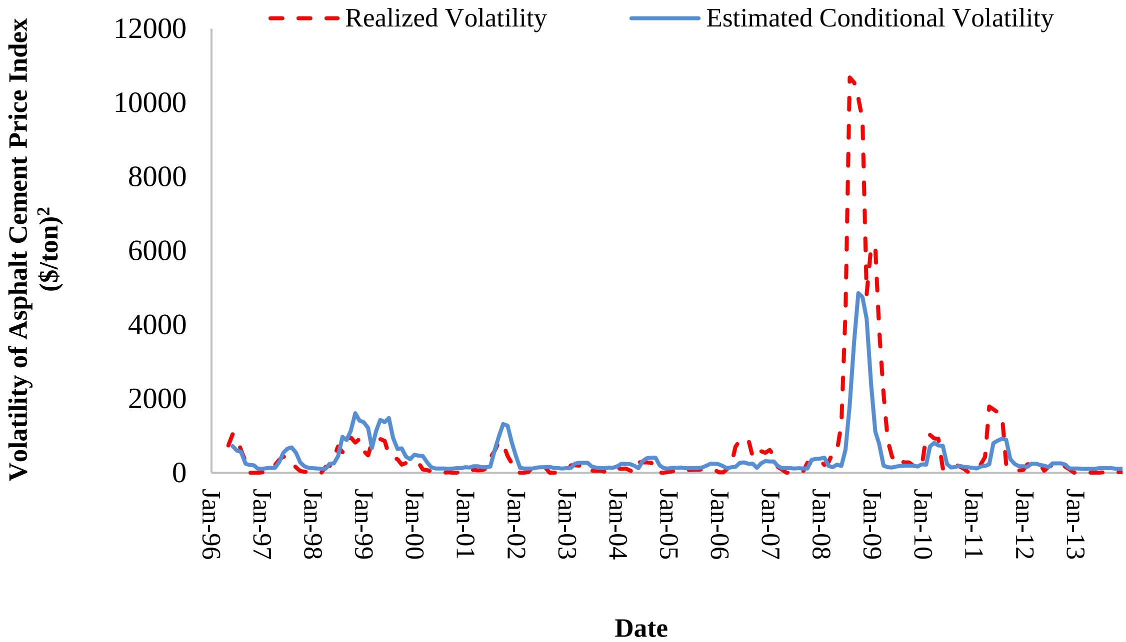

Figure 4-7: Comparison of conditional volatilities and average realized volatilities for 4-month intervals

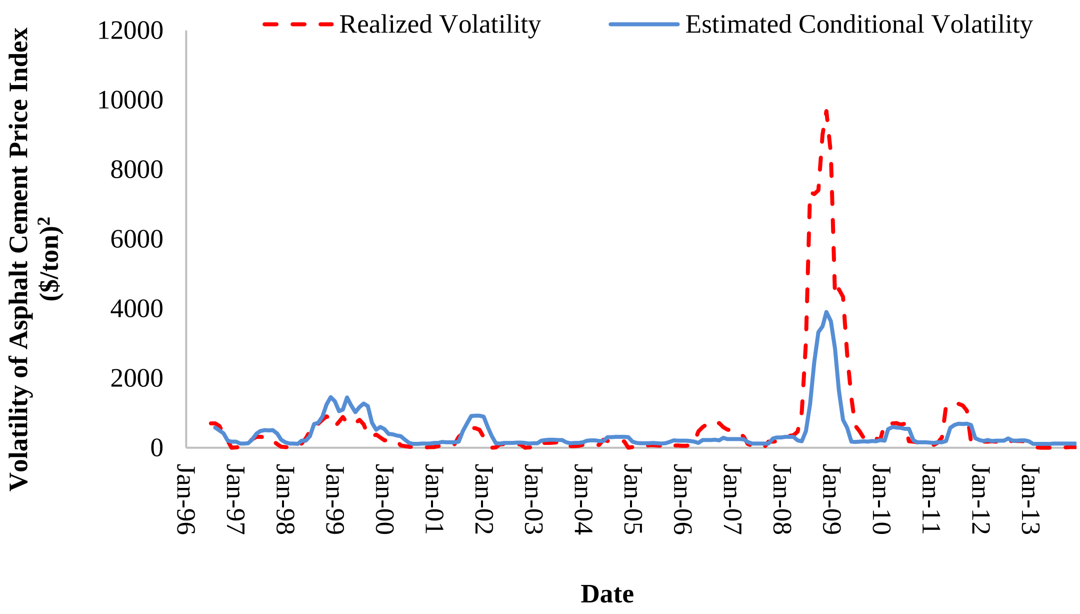

Figure 4-8: Comparison of conditional volatilities and average realized volatilities for 6-month intervals

The results of the Granger Causality test of the conditional volatilities and realized volatilities, calculated based on either the square of the monthly changes (Figure 4-5) or the average realized volatilities over two, four, or six months (Figure 4-6 to Figure 4-8), indicate that the estimated conditional and realized volatilities display statistically significant consonance. As an example, Table 4-4 shows the results of the Granger Causality test for the monthly conditional and monthly realized volatility; results indicate that the null hypothesis that time series data do not have information to explain each other are strongly rejected, even at the 1% significance level.

4.8. Forecasting Conditional Volatility

After creating the GARCH model, estimating its parameters, measuring the conditional volatility for the in-sample data points, and validating the results of the in-sample model fitting, the model can be extrapolated to conduct out-of-sample forecasting. As noted earlier, the out-of-sample period is from January 2014 to December 2014.

Table 4-4: Results of the Granger Causality test for conditional and realized volatility

Dependent Variable: Conditional Volatility			
Explanatory Variable	**Chi-square**	**Degree of Freedom**	**P-Value**
Realized Volatility	210.5807	2	0.0000
Dependent Variable: Realized Volatility			
Explanatory Variable	**Chi-square**	**Degree of Freedom**	**P-Value**
Conditional Volatility	13.3457	2	0.0013

Figure 4-9 compares the forecast and estimated values of asphalt cement price volatility during the out-of-sample period. The forecast values are calculated by extrapolating the developed model. The estimated values of asphalt cement price volatility are quantified using the GARCH model if the in-sample period is extended to cover the entire dataset (Ilbeigi et al. 2017). The results show that the MAPE is less than 2.7%, indicating that the model can be extrapolated to conduct the out-of-sample forecasting properly.

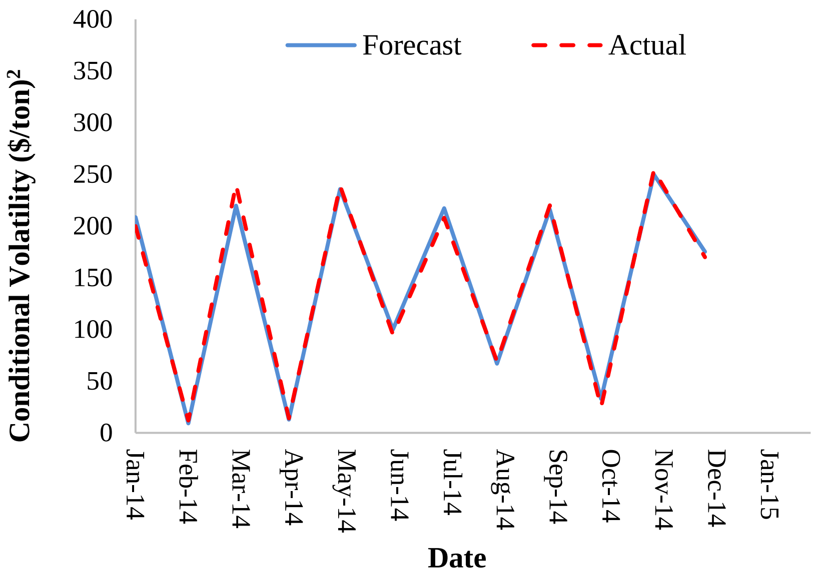

Figure 4-9: Forecast volatility of the asphalt cement price index using GARCH(2,1)

The results correctly indicate that the forecast volatility values for the out-of-sample forecasting period are relatively low. Therefore, the unpredictability and level of uncertainty in the conditional mean model will be low in that period.

4.9. Summary

Asphalt cement is one of the most important materials in highway construction projects. However, significant volatility in the price of asphalt cement increases risk for contractors and can lead to price speculation and inflated bid prices. Many transportation agencies use different risk management strategies, such as offering PACs in contracts, utilizing owner buying power, or providing flexible project start times, to control the consequences of the uncertainty in the price of asphalt cement. However, before applying those strategies, transportation agencies need to measure, analyze, and forecast uncertainty in the price of asphalt cement to make decisions properly about implementing the strategies. In this chapter, the uncertainty in asphalt cement price was measured and forecast using ARCH/GARCH models. Results indicate that a GARCH(2,1) model with a conditional mean function of ARMA(2,2) can properly model the conditional volatilities in the price of asphalt cement.

The outcomes of the GARCH model show that the uncertainty of the asphalt cement price index was considerable between March 1996 and January 2002 and between July 2007 and August 2012. Between August 2012 and December 2013, uncertainty was comparatively low. Furthermore, the results of the out-of-sample forecasting process indicate that the developed model can predict the uncertainty in the price of asphalt cement with less than 3% error.

This study's primary contributions to the existing body of knowledge are measuring, modeling, and forecasting uncertainties in the price of asphalt cement over time. The results of this study can help transportation agencies systematically measure, analyze, and forecast the uncertainties in the price of asphalt cement and implement risk management strategies at the right time. Although this study was conducted using the state of Georgia's asphalt cement price index, the proposed methodology can be used for similar datasets in other states and internationally. After quantifying the uncertainties in the price of asphalt cement, development of quantitative models to determine the proper risk premiums and financial value of the risk management strategies could be a topic for future works and studies.

CHAPTER 5. EFFECTS OF PACS ON SUBMITTED BID PRICES

5.1. Introduction

The primary purpose of offering PACs in construction projects is to encourage contractors to exclude extra risk premiums from their cost estimations and submit lower bid prices. However, there is little knowledge about empirical assessment of PACs and their actual effects on bid prices. The third research objective of this dissertation is addressed in this chapter. To achieve the objective, the remainder of this chapter is structured as follows. After describing the research methodology and the steps taken in this empirical investigation, the characteristics of the dataset used in this research are defined. The multiple steps involved in modeling the variations in contractors' submitted bid prices for major asphalt line items then are explained. Finally, the results of the statistical models are interpreted, and the findings of this research and indications for future work are summarized. The primary contributions of this chapter to the body of knowledge are (1) the creation of several multivariate regression models that have the power to explain the variations in highway contractors' submitted bid prices for major asphalt line items; and (2) the empirical assessment of whether offering PACs contributes to the variations in contractors' submitted bid prices for major asphalt line items in highway projects. This work is expected to contribute to the construction engineering and management community by helping capital planners of transportation agencies systematically evaluate the effects that their risk-sharing strategies, such as material PACs, have on bids submitted by their contractors.

5.2. Research Methodology

Multivariate regression analysis was devised to identify significant variables that can explain variations in contractors' submitted bids for major asphalt line items. Several steps were followed to create multivariate regression analysis models:

1. Conduct a literature review and interview transportation cost professionals to identify a potential list of explanatory variables for modeling the variations in contractors' submitted bid prices (e.g., project duration, number of bidders, quantity of asphalt line items, average price of asphalt cement, and availability of PACs in the contract)
2. Develop a dataset of submitted bid prices for major asphalt line items in transportation projects and gather information about the potential explanatory variables for these projects
3. Categorize the projects into two groups of asphalt-intensive and non-asphalt-intensive projects
4. Identify unusual observations (i.e., outliers) in the dataset using a statistical test based on standardized residuals and remove these data points from the dataset
5. Develop scatter plots of the contractors' submitted bids against the potential explanatory variables and conduct the Pearson correlation test to determine whether any nonlinear relationships (e.g., quadratic, cubic, logarithmic, exponential, or power) exist between the submitted bid prices and any of the potential explanatory variables and, if needed, apply respective variable transformation

6. Apply a backward elimination algorithm to create the best subset multivariate regression model using information from potential explanatory variables to describe variations in the contractors' submitted bids
7. Evaluate the explanatory power of the multivariate regression model using ANOVA
8. Diagnose multicollinearity in the developed multivariate regression model using the variance inflation factor (VIF) test to confirm that the model is reliable and the results are not misleading
9. Analyze the residuals of the multivariate regression model to examine the appropriateness of the modeling assumptions
10. Analyze the results and interpret the findings of the multivariate regression model

Figure 5-1 shows the process of conducting the multivariate linear regression analysis to examine the effects of PACs on bid prices.

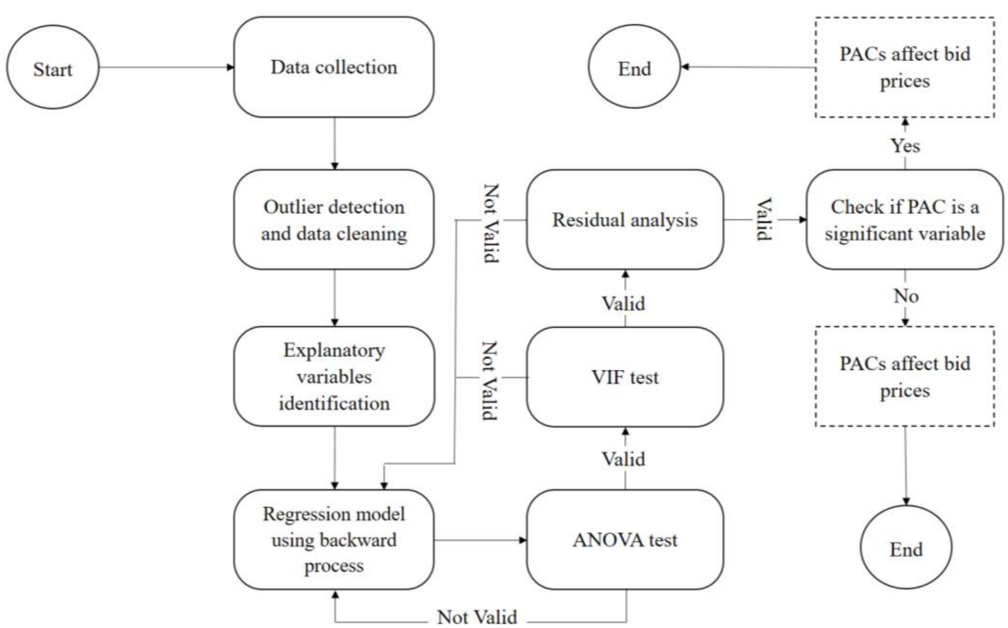

Figure 5-1: Process to create regression models to examine effects of PACs on bid prices

5.3. Dataset

Contractors' submitted bid data were collected from 841 highway project contracts awarded in the state of Georgia from August 2009 to November 2012. These projects were distributed geographically across the seven districts throughout the state. The contract values of these projects range from $33,900 to $67,494,183 with an average value of $2,687,833 and a median of $871,909. The duration of these projects ranges from 102 to 2049 days, with an average of 366 days and a median of 312 days. Unit-price bids ($/ton) submitted by contractors were collected for five major asphalt line items from these project contracts. These asphalt line items represent five major types of asphalt mixtures widely used in highway projects in the state. Table 5-1 describes these items and identifies the number of observations for each line item in our dataset.

Highway projects differ with regard to the relative significance of asphalt line item costs in the total project cost. To address this major difference, the projects in the dataset were classified into two large groups: (1) asphalt-intensive projects, such as resurfacing, widening, and intersection improvement projects, in which there are several asphalt line items, and the costs of these items represent a considerably large portion of total project cost; and (2) non-asphalt-intensive projects, such as bridge replacement and drainage construction, in which the costs of asphalt line items are a small portion of total project cost.

Table 5-1: Major asphalt mixture line items in Georgia

Line Item ID	Description
3130	Recycled Asphaltic Concrete 12.5mm, Superpave, GP2, Including Bitumen Materials
3190	Recycled Asphaltic Concrete 19mm, GP1 or GP2 Including Bitumen Materials
1812	Recycled Asphaltic Concrete Levelling Including Bitumen Materials
1802	Recycled Asphaltic Concrete Patching Including Bitumen Materials
4510	Recycled Asphaltic Concrete 12.5mm, Superpave, GP2, Including Polymer-Modified Bitumen Materials

5.4. Modeling the Variations of Contractors' Submitted Bid Prices for Major Asphalt Line Items

A multivariate linear regression analysis was devised to create proper models for explaining variations in contractors' submitted bid prices for main asphalt line items using the information available from the set of identified potential explanatory variables.

5.4.1. Defining the Variables

An extensive literature review and an interview with transportation cost professionals were conducted to identify a potential list of explanatory variables for modeling the variations in contractors' submitted bid prices. The following factors were identified as potential explanatory variables.

1- ***Duration of the project:*** The duration of a project may be an important effective factor in determining the bid price. Sonmez (2008), Lowe et al. (2006), and Trost and Oberlender (2003) considered project duration to model costs of construction projects. The unit of measure for project duration in this study is days.

2- ***Quantity of the line item:*** The quantity of the line item may be an important factor in determining its price, possibly due to the existence of economy of scale. Carr

(1989) found that the cost of an activity is related to the quantity of the activity in construction projects.

3- ***Total bid price:*** Total bid price shows the size of the project. Ahmad and Minkarah (1998) revealed that bid pricing decisions are affected by the project size.

4- ***Relative value of the asphalt line item:*** This variable shows the relative dollar value of the line item compared to the total bid price of the project by calculating the ratio of the total price of the item over the total bid price. This variable is an indicator of the relative importance of the line item compared to the other line items in the project. Our interviews with transportation cost professionals indicated the importance of this factor in explaining variations in the bid prices submitted by contractors.

5- ***Number of bidders:*** The number of bidders is an indicator of competition in the market. Carr (2005) presented a quantitative analysis of the impact of competition on project bid prices and concluded that bid prices submitted for a project increase as the level of competition in the market decreases.

Asphalt cement is one of the most important input commodities in transportation projects. Wang and Liu (2012) statistically showed that there is a direct relationship between asphalt cement price and the submitted bid prices of asphalt mixtures. The following two explanatory variables are used to investigate the relationship between the price of asphalt cement and the submitted bid prices of the five major asphalt line items.

6- ***Asphalt cement price index at the bid date:*** GDOT determines the asphalt cement price index based on the arithmetic average of asphalt cement prices from the department's monthly survey of approved asphalt cement suppliers. The maximum and minimum prices are excluded from the calculation of the index.

7- ***Past trend of asphalt cement price index:*** The past trend of the asphalt cement price index might be an informative factor that affects contractors' submitted bid prices for asphalt line items. This variable is determined for each month based on the slope of the trend line fitted to the last three months of price indexes.

8- ***Location of the project:*** A distinction should be made between urban and rural locations considering that projects in urban areas may have access to more suppliers of liquid asphalt or may be closer to these suppliers compared to projects in rural locations. GDOT divides the state into seven districts: District One – Gainesville, District Two – Tennille, District Three – Thomaston, District Four – Tifton, District Five – Jesup, District Six – Cartersville, and District Seven – Chamblee. All projects in District Seven (Metro Atlanta) are urban projects, whereas most projects in the other districts, especially Districts Two, Three, and Four, are rural projects. Considering the availability of resources, distance from suppliers of liquid asphalt, and weather conditions, the location of a project may affect submitted bid prices. Ahmad and Minkarah (1988) surveyed 400 general contractors and found that project location is one of the most important criteria that affect bid prices. We have used several binary indicators to address this issue. The value of the binary indicator of each region is 1 if the project is located in the region. These binary variables representing project geographical location have been used as control variables in our regression models as possible candidates to explain variations in submitted bid prices.

9- ***Eligibility of the projects for PAC:*** One of the major goals of this research is to examine the effect of offering PAC on submitted bid prices for main asphalt line items. If a project is eligible for PAC the value of this binary variable becomes 1 and otherwise, it becomes 0.

Information about existing and upcoming projects in the market might affect contractors' bidding behaviors; Akintoye (2000) identified market conditions as one of the main factors influencing bid prices. GDOT announces its upcoming new projects for each fiscal year (from July 1 to the following June 30) in advance. Thus, the number of existing and upcoming projects, estimated dollar values of these projects, and total quantity of main asphalt line items in these projects might affect contractors' bid price decisions for a specific project. We consider the following three variables to capture information about existing and upcoming projects in the region where the project was let.

10- ***Annual number of projects in the region:*** This variable is the total number of existing and upcoming projects in the project's region in the fiscal year that the project was let.

11- ***Annual value of the projects in the region:*** This variable is the total annual dollar value of all existing and upcoming projects in the project's region in the fiscal year that the project was let.

12- ***Annual quantity of asphalt mixtures in the region:*** This variable is the total quantity of existing and upcoming asphalt mixtures in the project's region in the fiscal year that the project was let.

In addition, we consider similar variables to capture market conditions in GDOT districts other than the region in which the project was let. These variables represent market conditions in the neighboring regions that might affect bidders' pricing decisions.

13- ***Annual number of projects in other regions:*** This variable is the total number of existing and upcoming projects in the other regions in the fiscal year that the project was let.

14- ***Annual value of the projects in other regions:*** This variable is the total annual dollar value of all existing and upcoming projects in the other regions in the fiscal year that the project was let.

15- ***Annual quantity of asphalt mixture in other regions:*** This variable is the total quantity of existing and upcoming asphalt mixtures in the other regions in the fiscal year that the project was let.

5.4.2. Detecting Unusual Observations

Outliers should be identified and removed from the dataset because unusual observations are distant from other observations and therefore make the results of regression analysis unreliable. A statistical test based on standardized residuals and leverage values (Neter et al. 1996) was used to detect unusual observations. A data point was considered unusual if the absolute value of the standardized residual is greater than 2 or if the leverage value is more than 3 times the number of model coefficients divided by the number of observations. Table 5-2 shows the number of unusual observations removed from the dataset for each asphalt line item. Only a small fraction of data points was identified as outliers for these asphalt line items; most unusual observations were from projects with very small quantities of asphalt mixtures. The remaining data points were large enough to conduct meaningful statistical analysis.

Table 5-2: Number of unusual observations in the dataset for each major asphalt line item

Line Item ID	Number of Observations		Number of Unusual Observations	
	Asphalt Intensive	Non-Asphalt-Intensive	Asphalt Intensive	Non-Asphalt-Intensive
3130	216	45	8	0
3190	98	82	4	0
1812	611	92	13	2
1802	326	134	9	3
4510	79	18	3	0

5.4.3. Scatter Plots and Variable Transformation

Scatter plots of the identified potential explanatory variables and contractors' submitted bid prices were developed to determine whether any nonlinear relationships (e.g., quadratic, cubic, logarithmic, exponential, or power) exist between submitted bid prices and any of the potential explanatory variables. The results indicate that using the natural logarithm of quantity and total bid price, instead of these variables in their original forms, leads to more appropriate regression models. Furthermore, Pearson correlation coefficients between submitted bid prices and the potential explanatory variables were calculated. The results indicate that the linear correlations between natural logarithm transformed forms of quantity and total bid price and submitted bid prices are higher than those between the original forms of quantity and total bid price and submitted bid prices.

5.4.4. Best Subset Regression Models

A best subset regression model was created to explain the variations in submitted bid prices for each main asphalt line item using the information available in the potential explanatory variables. A backward elimination algorithm (Webster 2013) was applied to determine the combination (i.e., subset) of potential explanatory variables that can best model the variations in submitted bids for main asphalt line items in each group of projects. Table 5-3 and Table 5-4 show the coefficients and t-statistics of the best subset regression models created for explaining the variations in the five main asphalt line items for asphalt-intensive and non-asphalt-intensive projects, respectively. A regression model for item 4510 for non-asphalt-intensive projects was not possible due to lack of observations.

All specified coefficients are significant at the 5% level; therefore, the contribution of the variables with non-zero coefficients statistically significantly explains the variations in the submitted bid prices for each asphalt line item. The adjusted R-squared values indicate that all regression models can be considered good fits for observed submitted bid prices for major asphalt line items.

Table 5-3: Coefficients and t-statistics of the regression models for major asphalt line items of the asphalt-intensive projects

Variables	3130	3121	1812	1802	4510
Constant	59.53 *(12.35)*	–14.12 *(–1.06)*	45.694 *(6.68)*	116.54 *(9.07)*	53.66 *(4.72)*
Ln Quantity for the Item	–2.7527 *(–9.68)*	–10.252 *(–7.86)*	–6.272 *(–13.79)*	–12.374 *(–11.03)*	–5.574 *(–8.24)*
Ln Total Bid Price	N/A	9.249 *(6.58)*	3.653 *(6.17)*	N/A	2.87 *(3.98)*
AC Index at the Bid Date	0.0565 *(9.320)*	0.0308 *(3.59)*	0.033 *(6.04)*	0.074 *(4.19)*	0.051 *(4.76)*
Number of Bidders	–0.789 *(–2.90)*	N/A	–0.579 *(–3.50)*	N/A	N/A
Relative Value of the Line Item	N/A	69.53 *(3.62)*	48.503 *(10.25)*	51.84 *(3.66)*	N/A
Duration of the Project	N/A	N/A	–0.011 *(–3.48)*	N/A	N/A
Past Trend of the AC Index	N/A	N/A	0.056 *(2.34)*	N/A	N/A
PAC Eligibility of the Project	N/A	N/A	9.235 *(6.48)*	N/A	N/A
Location of the Project: Region 1	–4.547 *(–2.97)*	N/A	N/A	N/A	–6.052 *(–2.77)*
Location of the Project: Region 2	N/A	N/A	N/A	10.661 *(3.14)*	N/A
Location of the Project: Region 3	–3.678 *(3.010)*	N/A	–4.812 *(–5.68)*	N/A	–4.392 *(–2.22)*
Location of the Project: Region 4	3.183 *(2.52)*	5.094 *(2.14)*	4.196 *(5.17)*	16.694 *(3.22)*	N/A
Location of the Project: Region 5	5.806 *(5.31)*	9.940 *(5.12)*	6.556 *(8.19)*	16.703 *(3.88)*	N/A
Location of the Project: Region 6	N/A	N/A	N/A	–12.204 *(–2.69)*	N/A
Location of the Project: Region 7	N/A	N/A	N/A	N/A	N/A
Annual Number of Projects in the Region	N/A	N/A	NA	N/A	N/A
Annual Value of Projects in the Region	N/A	N/A	N/A	N/A	N/A
Annual Quantity of Asphalt Mixture in the Region	5.16×10^{-6} *(2.43)*	N/A	2.93×10^{-6} *(4.750)*	1.17×10^{-5} *(2.33)*	N/A
Annual Number of Projects in Other Regions	N/A	N/A	–0.016 *(–2.81)*	N/A	N/A
Annual Value of Projects in Other Regions	N/A	N/A	N/A	N/A	N/A
Annual Quantity of Asphalt Mixture in Other Regions	N/A	N/A	N/A	N/A	N/A
R-Sq (adj)	**60.1%**	**66.2%**	**57.7%**	**57.8%**	**64.2%**

Note: t-statistics are shown in parentheses

Table 5-4: Coefficients and t-statistics of the regression models for major asphalt line items of the non-asphalt-intensive projects

Variables	3130	3121	1812	1802	4510
Constant	64.94 *(4.35)*	18.86 *(1.40)*	36.35 *(2.62)*	–100.26 *(–1.80)*	Lack of enough observations to conduct the regression analysis
Ln Quantity for the Item	–6.56 *(–8.48)*	–10.463 *(–9.59)*	–5.557 *(–9.94)*	–13.959 *(–14.92)*	
Ln Total Bid Price	4.50 *(4.57)*	6.870 *(5.64)*	3.146 *(3.25)*	8.066 *(4.40)*	
AC Index at the Bid Date	N/A	0.035 *(4.66)*	0.051 *(5.29)*	0.116 *(2.20)*	
Number of Bidders	–1.002 *(–2.22)*	N/A	N/A	N/A	
Relative Value of the Line Item	N/A	81.06 *(3.26)*	N/A	N/A	
Duration of the Project	N/A	N/A	N/A	N/A	
Past Trend of the AC Index	N/A	N/A	N/A	0.935 *(2.86)*	
PAC Eligibility of the Project	N/A	N/A	N/A	N/A	
Location of the Project: Region 1	N/A	N/A	N/A	N/A	
Location of the Project: Region 2	N/A	N/A	7.216 *(2.79)*	N/A	
Location of the Project: Region 3	–3.662 *(1.42)*	N/A	N/A	–15.566 *(–2.57)*	
Location of the Project: Region 4	11.559 *(2.58)*	7.935 *(3.52)*	10.232 *(4.20)*	N/A	
Location of the Project: Region 5	8.786 *(2.55)*	5.884 *(3.26)*	8.945 *(3.29)*	N/A	
Location of the Project: Region 6	N/A	N/A	N/A	N/A	
Location of the Project: Region 7	N/A	N/A	N/A	N/A	
Annual Number of Projects in the Region	N/A	N/A	N/A	N/A	
Annual Value of Projects in the Region	N/A	N/A	N/A	1.4×10^{-7} *(3.01)*	
Annual Quantity of Asphalt Mixture in the Region	N/A	N/A	N/A	N/A	
Annual Number of Projects in Other Regions	–0.036 *(–2.61)*	N/A	N/A	N/A	
Annual Value of Projects in Other Regions	N/A	N/A	N/A	2.1×10^{-7} *(4.06)*	
Annual Quantity of Asphalt Mixture in Other Regions	N/A	N/A	N/A	-1.63×10^{-5} *(–2.24)*	
R-Sq (adj)	**70.7%**	**73.2%**	**63.9%**	**69.0%**	

Note: t-statistics are shown in parentheses

5.4.5. ANOVA Tests

ANOVA (Webster 2013) is a statistical test that was used to diagnose the goodness of the developed regression models for the five asphalt line items. ANOVA was used to examine the statistical explanatory power of the developed regression models for asphalt line items. The results of the ANOVA tests indicate that the null hypotheses are strongly rejected at the 1% significance level for all models. In other words, we cannot reject the statement that the developed regression models for explaining the variations in the submitted bid prices are statistically reliable; therefore, the models have statistically significant explanatory power to describe the variations in the submitted bid prices for major asphalt line items. Table 5-5 shows an example of the results of the ANOVA performed on the regression model created for asphalt line item 3130 in asphalt-intensive projects. Because the p-value is much smaller than the significance level (i.e., it was considered 1% in this study), the null hypothesis is rejected, thus indicating that the model has significant explanatory power.

Table 5-5: Results of the ANOVA test for item 3130 in asphalt-intensive projects

Source	Degree of Freedom	Sum of Squares	Mean Squares	F-Value	P-Value
Regression	9	11238.8	1248.8	35.67	0.000
Residual Error	198	6931.1	35.0		
Total	207	18170.0			

5.4.6. Multicollinearity Diagnosis

The VIF (Webster 2013) was calculated for the developed regression models to diagnose any multicollinearity issues (i.e., if two or more explanatory variables in a multivariate regression model are highly correlated, the results might be misleading). Table

5-6 and Table 5-7 show the calculated VIFs for explanatory variables in the regression models of asphalt-intensive and non-asphalt-intensive projects, respectively. All calculated VIFs are less than 10, which is the recommended threshold for detecting multicollinearity in regression models (Webster 2013); therefore, multicollinearity does not exist in any of the five regression models.

5.4.7. Residual analysis

Q-Q plots, histogram of residuals, and scatter plots of residuals against fitted values and observation orders were built for the developed regression models to examine whether the model residuals follow any particular pattern. For example, Figure 5-2 depicts the residual plots of the regression model for item 1812 in asphalt-intensive projects. This figure indicates no violation of the basic assumptions of a regression model. The Q-Q plot of the residuals against normal distribution is close to a straight line, the histogram of the residuals is similar to a normal distribution, and no considerable pattern or trend is observed in the scatter plots of residuals against fitted values and observation orders. The results of the residual analysis for four other regression models are similar.

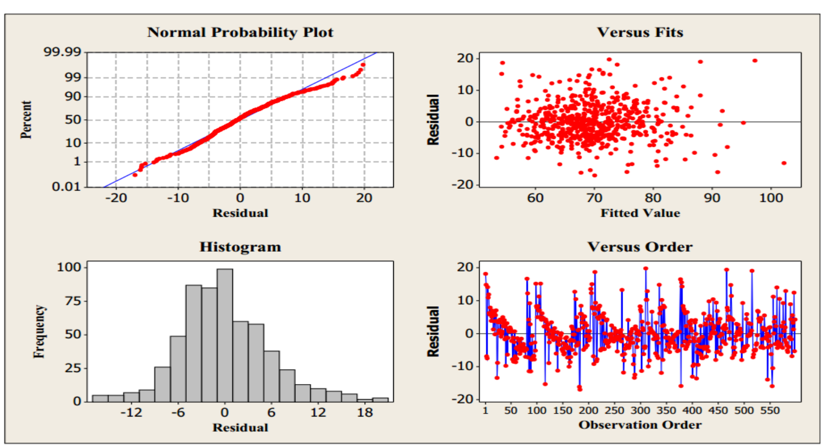

Figure 5-2: Residual plots of the regression model for item 1812 in asphalt-intensive projects

Table 5-6: Variance inflation factor for the explanatory variables in the regression models of asphalt-intensive projects

Variables	3130	3121	1812	1802	4510
Ln Quantity for the Item	1.152	8.79	6.384	2.577	1.285
Ln Total Bid Price	N/A	7.12	6.870	N/A	1.206
AC Index at the Bid Date	1.273	1.102	2.820	1.361	1.091
Number of Bidders	1.513	N/A	1.300	N/A	N/A
Relative Value of the Line Item	N/A	4.280	3.884	1.754	N/A
Duration of the Project	N/A	N/A	3.625	N/A	N/A
Past Trend of the AC Index	N/A	N/A	1.328	N/A	N/A
PAC Eligibility of the Project	N/A	N/A	2.914	N/A	N/A
Location of the Project: Region 1	1.314	N/A	N/A	N/A	1.178
Location of the Project: Region 2	N/A	N/A	N/A	1.201	N/A
Location of the Project: Region 3	1.545	N/A	1.694	N/A	1.163
Location of the Project: Region 4	1.417	1.034	1.557	1.824	N/A
Location of the Project: Region 5	1.197	1.052	1.213	1.428	N/A
Location of the Project: Region 6	N/A	N/A	N/A	1.440	N/A
Location of the Project: Region 7	N/A	N/A	N/A	N/A	N/A
Annual Number of Projects in the Region	N/A	N/A	N/A	N/A	N/A
Annual Value of Projects in the Region	N/A	N/A	N/A	N/A	N/A
Annual Quantity of Asphalt Mixture in the Region	1.553	N/A	1.951	1.723	N/A
Annual Number of Projects in Other Regions	N/A	N/A	3.064	N/A	N/A
Annual Value of Projects in Other Regions	N/A	N/A	N/A	N/A	N/A
Annual Quantity of Asphalt Mixture in Other Regions	N/A	N/A	N/A	N/A	N/A

Table 5-7: Variance inflation factor for the explanatory variables in the regression models of non-asphalt-intensive projects

Variables	3130	3121	1812	1802	4510
Ln Quantity for the Item	1.754	5.121	1.235	1.106	Lack of enough observations to conduct the regression analysis
Ln Total Bid Price	1.728	3.801	1.241	1.096	
AC Index at the Bid Date	N/A	1.009	1.036	3.575	
Number of Bidders	1.328	N/A	N/A	N/A	
Relative Value of the Line Item	N/A	3.280	N/A	N/A	
Duration of the Project	N/A	N/A	N/A	N/A	
Past Trend of the AC Index	N/A	N/A	N/A	2.761	
PAC Eligibility of the Project	N/A	N/A	N/A	N/A	
Location of the Project: Region 1	N/A	N/A	N/A	N/A	
Location of the Project: Region 2	N/A	N/A	1.120	N/A	
Location of the Project: Region 3	1.363	N/A	N/A	1.440	
Location of the Project: Region 4	1.614	1.035	1.215	N/A	
Location of the Project: Region 5	1.163	1.086	1.093	N/A	
Location of the Project: Region 6	N/A	N/A	N/A	N/A	
Location of the Project: Region 7	N/A	N/A	N/A	N/A	
Annual Number of Projects in the Region	N/A	N/A	N/A	N/A	
Annual Value of Projects in the Region	N/A	N/A	N/A	2.567	
Annual Quantity of Asphalt Mixture in the Region	N/A	N/A	N/A	N/A	
Annual Number of Projects in Other Regions	1.346	N/A	N/A	N/A	
Annual Value of Projects in Other Regions	N/A	N/A	N/A	4.748	
Annual Quantity of Asphalt Mixture in Other Regions	N/A	N/A	N/A	5.337	

5.5. Interpretation of the Results

In the previous sections, regression analysis was conducted to model the variations in the submitted bid prices for major asphalt line items of asphalt-intensive and non-asphalt-intensive projects.

5.5.1. Asphalt-Intensive Projects

The results of the five regression models created for asphalt-intensive projects indicate that the quantity of the asphalt line item is a statistically significant explanatory variable with a negative sign in all five models for asphalt-intensive projects. The negative sign indicates that the larger the quantity of the asphalt in the project, the lower the contractor's unit price for the asphalt line item (i.e., the existence of economy of scale). The quantity variable has the highest absolute t-statistics value among all potential explanatory variables in all models and has the highest power to explain the variations in the submitted bid prices for major asphalt line items.

Asphalt cement price index at the bid date is a statistically significant explanatory variable in all five models of asphalt-intensive projects with a positive coefficient, indicating that the expected bid prices increase as the asphalt cement price index increases.

The explanatory variable of total bid price is statistically significant in three out of five models developed for asphalt-intensive projects with a positive coefficient, indicating that the expected bid prices for major asphalt line items are relatively greater for larger projects than for smaller projects.

Similar to the total bid price, the relative value of the asphalt line item is statistically significant with a positive coefficient in three out of five models for asphalt-intensive projects, indicating that the expected bid price for those major asphalt line items increases as the relative value of the line item increases. The number of bidders is a statistically significant explanatory variable with a negative coefficient in two models for asphalt-intensive projects, which indicates that expected bid prices decrease as the number of bidders increases.

Project duration is not a statistically significant explanatory variable for all models created for asphalt-intensive projects except for the model of line item 1812. Even for this model, the t-statistic for project duration is relatively low; therefore, project duration does not have considerably high explanatory power to describe the variation in submitted bid prices for major asphalt line items in asphalt-intensive projects.

Although the asphalt cement price index is a significant explanatory variable in all models created for asphalt-intensive projects, the explanatory variable of the past trend of the asphalt cement price index is only significant in the model developed for line item 1812. Thus, the past trend of the asphalt cement price is not a significant variable to describe the variations in the submitted bid prices for most asphalt line items. It can be concluded that from contractors' point of view, the past trend of the asphalt cement price index is not an appropriate factor to use to determine their bid prices. This might be due to the significant volatility in the asphalt cement price index, indicating that future prices do not follow past trends in many cases. Thus, contractors do not consider the past trends in their bids.

Variables representing the location of the project do not show any similar effects in explaining the variations in submitted bid prices for different asphalt line items. The variables representing regions 4 and 5 are statistically significant in four out of the five models created for asphalt-intensive projects with positive coefficients (i.e., expected bid prices for projects in regions 4 and 5 are relatively higher than those in the other regions). None of the location variables has a considerably large t-statistic. Overall, location is not a powerful explanatory variable to describe the variations in submitted bid prices for major asphalt line items in asphalt-intensive projects. Similarly, the three variables representing the market conditions in the region where the project was let and the three variables representing market conditions in the neighboring regions do not have considerable explanatory power to explain variations in submitted bid prices for major asphalt line items.

The annual number and value of projects in the region where the project was let, the annual value of the projects in other regions, and the annual quantity of asphalt mixture in other regions are not statistically significant in any models developed for asphalt-intensive projects. The annual number of projects in other regions and the annual quantity of asphalt mixture in the region are statistically significant in only one and three of the models for asphalt-intensive projects, respectively. The t-statistics of those variables in those models are not considerably large. Thus, variables related to existing and upcoming projects in the market do not have considerable explanatory power to explain the variations in submitted bid prices for asphalt line items in asphalt-intensive projects.

Finally, PAC eligibility is not a statistically significant explanatory variable in all models created for asphalt-intensive projects, except the model for line item 1812. Even in this model, the project's PAC eligibility is statistically significant with a positive sign (i.e., the expected bid prices for asphalt line item 1812 is greater in PAC-eligible projects than in PAC-ineligible projects). This line item is related to leveling and requires more liquid asphalt cement (approximately 6.5-7% of hot mix asphalt volume) compared to the other line items. The t-statistic of the PAC variable in this model is not substantially large. Thus, the project's eligibility for the PAC program does not have much power to explain the variations in the submitted bid prices for this line item. Overall, no evidence was found to support the hypothesis that offering PAC would reduce the submitted bid prices of major asphalt line items in asphalt-intensive projects.

5.5.2. Non-Asphalt-Intensive Projects

The results of the regression analysis for non-asphalt-intensive projects indicate that the quantity of the asphalt line item is a statistically significant explanatory variable with a negative coefficient in all four models, indicating that the submitted bid prices for major asphalt line items in non-asphalt-intensive projects are expected to decrease as the quantity of the line items increases.

The explanatory variable of total bid price is statistically significant in all four models created for non-asphalt-intensive projects with a positive coefficient, indicating that the expected bid prices for major asphalt line items in non-asphalt-intensive projects are relatively greater for large projects than for small projects.

Asphalt cement price index is a statistically significant explanatory variable with a positive sign in three out of four models, indicating that the expected value of bid prices for major asphalt line items in non-asphalt-intensive projects increases as the asphalt cement price index increases.

Number of bidders, relative value of the line item, and past trend of the asphalt cement index are statistically significant in only one out of the four models, with a not considerably large t-statistic. Thus, these variables are not among the powerful explanatory variables to explain the variations in submitted bid prices.

Project duration and the three binary variables representing the location of the project in regions 1, 6, and 7 are not statistically significant in any models. The variables representing regions 4 and 5 are statistically significant in three out of the four models created for non-asphalt-intensive projects with positive coefficients (i.e., expected bid prices for projects in regions 4 and 5 are relatively higher than those in the other regions). None of the location variables has a considerably large t-statistic. Overall, location is not a powerful explanatory variable to describe the variations in submitted bid prices for major asphalt line items in non-asphalt-intensive projects.

The annual number of projects and quantity of asphalt mixture in the region where the project was let are not statistically significant in any models. The other four explanatory variables related to market conditions (i.e., annual value of the projects in the region, annual number of projects, value of the projects, and quantity of asphalt mixture in other regions) are statistically significant in only one model with no considerably large t-statistics. Overall, the variables representing market conditions do not have considerable explanatory power to explain the variations in the submitted bid prices for major asphalt line items. The explanatory variable of the project's PAC eligibility is not a statistically significant variable in any models created for non-asphalt-intensive projects.

5.6. Summary

It is concluded that the variations in the submitted bid prices for major asphalt line items in transportation projects can be explained by a linear combination of several variables, such as the quantity of the asphalt line items in the project, total bid price, and the asphalt cement price index. The most powerful explanatory variables for explaining the variations in the submitted bid prices are the quantity of the line item, the total bid price of the projects, and the asphalt cement price index at the bid date.

Variables, such as the duration of the project, the past trend of the asphalt cement price index, the location of the project, and the variables related to market conditions in the region in which the project was let or in neighboring regions are typically not statistically significant and do not have considerable explanatory power in most cases to explain the variations in the submitted bid prices.

Eligibility for the PAC is statistically nonsignificant in all models except the one developed for line item 1812 (Recycled Asphaltic Concrete Leveling) in asphalt-intensive projects. This variable has a positive coefficient, indicating that expected bid prices for this line item in PAC-eligible projects are higher than those in PAC-ineligible projects. Thus, no evidence was found to support the hypothesis that offering PAC would reduce the submitted bid prices of major asphalt line items in both asphalt-intensive and non-asphalt-intensive projects.

Timing of asphalt work may affect contractors' submitted bid prices. Contractors may submit relatively higher bids for new construction projects with asphalt work scheduled in the distant future than for overlay projects with asphalt work scheduled close to the contract award date. However, this likelihood could not be examined in this study due to the limitations of our dataset. No further timing information is available other than the total project duration that has been used in this study. In a future study, detailed information about project schedule, especially information about the exact timing of asphalt work, should be used to enhance the quality of the developed regression models.

Unbalanced bids can be a major issue in the assessment of submitted bid prices for construction projects (Arditi and Chotibhongs 2009). For the last two decades, GDOT has adopted a rigorous process for analyzing bid reasonableness in order to detect and reject unbalanced bids. In essence, every bid is evaluated against the engineer’s estimate, and GDOT rejects those nonresponsive bids that significantly differ from the engineer’s estimate. This comparative assessment is done for all major line items, including asphalt line items, both in terms of quantities and unit prices. Therefore, the dataset used in this study does not include rejected bids, and unbalancing has not been an issue in this analysis.

Although this study was conducted using data from transportation projects in the state of Georgia, the proposed framework for conducting rigorous empirical studies can be used for similar datasets in other states and internationally. A more elaborate study with a larger dataset from several state DOTs and more potential explanatory variables can be the next step to compare the results across different owner organizations.

The primary contributions of this research to the body of knowledge are (1) the creation of several multivariate regression models that have the power to explain the variations in highway contractors’ submitted bid prices for major asphalt line items; and (2) the empirical assessment of whether offering PACs contributes to the variations in contractors’ submitted bid prices for major asphalt line items in highway projects. This work is expected to contribute to the construction engineering and management community by helping capital planners of transportation agencies and owners of major capital projects systematically evaluate the effect of their PACs on the submitted bid prices for their capital projects.

CHAPTER 6. EFFECTS OF PACS ON COMPETITION AMONG BIDDERS

6.1. Introduction

In addition to receiving lower bid prices, transportation agencies may benefit from PACs through higher competition among bidders. Theoretically, offering PACs in contracts can stabilize the construction market and support all contractors regardless of their size and access to the sources of critical materials such as asphalt cement. Therefore, offering PACs in construction contracts can potentially encourage greater competition and result in more bidders and less dispersion in the bid prices received for a project (Ilbeigi and Castro-Lacouture 2017). However, there is little knowledge about the actual effects of PACs on the number of bidders for a project and the dispersion of submitted bid prices. This chapter addresses the fourth research objective of this dissertation: an empirical assessment of the effects of offering PACs on competition among bidders in transportation projects.

The level of competition can be quantified based on the number of bidders (Skolnik 2011) and the dispersion of the submitted bid prices (Dufwenberg and Gneezy 2000). The average number of bidders per project for each month, the number of unique contractors bidding each month divided by the number of projects delivered in that month, and the dispersion of submitted bid prices for each month are analyzed over time to determine whether these values statistically changed after PACs were offered. To conduct the empirical analysis and achieve the research objective, the reminder of this chapter is structured as follows. The proposed research methodology and steps taken in this study are described in the next section. The datasets used in this empirical study then are introduced. The average number of bidders per project and the number of unique bidders divided by the total number of projects for each month are analyzed over time using CUSUM control charts to check whether their processes statistically changed after the introduction of PACs. Dispersion of the submitted bid prices for projects is analyzed using standard deviation control charts with variable sample size. Finally, the conclusions and suggestions for future work are presented. The primary contribution of this research to the body of knowledge is the empirical assessment of whether offering PACs contributes to the number of bidders and/or dispersion of the received bid prices in highway projects. This study can help capital planners and transportation agencies systematically evaluate the effects of their risk management strategies, such as PACs, on received bid prices.

6.2. Research Methodology

One approach for statistically analyzing the effects that offering PACs has on the number of bidders or dispersion of submitted bid prices is to model the relationships between these dependent variables (i.e., the number of bidders and dispersion of bid prices) and various potential explanatory variables and see whether availability of PACs is a statistically significant explanatory variable in those models. However, properly identifying and quantifying all potential factors to accurately investigate their effects on the variations in the number of bidders and the dispersion of submitted bid prices may not be efficiently feasible in many cases due to lack of information and data. Alternatively, the historical records of the average number of bidders and dispersion of submitted bid prices can be monitored over time using system monitoring processes to check whether their variations have statistically changed after the introduction of the PAC program. The latter approach does not require a large amount of input data and produces reliable, unbiased, and robust results (Montgomery 2007).

The CUSUM system monitoring method combined with time series analysis is used to check whether the average number of bidders per job and the number of unique contractors divided by the number of projects for each month have statistically changed after the introduction of the PAC program. A standard deviation control chart with variable sample size then is used to check whether the dispersion of the bid prices changed after PACs were offered. Several steps are followed to conduct the CUSUM analysis:

1- The time series of the average number of bidders per project and the number of unique bidders divided by the total number of projects for each month are created.
2- Autocorrelation in time series is checked.
3- If the time series are autocorrelated, a proper time series model is created and fitted to the data, and the CUSUM analysis is conducted on the residuals of the time series model instead of the original data.
4- CUSUM control charts are created, and their lower and upper control limits are estimated using the historical data before the introduction of the PAC program.
5- Historical data after offering of PACs are checked for inclusion within the control limits.

Figure 6-1 shows the process used to analyze the effects of PACs on the number of bidders using the CUSUM system monitoring process.

To create the standard deviation control chart and analyze the dispersion of the submitted bid prices, the following steps are taken:

1- Datasets of contractors' submitted bid prices for major asphalt line items in transportation projects are gathered.
2- Outliers of the submitted bid prices are detected using the modified Thompson Tau method and are removed from the datasets.
3- Expected bid prices for each line item in each project are estimated using multivariate linear regression models.
4- Residuals of the regression models that represent the difference between the submitted bid prices and the expected bid prices are calculated.

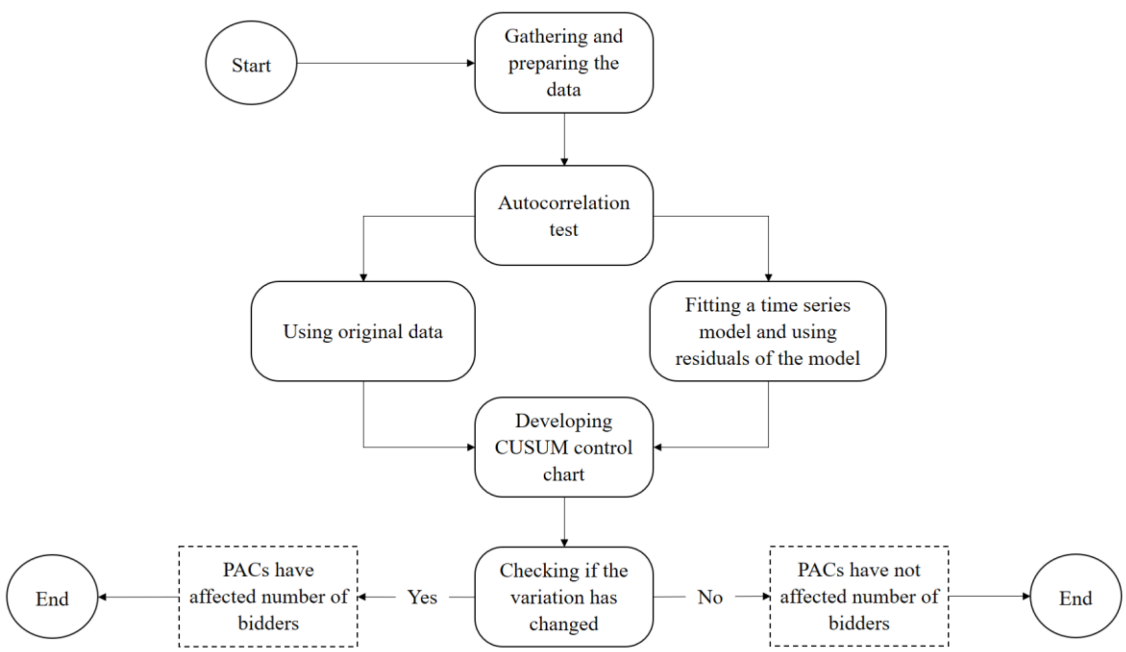

Figure 6-1: Process to conduct CUSUM control charts to examine effects of PACs on number of bidders

5- Standard deviation control charts with variable sample size are created for each major asphalt line item using the difference between submitted bid prices and expected bid prices before the start date of the PAC program.

6- Standard deviations of the submitted bid prices after offering of PACs are monitored using the developed control charts to check whether the dispersion of the bid prices has statistically changed.

Figure 6-2 shows the steps of conducting a standard deviation system monitoring process to investigate the effects of PACs on the dispersion of submitted bid prices.

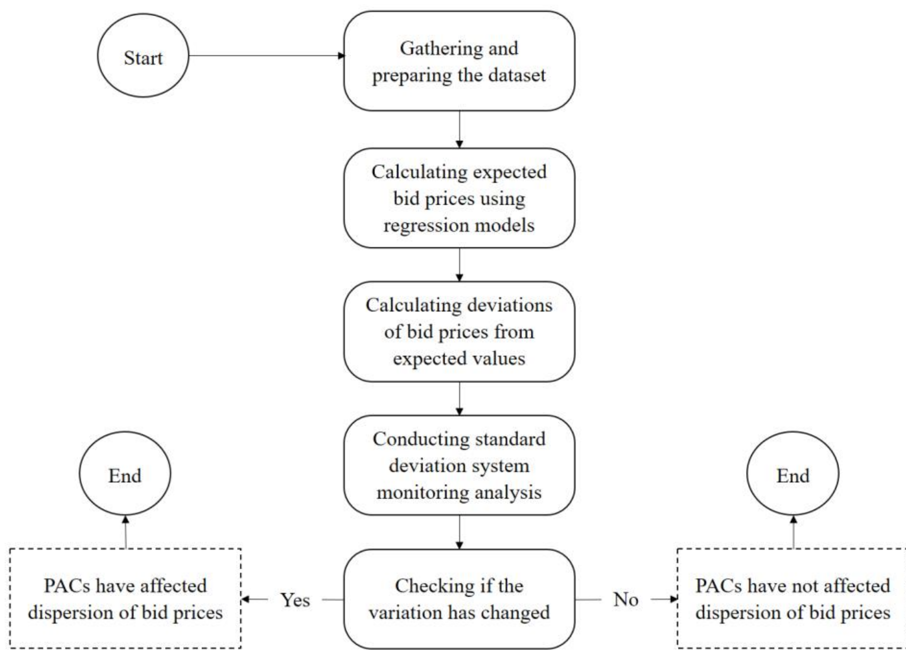

Figure 6-2: Process to conduct a standard deviation system monitoring process to examine effects of PACs on dispersion of bid prices

6.3. Dataset

Bid data were collected from 1,602 highway projects awarded in the state of Georgia from September 2000 to September 2007. These projects were distributed geographically across the seven districts in the state. Contract values of these projects range from $57,650 to $218,024,661 with an average contract value of $5,282,814 and a median of $1,392,159. Durations of these projects range from 67 to 2,043 days, with an average duration of 448 days and a median of 379 days.

6.4. Analysis of Effects of PACs on Number of Bidders

Figure 6-3 shows the average number of bidders per highway construction project in the state of Georgia from September 2000 to September 2007.

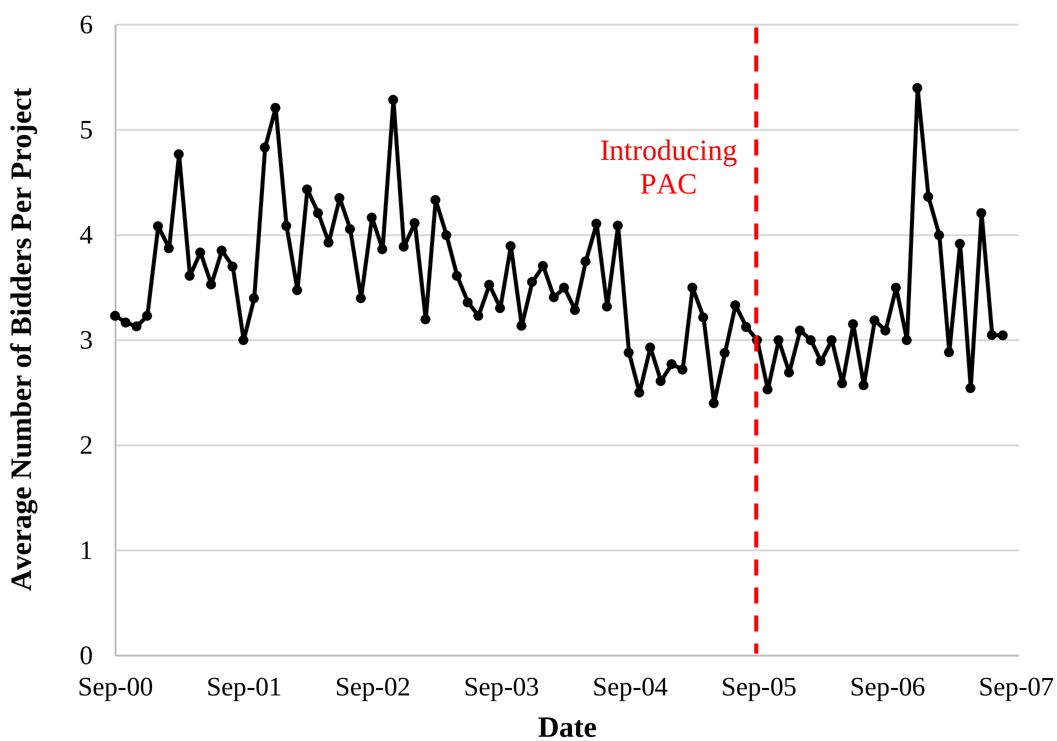

Figure 6-3: Average number of bidders per highway construction project in the state of Georgia

GDOT has been offered PAC for asphalt line items in highway construction projects since September 2005. The recorded average number of bidders per project from September 2000 to August 2005 are used to create the CUSUM system monitoring control chart and estimate its upper and lower control limits. The control chart created is used to check whether the observations after offering of PAC in September 2005 are still within the control limits or whether their behavior has statistically changed.

CUSUM control charts are designed to analyze variables that are not autocorrelated and follow a white noise process (Montgomery 2007). If the historical records of a variable are autocorrelated, a proper time series model should be fitted to the data and the CUSUM analysis should be conducted on the residuals of the time series model (Lu and Reynolds 2001).

The results of the Ljung-Box Q test (Ljung and Box 1978) on the average number of bidders per project specify that the time series of this variable is autocorrelated. Therefore, first, the time series analysis should be conducted. In the time series analysis, the main properties of the historical data are identified and characterized to build the time series model that can properly explain the variations of the data over time. AR models are among the time series models used most often. An *AR(p)* model represents the AR model of order *p*, which defines the current value of a process based on its *p* past values using the following equation (Diebold 1998):

$$X_t = c + \sum_{i=1}^{p} \varphi_i X_{t-i} + \varepsilon_t$$

Where:

φ_i is the parameter of the model

c is a constant

ε_t is the error term

The AR models are designed for stationary time series (i.e., historical data that show a trend and have a mean and variance that are constant over time). Therefore, if the historical data are not stationary, a trend variable might be required in the model. The results of the time series analysis indicate that an autoregressive model of order one (i.e., *AR(1)*) with a trend variable is properly fitted to the historical data. Table 6-1 shows the results of the Ljung-Box Q test on the residuals of the time series model. Because the calculated p-values of the Q-statistics for all lags are greater than the significance level (i.e., 5%), the null hypothesis that the data are independently distributed cannot be rejected. Therefore, the residuals do not show any serial correlation, and the time series model is acceptable (Diebold 1998).

CUSUM control charts monitor a process by accumulating derivations from the mean of the process using the following statistics (Montgomery 2007):

$$C_i^+ = max[0, x_i - (\mu_0 + K) + C_{i-1}^+]$$

$$C_i^- = max[0, (\mu_0 - K) - x_i + C_{i-1}^-]$$

Where:

C_i^+ is the cumulative derivation of point *i* above the target value

C_i^- is the cumulative derivation of point *i* below the target value

μ_0 is the mean of the process

K is the reference value that is typically defined as being halfway between the target mean (i.e., μ_0) and the out-of-control value of the mean that should be detected

If either C_i^+ or C_i^- exceeds the decision interval H, the process has statistically changed. A reasonable value for H is five times the process standard deviation (Montgomery 2007).

Table 6-1: Results of the Ljung-Box Q test on the residuals of the time series model

Lag	Autocorrelation	Q-Statistic	P-Value
1	–0.070	0.4231	
2	0.152	2.4466	0.118
3	–0.093	3.2209	0.200
4	0.091	3.9660	0.265
5	0.092	4.7373	0.315
6	0.090	5.4802	0.360
7	–0.020	5.5163	0.479
8	0.071	5.9913	0.541
9	–0.106	7.0761	0.528
10	0.084	7.7617	0.558
11	0.032	7.8602	0.642
12	0.118	9.2549	0.598
13	–0.097	10.222	0.597
14	–0.078	10.844	0.624
15	–0.007	10.848	0.698
16	–0.073	11.422	0.722
17	0.056	11.765	0.760
18	–0.071	12.320	0.780
19	–0.073	12.917	0.796
20	0.044	13.134	0.832

Figure 6-4 shows the CUSUM control chart for the average number of bidders per project. The lower and upper control limits are estimated as –2.408 and 2.408, respectively. Although the C^+ in February 2007 is very close to the upper limit, it does not pass the control limit and decreases immediately in the following month, indicating that it was not a statistically significant and long-lasting change in the behavior of the variable. Therefore, the control chart indicates that the process has not changed statistically after the introduction of the PAC program in Georgia in September 2005.

Other than the overall number of bidders per project, a PAC program may lead to a fairer market that attracts more companies to be active. Therefore, the number of unique contractors that participate in bids in a month divided by the total number of projects (Figure 6-5) is another indicator that is investigated as a proxy for competition.

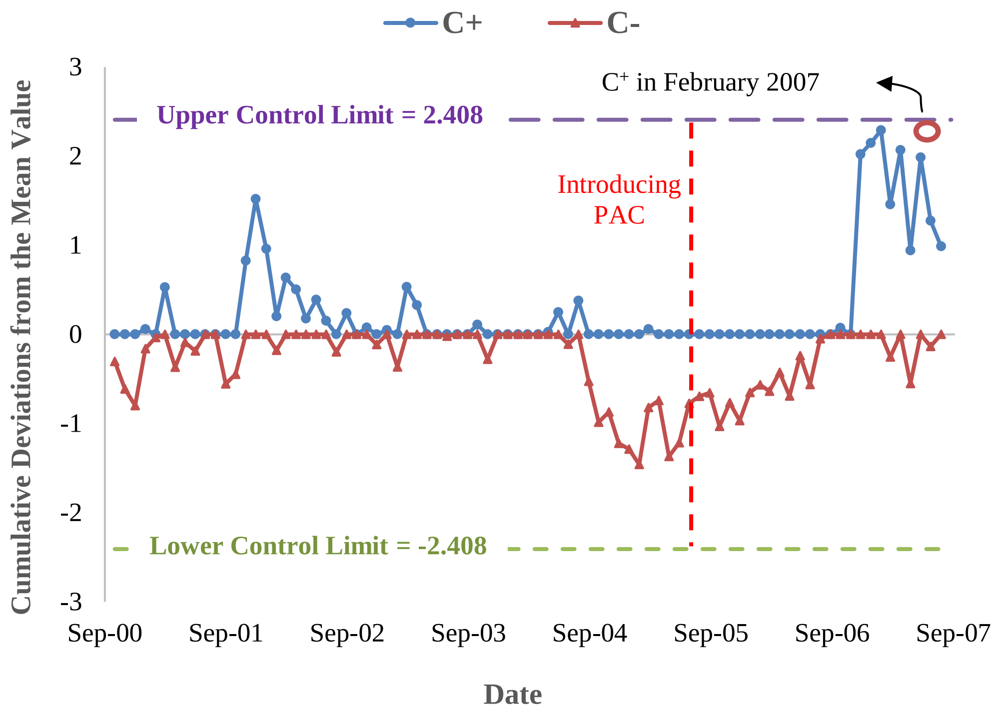

Figure 6-4: CUSUM control chart for the average number of bidders per project

The results of the Ljung-Box Q test for the historical records of this variable indicate that the p-values of the Q-statistics for all lags are greater than 5%. Thus, the time series is not autocorrelated, and the CUSUM control chart can be created using the original data. Figure 6-6 shows the control chart for the number of unique contractors bidding in Georgia divided by the total number of projects for each month. Similar to the previous control chart for the average number of bidders per project, the upper and lower control limits are estimated using the historical records before the introduction of the PAC program (i.e., from September 2000 to August 2005).

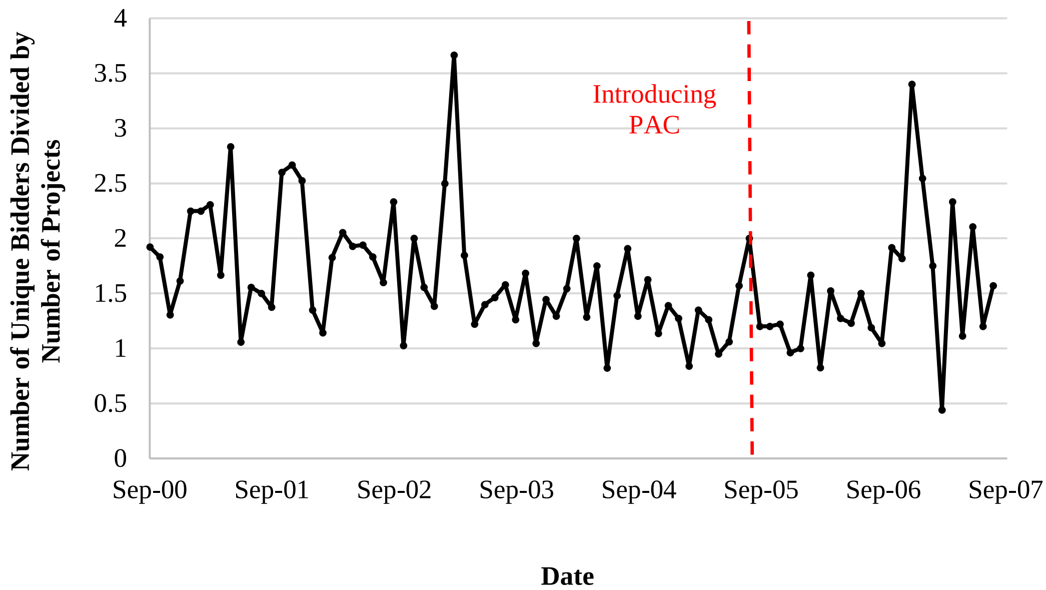

Figure 6-5: Number of unique bidders divided by total number of projects for each month

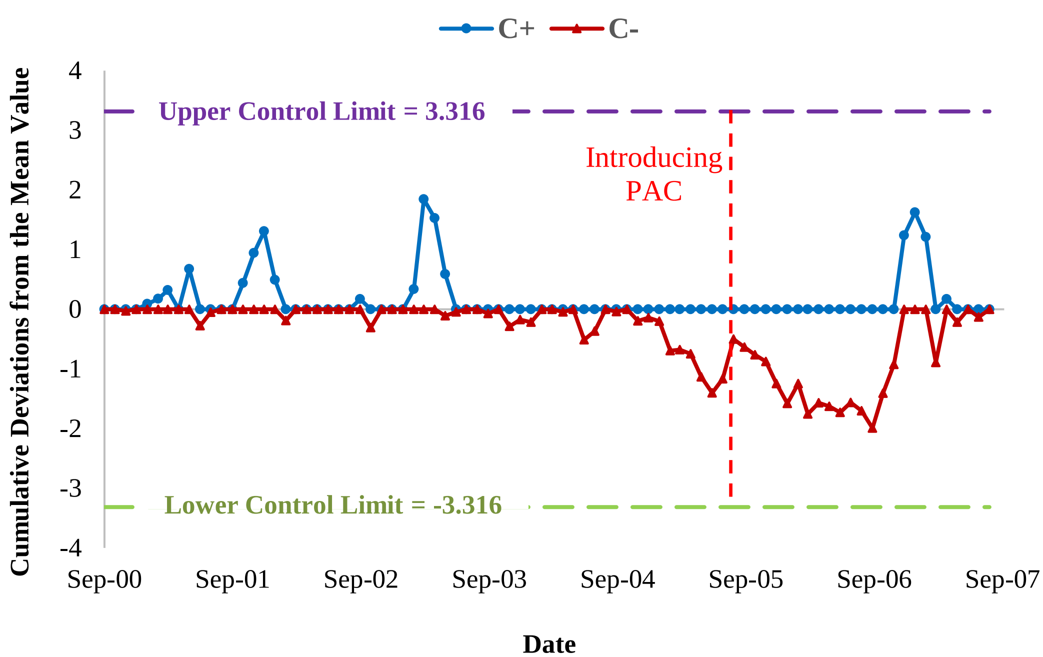

Figure 6-6: CUSUM control chart for the number of unique contractors bidding in Georgia divided by total number of projects each month

The lower and upper control limits are estimated as –3.316 and 3.316, respectively. The control chart shows that the number of unique bidders divided by the number of projects stays within the control limits after September 2005, and the behavior of this variable has not statistically changed after introduction of the PAC.

In summary, the results of the system monitoring process using the CUSUM control charts for both variables, the average number of bidders per project for each month and the number of unique bidders divided by the total number of projects in each month, show that there is no evidence to indicate that offering PAC has statistically affected these two variables.

6.5. Analysis of PAC Effects on Dispersion of Submitted Bid Prices

In a stable and reasonable market in which many contractors can properly compete, prices converge and owner organizations face less-dispersed bid prices (Dufwenberg and Gneezy 2000). Theoretically, offering PACs in contracts can stabilize the market by managing the risk of material price volatility and supporting all contractors regardless of their size and access to critical resources (Skolnik 2011). In this section, submitted bid prices for four major asphalt line items in highway projects in Georgia from September 2000 to September 2007 are analyzed to check whether the offering of PACs has affected the dispersion of bid prices. These asphalt line items represent four major types of asphalt mixtures widely used in highway projects in the state. Table 6-2 describes these line items and their number of observations in the dataset.

Table 6-2: Major asphalt mixture line items in Georgia

Line Item ID	Description
3121	Recycled Asphaltic Concrete 25mm Superpave, GP1 or GP2
3130	Recycled Asphaltic Concrete 12.5mm, Superpave, GP2, Including Bitumen Materials
3190	Recycled Asphaltic Concrete 19mm, GP1 or GP2 Including Bitumen Materials
1812	Recycled Asphaltic Concrete Levelling Including Bitumen Materials

The modified Thompson Tau test is used to detect the outliers in the submitted bid prices. Table 6-3 shows the number of observations and the number of outliers removed from the dataset for each asphalt line item. Only a small fraction of data points was identified as outliers for these asphalt line items. Most outliers were from projects with very small quantities of asphalt mixtures. The remaining data points are large enough to conduct meaningful statistical analysis.

Table 6-3: Number of observations and outliers in the dataset for each major asphalt line item

Line Item ID	Number of Observations	Number of Unusual Observations
3121	4633	77
3130	4463	136
3190	5545	123
1812	13501	155

First, the standard deviation system monitoring process for one of the line items (i.e., 3190) is described in detail to explain the steps and the methodology. Then the presented methodology is repeated on the other three line items. Figure 6-7 shows the scatter plot of the submitted bid prices for line item 3190 from September 2000 to September 2007 after removal of the detected outliers.

Because factors such as project size, location, contract duration, bid dates, and number of bidders may affect the bid prices (Ilbeigi et al. 2015a), the scales of the submitted bid prices for different projects might be different. Therefore, before analyzing the historical records of the bid prices using standard deviation control charts, the effects of other potential factors should be identified and captured. In chapter 5, multivariate linear regression models were created to explain the variations in the submitted bid prices for the major asphalt line items in highway construction projects. Potential explanatory variables such as quantity of the asphalt line item, asphalt cement price at bid date, project duration, total contract value of the project, location of the project, and number of bidders were identified.

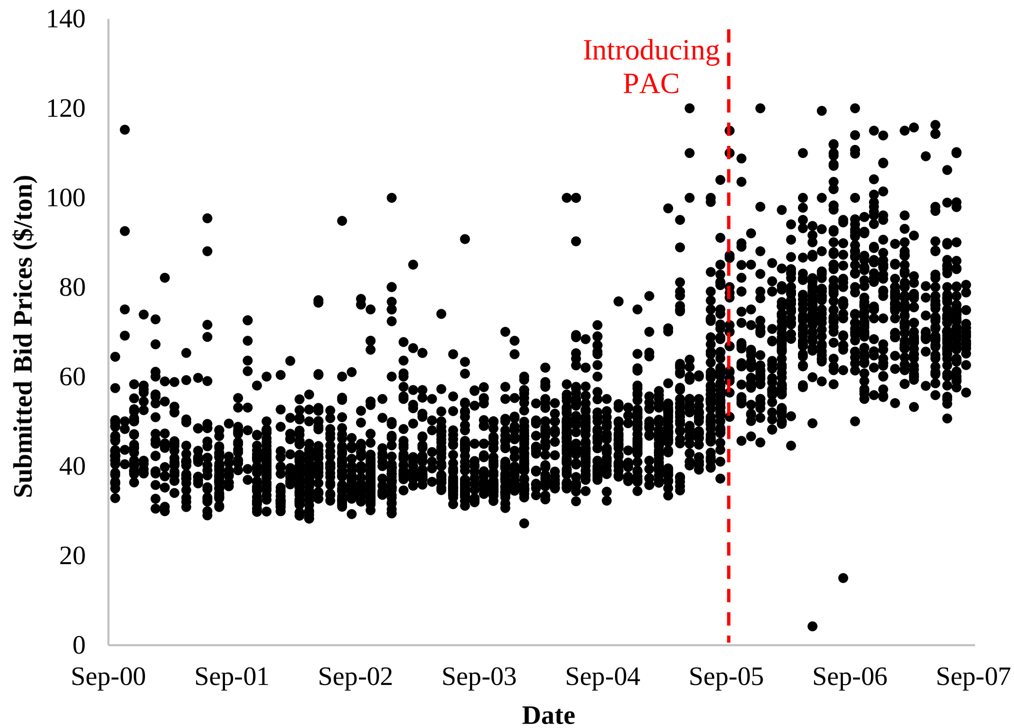

Figure 6-7: Submitted bid prices for line item 3190

Using the regression models developed in the previous chapter, the expected value for the submitted bid prices for each line item in each project is estimated. Then the error term (i.e., the difference between the actual submitted bid prices and the expected bid prices) for each observation is calculated. The error terms represent the variation of the actual submitted bid prices from the estimated expected bid prices. In chapter 5, the error terms (i.e., the residuals of their models) were shown to follow a normal distribution, indicating that the identified explanatory variables can properly explain the variations of the submitted bid prices.

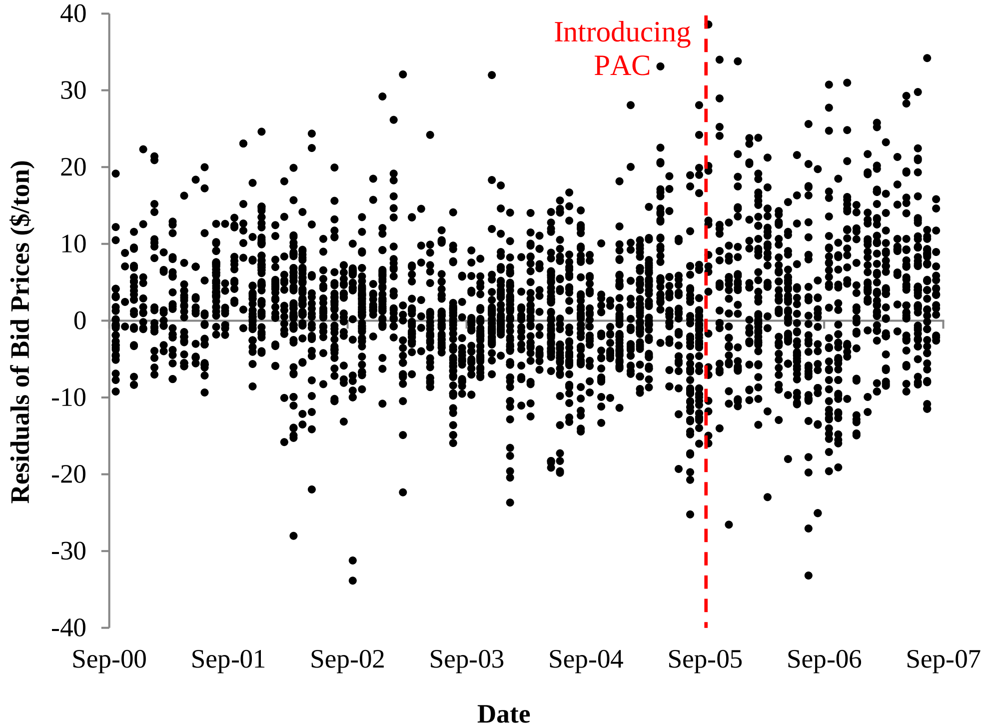

Figure 6-8: Deviations of the actual submitted bid prices from the expected bid prices for line item 3190

Basically, the error terms represent the bid prices after capturing and removing the effects of the most important effective factors. Therefore, the error terms are examined to check whether the dispersion of the deviations of the submitted bid prices from the expected bid prices statistically changed after the introduction of the PAC program. Figure

6-8 shows the deviation of the actual submitted bid prices from the expected bid prices (i.e., the residuals of the regression model) for line item 3190.

After cleaning and preparing the dataset, the dispersion of the deviations of the submitted bid prices from the expected bid prices is analyzed. The standard deviation control chart with variable sample size is used to monitor the dispersion over time and determine if the pattern changed statistically after introduction of the PAC program in September 2005. The standard deviation of the observations in each month is calculated, and the center line of the control chart is determined using the data from September 2000 to August 2005 (i.e., the period before the introduction of the PAC program) as follows (Montgomery 2013):

$$\bar{s} = \left[\frac{\sum_{i=1}^{m}(n_i - 1)s_i^2}{\sum_{i=1}^{m} n_i - m}\right]^{1/2}$$

Where:

m is the number of months

n_i is the number of submitted bid prices in the *i^th^* month

s_i is the standard deviation of the deviations of the submitted bid prices from the expected bid prices (i.e., the residuals of the regression model for bid prices) in the *i^th^* month

Because the number of submitted bid prices might be different for each month, the upper and lower control limits may not be constant and are determined as follows:

$$UCL = \bar{s} + 3\times\frac{\bar{s}}{c_4}\sqrt{1 - c_4^2}$$

$$LCL = \bar{s} - 3\times\frac{\bar{s}}{c_4}\sqrt{1 - c_4^2}$$

Where:

UCL is the upper control limit of the control chart

LCL is the lower control limit of the control chart

C_4 is a tuning constant that depends on the sample size (i.e., n)

The estimated center line of the control chart for item 3190 is *6.69*, and Figure 6-9 presents the created standard deviation control chart for this item. As shown by the control chart, the standard deviations after the introduction of the PAC program did not go below the lower control limit; in some months, it is actually even higher than the upper control limit. Therefore, although the results of the surveys and interviews conducted in previous studies (Eckert and Eger 2005; Skolnik 2011; Pierce et al. 2012) concluded that offering PAC would lead to less dispersion in bid prices, the results of the system monitoring process using standard deviation control charts for item 3190 does not show any reduction in the dispersion of the submitted bid prices after September 2005, when the PAC program was introduced in Georgia.

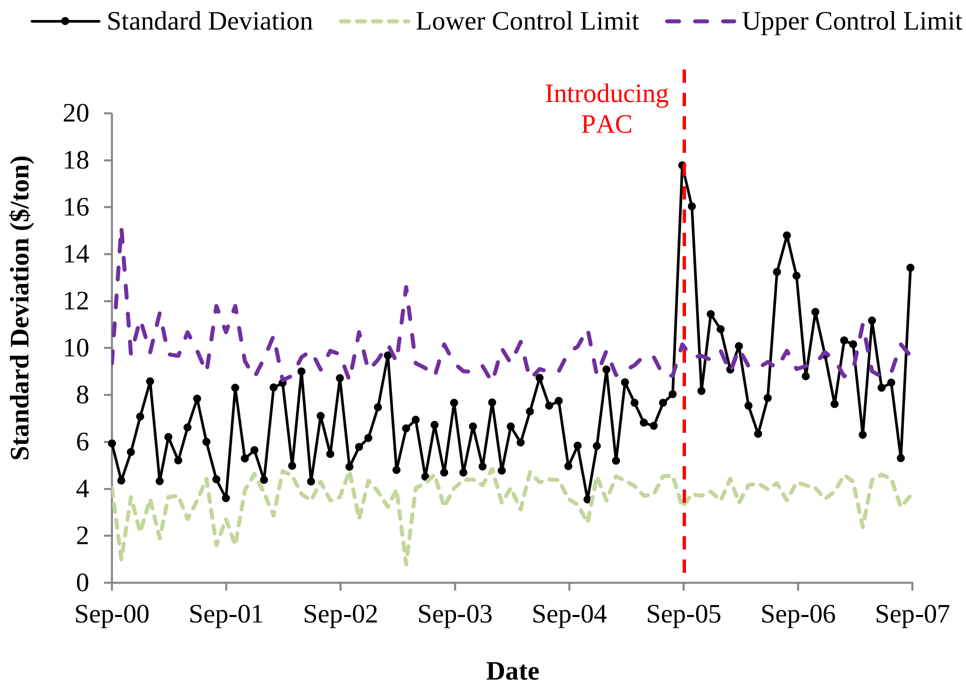

Figure 6-9: Standard deviation control chart for line item 3190

The proposed methodology is conducted on the other three major asphalt line items (i.e., 3121, 3130, and 1812) as well. Figure 6-10 to Figure 6-12 show the control charts for these items. Similar to the results for line item 3190, the results of the system monitoring process for the other major asphalt line items do not show any reduction in dispersion of the submitted bid prices after the introduction of the PAC program; actually, in some months after September 2005, the dispersions are even greater than the upper control limit. Therefore, there is no empirical evidence to support the hypothesis that offering PACs would reduce the dispersion of the submitted bid prices.

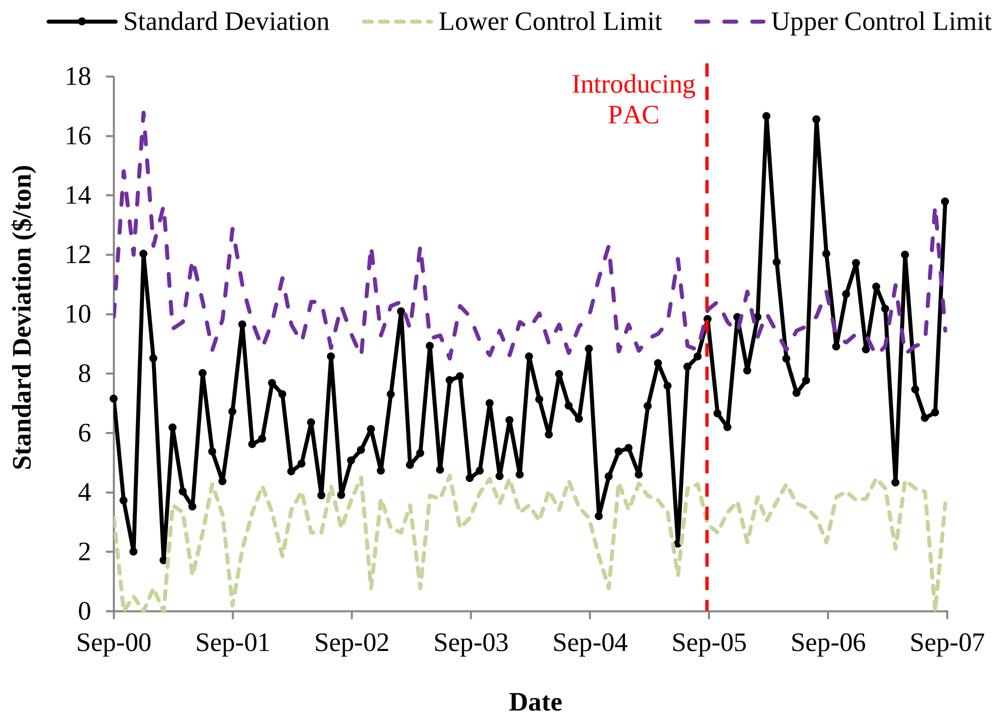

Figure 6-10: Standard deviation control chart for item 3121

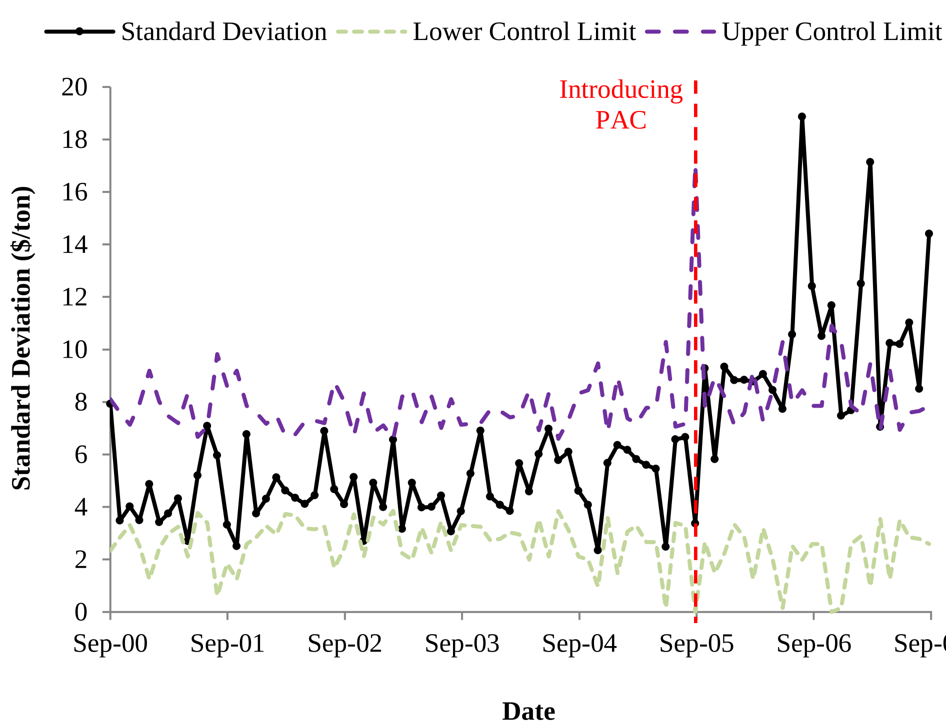

Figure 6-11: Standard deviation control chart for item 3130

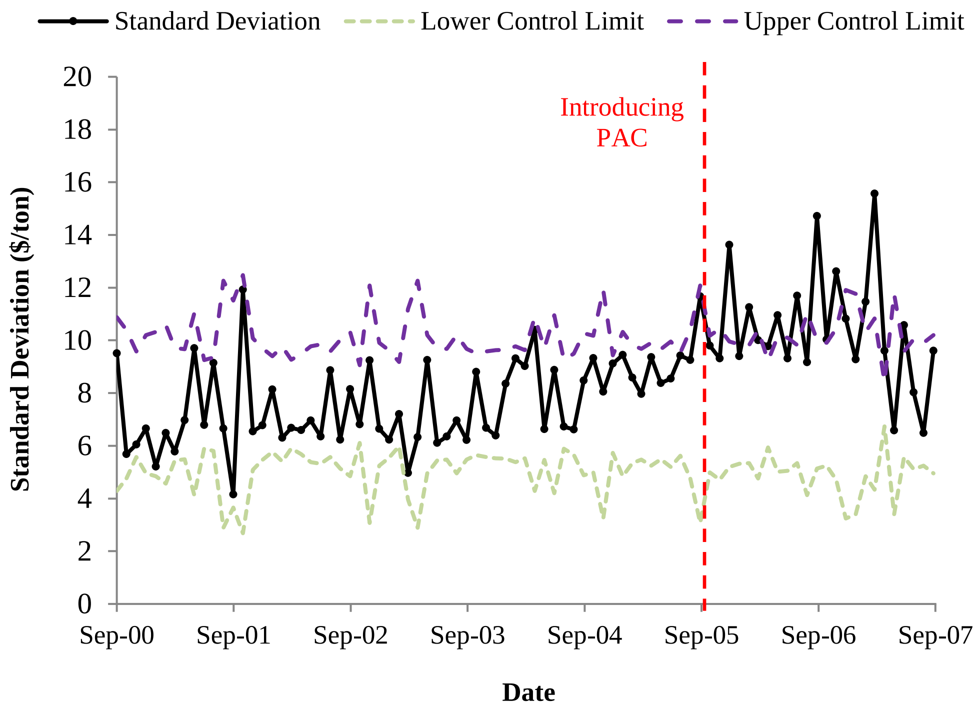

Figure 6-12: Standard deviation control chart for item 1812

6.6. Summary

In this chapter, the effects of the offering of PACs on the average number of bidders per project, the number of unique bidders divided by the number of total projects for each month, and the dispersion of the submitted bid prices for four major asphalt line items were analyzed. CUSUM control charts were used for the first two variables: the average number of bidders per project and the number of unique contractors bidding each month divided by the number of projects. Results from the system monitoring analysis using CUSUM control charts indicate that the variations and behaviors of these variables have not statistically changed after introduction of PAC in September 2005.

Dispersion monitoring analysis was conducted on historical records of the submitted bid prices for the four major asphalt line items using standard deviation control charts with variable sample size. The standard deviation control charts show that the dispersion of the submitted bid prices for all four line items has not decreased after the introduction of PAC. This research advances the literature because the results show that there is no empirical evidence to indicate that offering PACs would increase the number of bidders or decrease the dispersion of the submitted bid prices for asphalt line items.

Although this study was conducted using bid data from the state of Georgia, the proposed methodology can be used for similar datasets in other states and internationally. This chapter's primary contribution to the body of knowledge and state of practice is its empirical and statistical analysis of the effects that offering PACs has on the level of competition based on the number of bidders and on the dispersion of the submitted bid prices. The results of this study can help capital planners of transportation agencies and owners of major capital projects systematically evaluate their financial risk management strategies, such as PAC. Identifying and analyzing effective factors in the performance of PACs, finding more accurate means of improving their effectiveness on the submitted bid prices and level of competition, devising a systematic approach to designing PACs, finding the most suitable time to implement PACs, and identifying appropriate types of projects for PAC programs can be the basis for future studies.

CHAPTER 7. CONCLUSIONS AND FUTURE DIRECTIONS

7.1. Introduction

Volatility in material costs has been a serious challenge for state DOTs and contractors since the 2000s. Volatility and uncertainty in the price of critical materials increase risk for contractors in fixed-price contracts and can lead to price speculation and bid inflation. One of the most common strategies used to address inflated bid prices and encourage the submission of lower bids is PACs, which guarantee an adjustment in payments to contractors based on the size and direction of material price changes. Contrary to the widespread application of PACs by state DOTs, there is little knowledge about how asphalt cement prices fluctuate over time. Furthermore, there is little knowledge about measuring, analyzing, and forecasting asphalt cement price volatility. This gap in knowledge makes it difficult to develop material price risk management strategies properly. Moreover, it is not clear how offering PACs in transportation contracts affects submitted bid prices for major asphalt line items and their dispersions and the number of bidders.

After a comprehensive review of the existing body of knowledge on uncertainties in the price of critical materials in transportation projects and PACs, time series analysis was conducted in Chapter 3 to forecast the future price of asphalt cement. ARCH/GARCH time series analysis was conducted to quantify and forecast the level of uncertainties in the price of asphalt cement in Chapter 4. In Chapter 5, the impact that offering PACs has on submitted bid prices for major asphalt line items was analyzed using multivariate regression analysis. Finally, the effects that offering PACs has on dispersion of submitted bid prices and number of bidders were analyzed using system monitoring processes.

7.2. Summary of Results and Contributions to the Body of Knowledge

In chapter 3, the time series of asphalt cement price is analyzed and its major characteristics are identified. The results of this empirical study show that time series data of asphalt cement price is autocorrelated and non-stationary and does not show a very strong seasonal pattern. Based on the identified time series characteristics, four univariate time series forecasting models, Holt ES, Holt-Winters ES, ARIMA, and seasonal ARIMA, were created to take into account the short-term variations in asphalt cement price in forecasting its future values. The results of in-sample model fitting showed that all four models have proper goodness-of-fit. Residual analysis revealed that the underlying conditions of the models hold true and, therefore, these time series models are usable. The results of the out-of-sample forecasting show that all four time series models can predict the future values of asphalt cement price with proper accuracy, but among the four models, the ARIMA and Holt ES models are the most accurate with less than 2% error. The primary contributions of this chapter of the study to the existing body of knowledge are twofold: (1) characterizing the variations of asphalt cement prices over time; and (2) creating univariate time series forecasting models to predict future values of asphalt cement prices. The results of this study can help both owners and contractors improve the budgeting process, prepare more accurate cost estimates, and reduce the risk of asphalt cement price variations in transportation projects.

In chapter 4, the uncertainty of asphalt cement price was measured and forecast using ARCH/GARCH models. Results indicate that a GARCH(2,1) model with a conditional mean function of ARMA(2,2) can properly model the conditional volatilities in the price of asphalt cement. The primary contributions of this chapter of the study to the existing body of knowledge are measuring, modeling, and forecasting uncertainties in the price of asphalt cement over time. The results of this study can help transportation agencies systematically measure, analyze, and forecast uncertainties in the price of asphalt cement and implement their risk management strategies at the right time.

The primary contributions of chapter 5 of this study to the body of knowledge are (1) the creation of several multivariate regression models that have the power to explain the variations in highway contractors' submitted bid prices for major asphalt line items; and (2) the empirical assessment of whether offering PACs contributes to variations in contractors' submitted bid prices for major asphalt line items in highway projects. This work is expected to contribute to the construction engineering and management community by helping capital planners of transportation agencies and owners of major capital projects systematically evaluate the effect of their PACs on the submitted bid prices for their capital projects.

In chapter 6, system monitoring processes were used to analyze the impact of offering PACs on number of bidders and dispersion of submitted bid prices. The primary contribution of this chapter to the body of knowledge and state of practice is its empirical and statistical analysis of the effects that offering PACs has on the level of competition based on the number of bidders and on the dispersion of the submitted bid prices. The results of this study can help capital planners of transportation agencies and owners of major capital projects systematically evaluate their financial risk management strategies, such as PAC.

7.3. Future Works and Directions

As explained in the previous sections, this dissertation has focused on analyzing uncertainties in the price of asphalt cement to improve risk management strategies for material price volatility and on empirically analyzing the performance of PACs and their impact on submitted bid prices and level of competition.

Systematic design of PACs can be an important topic for future studies. As noted in chapter 1, a PAC program consists of different elements, such as trigger points; eligibility conditions based on duration, quantity of material, and dollar value of projects; eligible types of projects; maximum adjustment limit; and price index. Systematically determining these factors is very important to improve the performance of PACs. Currently, there is little knowledge about design of PACs. Future research can extend this dissertation in different ways:

- Trigger points, which refer to the percent changes in material prices that initiate the application of relevant adjustment clauses, may affect the performance of PACs significantly. The distribution of the trigger point is broad, and they range from 0% to 20%. However, there is little knowledge about systematically determining them. In a very rare study, Zhou and Damnjanovic (2011) used a weighted least squares regression model to create a generic algorithm for determining the amount of risk that should be transferred to owner organizations using strategies such as PACs. The results of their model can help determine trigger points in PACs. However, their model can be implemented only for materials with future prices that are traded in the market.

- Eligibility conditions for the PAC program based on factors such as duration of the project, quantity of asphalt, and dollar value of the project are important factors that affect the performance of PACs. The eligibility conditions differ significantly through various states DOTs. For example, GDOT defines eligibility for its PAC program only based on duration of a project, whereas many other state DOTs consider other factors such as quantity of asphalt. An empirical analysis by Ilbeigi et al. (2015b), using unsupervised statistical methods, showed that GDOT could improve performance of its PAC program for asphalt cement by defining eligibility conditions based on quantity of asphalt and the contract value of the project. Developing a systematic approach to determine eligibility conditions is a topic for future studies.
- Some state DOTs offer PACs with an opt-in policy, which gives contractors the right to decide whether to accept the PAC (Skolnik 2011). However, there is little knowledge about a systematic decision analysis approach to evaluate PACs in given market conditions. This, too, can be a basis for future research.
- Typically, PAC programs define a maximum adjustment limit that determines the maximum amount of financial risk that is shifted to owner organizations. Currently, state DOTs determine the maximum adjustment limit solely based on their experiences. However, developing a quantitative approach to systematically determine the limits can improve the performance of PACs and be a basis for the future direction of studies.
- Contrary to the widespread application of PACs by state DOTs, there is little knowledge about the financial value of offering PACs in transportation contracts.

This gap in knowledge makes it difficult for contractors and state DOTs to systematically evaluate the impact of offering PACs on their risk profiles. Ilbeigi et al. (2016b) developed a real option model to estimate the financial value of PAC programs for asphalt cement. However, a more comprehensive approach for systematically quantifying the financial value of PACs in transportation contracts is necessary and can be another topic for future studies.

REFERENCES

AASHTO Task Force on Bidding and Contract Award Procedures. (1974). "Suggestions and Guidelines for Combating Shortages and Minimizing the Effect of Price Uncertainties for Materials and Fuel in Construction." FHWA Contract Administration.

AASHTO Subcommittee on Construction, Contract Administration Section. (2009). "Survey on the Use of Price Adjustment Clauses." FHWA Contract Administration, <http://www.fhwa.dot.gov/programadmin/contracts/aashto.cfm> (May 12, 2014).

Abu Hammad, A. A., Ali, S. M. A., Sweis, G. J., & Sweis, R. J. (2010). "Statistical analysis on the cost and duration of public building projects." *Journal of Management in Engineering*, 26(2), 105-112.

Ahmad, I., & Minkarah, I. (1988). "Questionnaire survey on bidding in construction." *Journal of Management in Engineering*, 4(3), 229-243.

Akaike, H. (1998). Information theory and an extension of the maximum likelihood principle. In Selected Papers of Hirotugu Akaike (pp. 199-213). Springer. New York.

Akintoye, A. (2000). "Analysis of factors influencing project cost estimating practice." *Construction Management & Economics*, 18(1), 77-89.

Andersen, T. G., & Bollerslev, T. (1998). "Answering the skeptics: Yes, standard volatility models do provide accurate forecasts." *International Economic Review*, 39(4), 885-905.

Anderson, S. D., Molenaar, K. R., & Schexnayder, C. J. (2006). Final Report for NCHRP Report 574: Guidance for Cost Estimation and Management for Highway Projects During Planning, Programming, and Preconstruction. National Cooperative Highway Research Program, Transportation Research Board.

Arditi, D., & Chotibhongs, R. (2009). "Detection and prevention of unbalanced bids." *Construction Management and Economics*, 27(8), 721-732.

Ashuri, B., & Lu, J. (2010). "Time series analysis of ENR construction cost index." *Journal of Construction Engineering and Management*, 136(11), 1227-1237.

Back, W. E., Boles, W. W., & Fry, G. T. (2000). "Defining triangular probability distributions from historical cost data." *Journal of Construction Engineering and Management*, 126(1), 29-37.

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

Baron, D. P., & De Bondt, R. R. (1979). "Fuel adjustment mechanisms and economic efficiency." *The Journal of Industrial Economics*, 27(3), 243-261.

Behmardi, B., Doolen, T., & Winston, H. (2013). "Comparison of predictive cost models for bridge replacement projects." *Journal of Management in Engineering*, 31(4), 04014058.

Bollerslev, T. (1986). "Generalized autoregressive conditional heteroscedasticity." *Journal of Econometrics*, 31(3), 307-327.

Carr, R. I. (1989). "Cost-estimating principles." *Journal of Construction Engineering and Management*, 115(4), 545-551.

Carr, P. G. (2005). "Investigation of bid price competition measured through prebid project estimates, actual bid prices, and number of bidders." *Journal of Construction Engineering and Management*, 131(11), 1165-1172.

Carroll, D., Eger III, R., and Kray, M., (2006). "A Study of Fuel Price Adjustment." Georgia Department of Transportation, Final Supplementary Report: GDOT RP 06-06.

Cheung, S. O., & Shen, L. (2016). "Concentration analysis to measure competition in megaprojects." *Journal of Management in Engineering*, 04016023.

Christian, J., & Pandeya, A. (1997). "Cost predictions of facilities." *Journal of Management in Engineering*, 13(1), 52-61.

Crocker, K. J., & Masten, S. E. (1991). "Pretia ex machina? Prices and process in long-term contracts." *Journal of Law and Economics*, 34(1), 69-99.

Damnjanovic, I., Anderson, S., Wimsatt, A., Reinschmidt, K., & Pandit, D. (2009). "Evaluation of ways and procedures to reduce construction cost and increase competition." *Texas Transportation Institute, Texas A&M University System*.

Daníelsson, J. (2011). Financial risk forecasting: The theory and practice of forecasting market risk with implementation in R and Matlab (Vol. 588). John Wiley & Sons. New York.

Diebold, F. X. (1998). Elements of forecasting. South-Western. Nashville, Tennessee.

Dufwenberg, M., & Gneezy, U. (2000). "Price competition and market concentration: An experimental study." *International Journal of industrial Organization*, 18(1), 7-22.

Eckert, C., & Eger, R. J. (2005). "A study of liquid asphalt price indices applications to Georgia pavement contracting." *Georgia Tech Research Institute*, Report: A-7319 No.2. Atlanta, Georgia.

Enders, W. (2008). Applied econometric time series. John Wiley & Sons. Hoboken, New Jersey.

Engle, R. F. (1982). "Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation." *Journal of the Econometric Society*, 50(4), 987-1007.

Engle, R. F., & Patton, A. J. (2001). "What good is a volatility model?" *Quantitative Finance*, 1(2), 237-245

Federal Highway Administration (FHWA). (2013). "Highway Statistics 2013." <https://www.fhwa.dot.gov/policyinformation/statistics/2013/> (November 14, 2015)

Fleming, J., & Ostdiek, B. (1999). "The impact of energy derivatives on the crude oil market." *Energy Economics*, 21(2), 135-167.

Freedonia. (2015). US Asphalt Market, Cleveland, Ohio. <http://www.freedoniagroup.com/industry-study/3304/asphalt.htm> (November 14, 2015)

Fuller, W. A. (1976). Introduction to statistical time series. John Wiley and Sons. New York.

Gallagher, J. P., & Riggs, F. (2006). "Material price escalation: Allocating the risks." *Construction Briefings*, (2006-12).

Gardner, E. S. (1985). "Exponential smoothing: The state of the art." *Journal of forecasting*, 4(1), 1-28.

Georgia Department of Transportation. (2016) “Asphalt & Fuel Index.” <http://www.dot.ga.gov/PS/Materials/AsphaltFuelIndex> (July 4, 2016)

Golec, J. (1990). “The financial effects of fuel adjustment clauses on electric utilities.” *The Journal of Business*, 63(2), 165-186.

Gollop, F. M., & Karlson, S. H. (1978). “The impact of the fuel adjustment mechanism on economic efficiency.” *The Review of Economics and Statistics*, 60(4), 574-584.

Granger, C. W. J. (2001). “Investigating causal relations by econometric models and cross-spectral methods.” *Econometric Society Monographs*, 33, 31-47.

Heravi, G., & Ilbeigi, M. (2012). “Development of a comprehensive model for construction project success evaluation by contractors.” *Engineering, Construction and Architectural Management*, 19(5), 526-542.

Holmgren, M., Casavant, K. L., & Jessup, E. (2010). “Evaluation of fuel usage factors in highway construction in Oregon.” *School of Economic Sciences, Washington State University*, Pullman, WA.

Holt, C. C. (2004). “Forecasting seasonals and trends by exponentially weighted moving averages.” *International Journal of Forecasting*, 20(1), 5-10.

Hwang, S., & Liu, L. Y. (2009). “Contemporaneous time series and forecasting methodologies for predicting short-term productivity.” *Journal of Construction Engineering and Management*, 136(9), 1047-1055.

Ilbeigi, M., Ashuri, B., & Shayegh, S. (2015a). “Price adjustment clauses and submitted bid prices for major asphalt line items in highway projects.” *Journal of Construction Engineering and Management*, 142(5), 04015103.

Ilbeigi, M., Ashuri, B., & Shayegh, S. (2015b). “A data mining approach for analyzing the effects of price adjustment clauses on bid prices considering material quantity and projects size.” *Transportation Research Board 94th Annual Meeting*. Washington DC. January 11-15, 2015.

Ilbeigi, M., Ashuri, B., & Kashani, H. (2016a). “A real option approach for financial valuation of material price adjustment clauses in transportation projects.” *Transportation Research Board 95th Annual Meeting*. Washington DC. January 10-14, 2016.

Ilbeigi, M., Ashuri, B., & Joukar, A. (2016b). “Time-series analysis for forecasting asphalt-cement price.” *Journal of Management in Engineering*, 33(1), 04016030.

Ilbeigi, M., Joukar, A., & Ashuri, B. (2016c). "Modeling and forecasting the price of asphalt cement using generalized auto regressive conditional heteroscedasticity." *Construction Research Congress*, ASCE, San Juan, Puerto Rico, May 31-June 2, 2016.

Ilbeigi, M., & Castro-Lacouture, D. (2017). "Effects of price-adjustment clauses on number of bidders and dispersion of bid prices in highway construction." *Journal of Management in Engineering*, 33(4), 04017013.

Ilbeigi, M., Castro-Lacouture, D., & Joukar, A. (2017). "Generalized Autoregressive Conditional Heteroscedasticity Model to Quantify and Forecast Uncertainty in the Price of Asphalt Cement." *Journal of Management in Engineering*, 33(5), 04017026.

Isaac, R. M. (1982). "Fuel cost adjustment mechanisms and the regulated utility facing uncertain fuel prices." *The Bell Journal of Economics*, 13(1), 158-169.

Joukar, A., & Nahmens, I. (2015). "Volatility forecast of construction cost index using general autoregressive conditional heteroskedastic method." *Journal of Construction Engineering and Management*, 142(1), 04015051.

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

Kaserman, D., & Tepel, R. C. (1982). "The impact of the automatic adjustment clause on fuel purchase and utilization practices in the U. S. electric utility industry." *Southern Economic Journal*, 48(3), 687-700.

Kendrick, J. W. (1975). "Efficiency incentives and cost factors in public utility automatic revenue adjustment clauses." *The Bell Journal of Economics*, 6(1), 299-313.

Laryea, S., & Hughes, W. (2009). "How contractors in Ghana include risk in their bid prices." *25th Annual ARCOM Conference*, Nottingham, UK, September 7-9, 2009.

Ljung, G. M., & Box, G. E. (1978). "On a measure of lack of fit in time series models." *Biometrika*, 65(2), 297-303.

Lowe, D. J., Emsley, M. W., & Harding, A. (2006). "Predicting construction cost using multiple regression techniques." *Journal of Construction Engineering and Management*, 132(7), 750-758.

Lu, C. W., & Reynolds, M. R. (2001). "CUSUM charts for monitoring an autocorrelated process." *Journal of Quality Technology*, 33(3), 316-324.

Montgomery, D. C. (2007). Introduction to statistical quality control. John Wiley & Sons. Hoboken, New Jersey.

National Asphalt Pavement Association (NAPA). (2015). Market Facts. <www.asphaltpavement.org> (November 14, 2015)

Neter, J., Kutner, M. H., Wasserman, W., & Nachtsheim, C. J. (1996). Applied linear statistical models. McGraw-Hill Irwin. New York.

Persad, K. R., O' Connor, J. T., & Varghese, K. (1995). "Forecasting engineering manpower requirements for highway preconstruction activities." *Journal of Management in Engineering*, 11(3), 41-47.

Pierce, C. E., Huynh, N. N., & Guimaraes, P. (2012). "Cost indexing and unit price adjustments for construction materials." Federal Highway Administration, Report No. FHWA-SC-12-06.

Schwarz, G. (1978). "Estimating the dimension of a model." *The Annals of Statistics*, 6(2), 461-464.

Shahandashti, S. M., & Ashuri, B. (2015). "Highway construction cost forecasting using vector error correction models." *Journal of Management in Engineering*, 32(2), 04015040.

Skolnik, J. (2011). "Price indexing in transportation construction contracts." Jack Faucett Associates. Bethesda, MD.

Sonmez, R. (2008). "Parametric range estimating of building costs using regression models and bootstrap." *Journal of Construction Engineering and Management*, 134(12), 1011-1016.

Sonmez, R., Ergin, A., & Birgonul, M. T. (2007). "Quantitative methodology for determination of cost contingency in international projects." *Journal of Management in Engineering*, 23(1), 35-39.

Taylor, R. G., & Bowen, P. A. (1987). "Building price-level forecasting: an examination of techniques and applications." *Construction Management and Economics*, 5(1), 21-44.

Trost, S. M., & Oberlender, G. D. (2003). "Predicting accuracy of early cost estimates using factor analysis and multivariate regression." *Journal of Construction Engineering and Management*, 129(2), 198-204.

Verleger, P. K. (1994). Adjusting to volatile energy prices. Institute for International Economics. Washington, DC.

Vilasuso, J. (2002). “Forecasting exchange rate volatility.” *Economics Letters*, 76(1), 59-64.

Walls III, J., & Smith, M. R. (1998). “Life-cycle cost analysis in pavement design-interim technical bulletin.” *Federal Highway Administration*, Report No. FHWA-SA-98-079.

Wang, Y., and Liu, M. (2012). “Prices of highway resurfacing projects in economic downturn: Lessons learned and strategies forward.” *Journal of Management in Engineering*, 28(4), 391-397.

Webster. A., (2013). Introductory regression analysis with computer application for business and economics. Routledge. New York.

Winters, P. R. (1960). “Forecasting sales by exponentially weighted moving averages.” *Management Science*, 6(3), 324-342.

Xu, J. W., & Moon, S. (2011). “Stochastic forecast of construction cost index using a cointegrated vector autoregression model.” *Journal of Management in Engineering*, 29(1), 10-18.

Zhou, X., & Damnjanovic, I. (2011). “Optimal hedging of commodity price risks in highway contracts.” *Transportation Research Record: Journal of the Transportation Research Board*, 2228, 19-25.