Improving Cost Estimation and Budget Planning with New Michigan Highway Construction Cost Index

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16. Abstract

Accurate cost estimation plays a pivotal role in effective budget planning for highway construction projects, ensuring that resources are allocated appropriately and projects are completed within financial constraints. Traditional cost estimation methods, commonly used by transportation agencies like the Michigan Department of Transportation (MDOT), often rely on historical data, which can fail to account for dynamic market conditions and inflation. This report explores advanced cost estimation approaches by developing contract- and item-level cost indices, integrating economic factor-based index predictive models, and applying index-based methods to cost estimation and budget planning. The report begins by identifying the key factors influencing construction pricing, including economic indicators, market factors, and project-specific variables. New cost indices are developed to track price trends for specific contracts and pay items, allowing for more accurate adjustments to historical prices. Next, the report introduces economic factor-based predictive models to forecast the Michigan Highway Construction Cost Index (MHCCI). These models incorporate economic trends, such as inflation and market dynamics, to predict future index fluctuations more effectively than traditional methods. Furthermore, the report details how these indices and the newly developed MHCCI tool can be integrated into budget planning and cost estimation processes. This index-based approach provides a more precise framework for estimating construction costs and improving budget planning. The report also includes a comparison of state and regional cost indices to highlight geographic variations in MHCCI and construction pricing, offering insights into how regional factors affect construction costs. In conclusion, the findings and recommendations in this report provide MDOT with innovative tools for cost estimation and budget planning, aiming at more accurate cost forecasting and better resource allocation.

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EXECUTIVE SUMMARY

Accurate cost estimation is fundamental to the success of highway construction projects, ensuring that projects are delivered within budget and on schedule. For the Michigan Department of Transportation (MDOT) and other transportation agencies, traditional bid-based cost estimation methods often fall short in accounting for the dynamic nature of construction pricing. This report explores innovative approaches to improve cost estimation and budget planning by leveraging detailed **Highway Construction Cost Index (HCCI)** and advanced index predictive models that incorporate economic factors and market conditions.

The report begins with a review of the factors influencing construction pricing. These include economic indicators such as inflation, material costs, labor wages, and project-specific conditions, all of which significantly impact the construction pricing. The traditional bid-based approach, while commonly used, often lacks the granularity to capture the true variability in construction costs of pay items, leading to inaccuracies in budgeting and forecasting. The report highlights these dynamic factors in cost estimation.

Then, the report introduces the development of **contract- and item-level cost indices**, tailored specifically to individual contracts and pay items. These indices offer a more detailed understanding of cost trends at both the contract and pay item levels, improving the accuracy of bid-based estimates. The report explains how these indices can be developed and used to track price changes for specific construction activities, enabling more precise adjustments of historical prices for pay items and construction contracts based on market conditions.

In addition to these indices, the report presents **economic factor-based predictive models** for Michigan HCCI. Unlike traditional methods, which rely solely on historical HCCI data, these models use economic trends and external factors to predict future index values, offering a more dynamic and accurate approach to cost estimation. This predictive capability allows transportation agencies to better anticipate future price fluctuations and adjust their budget planning accordingly.

The report also documents the integration of **index-based methods into cost estimation and budget planning**. It outlines a practical framework for using historical and forecasted cost indices in project development, helping agencies align their cost estimates with financial constraints and strategic goals. This approach enhances the ability of agencies to make informed decisions about resource allocation, and long-term budget management.

A **comparison of state and regional MHCCI** is also provided, offering insights into geographic variations in MHCCI and construction pricing. By examining regional trends and differences in MHCCI, the report identifies key factors driving index discrepancies and offers recommendations for improving cost management across different regions.

Key Findings:

- **Item Quantity** and **Total Amount per Year per Region** are critical factors influencing unit bid prices, for example, for 5010002 Cold Milling HMA Surface, with significant implications for cost estimation accuracy.
- **Contract- and item-level cost indices** provide greater precision in adjusting historical prices, offering a more tailored approach to cost estimation for specific projects/contract.
- Predictive models incorporating **economic factors** such as inflation and market trends can improve the accuracy of future MHCCI forecasts.
- Integrating **these indices into cost estimation and budget planning** processes enables agencies to better manage financial resources.
- The analysis of regional MHCCI trends showed that different regions experience varied rates of cost increases over time. The **Metro and University regions** exhibit higher median cost index, reflecting urbanization and higher demand for construction services. Conversely, the **North region** consistently shows lower cost indices with driving factors of number of bidders per contract and number of contracts per year in Michigan. The underlying factors of regional index variations are identified for each MDOT region.

1. INTRODUCTION

Accuracy in construction cost estimates has a significant impact on the Department of Transportation (DOTs). Inaccurate estimates can lead to cost overruns and create difficulties in budget planning. The highway construction cost index (HCCI) is a valuable tool in improving the precision of cost estimation by reflecting price changes of pay items over time. It can help with better cost estimation by accounting for past macroeconomic conditions and market fluctuations (Erickson, 2010). The Michigan Department of Transportation (MDOT) has developed the Michigan HCCI, which encompasses categorical, regional, and statewide indices, along with their historical values dating back to 2010. While the historical MHCCI provides valuable insights into past trends, cost estimation is focused on future projections. Relying solely on historical indices makes it challenging to achieve accurate engineering estimates and budget planning for future projects. In practice, budget planning requires accurate high-level estimates. Each of the seven MDOT regions is given a budget amount when putting together the annual Call for Projects. Region teams then scope, estimate, and program projects to fit within the allotted budget. When budgeting, a standard inflation rate of 4% is typically assumed for future years. However, with the consumer price index rising to 7.9% in February 2022 (driven by COVID Pandemic), relying on a fixed inflation rate for planning is no longer a sound practice.

Although the future trend of HCCI can be predicted through time series analysis, most forecasts fail to account for economic factors, such as pandemics or periods of high inflation, resulting in reduced accuracy of the projected index values (Liu et al., 2020). This makes it difficult to use the projected index for accurate engineers' estimates and budge planning. An advanced predictive model is needed to better understand the impacts of inflation, as well as labor, logistics, and economic factors on MHCCI and construction pricing. Such analysis would enable more informed decision-making, leading to improved accuracy in budget planning and financial forecasting.

In addition, construction projects differ in work type and vary significantly in terms of numbers and type of pay items. For example, some projects may have more pavement items, while others could have more Electrical Construction items. As such, statewide and/or categorical indices might not provide an accurate price change trend for a specific project or contract with multiple categories of pay items. For this reason, new HCCIs, including a calculation tool/program at the contract and pay item levels, are needed to accurately adjust the historical price of pay items to estimate the future cost of individual construction projects. They could improve the accuracy of the bid-based estimation and provide MDOT with a better understanding of price fluctuations for specific contracts and/or items over time.

In short, there is a pressing need for MDOT to enhance the accuracy of cost estimating and budget planning by leveraging HCCI. In particular, new estimation methods, incorporating contract/pay item-level index and economic factors-based index prediction, are needed to allow MDOT to estimate and budget construction projects with improved accuracy.

1.1 OBJECTIVES

The research team intends to investigate new HCCI-based estimation methods and provide recommendations to improve MDOT's estimation and budget practice. Specifically, the research objectives include:

1) Identify the construction pricing factors for highway construction projects.
2) Develop a contract-level and pay item-level construction cost index, including a calculation tool, for better cost estimation.
3) Develop an advanced approach to predict MHCCI, considering economic factors such as the pandemic and periods of high inflation, and evaluate the impact of the COVID-19 pandemic on the construction cost index trend.
4) Develop a new HCCI-based construction estimation method for Engineer's Estimate (EE).
5) Compare and analyze HCCI across different regions and states.

By addressing these objectives, the report offers an advanced framework for cost estimation and budget planning in highway construction, ensuring that transportation departments can make informed, data-driven decisions in an increasingly complex economic landscape.

1.2 SUMMARY OF TASKS

Overall, the proposed research aimed to assist MDOT in better estimating and budgeting construction projects. The research objectives were pursued through a coherent research plan consisting of nine tasks, as depicted in Figure 1.

Task 1: Data Collection
In this task, relevant data was successfully gathered from sources such as MDOT, Bid Express, and other agencies' websites. The resulting dataset includes detailed information on bids, regional economic profiles, contractor details, and key pricing factors. This comprehensive dataset serves as the foundation for subsequent analyses.

Task 2: Literature Review
A systematic literature review was conducted using established databases, including TRID, TRIS, TRB, and Scopus. This review focused on evaluating the effects of significant external factors such as COVID-19, inflation, and logistical challenges on construction costs and HCCI.

Task 3: Identification of Factors in Construction Pricing
To determine the key factors impacting construction pricing, a detailed analysis of bid data was performed, incorporating scatter plots, correlation tests, and other advanced analysis. This task identified significant variables such as item quantity, GDP, and regional differences in pricing construction pay items. Statistical models were developed to quantify the effects of these factors, offering deeper insights into their relative influence on unit bid prices of pay items.

Task 4: Development of Contract and Item-Level Cost Index
New cost indices were developed at both the contract and item levels. This was achieved through

advanced data cleaning techniques and selective inclusion of relevant bid items. The outcome of this task is a refined cost index methodology and historical index values of these new indices, which provide a more accurate reflection of contract-specific and item price changes.

Task 5: Economic Factors-Based Cost Index Prediction
Using techniques such as multivariate regression, time-series analysis, and machine learning, models were developed to predict future cost index trends based on underlying economic factors. These predictive models demonstrate strong potential for forecasting index fluctuations in relation to macroeconomic indicators, such as inflation rates and GDP.

Task 6: Development of Index-Based Estimation Methods and Budget Planning
An enhanced estimation workflow was created to improve the accuracy of the Engineer's Estimate and budget planning. This workflow incorporates the newly developed cost indices and predictive models to streamline estimation and ensure alignment with MDOT's operational needs.

Task 7: State/Regional Cost Index Comparison
This task involved a comparative analysis of MHCCI across different regions. Using visualizations and statistical methods, the analysis provided a clear understanding of how construction cost indices vary regionally and over time, as well as the underlying contributing factors, offering valuable benchmarks for MDOT's planning and estimation efforts.

Task 8: Development of a Tool for Cost Index Calculation and Price Analysis
A software tool was developed to support MHCCI calculation and prediction. This tool integrates seamlessly with MDOT's existing systems and provides users with a user-friendly interface for conducting complex pricing analyses. A comprehensive user guide was also developed to facilitate ease of use.

Task 9: Development of Recommendations and Final Report
The final report synthesizes all the findings from previous tasks. It includes actionable recommendations for MDOT, focusing on improving cost estimation processes, enhancing budget planning, and adopting the new cost index methodology. An implementation plan and final presentation were also prepared to guide MDOT in incorporating these insights into their operations.

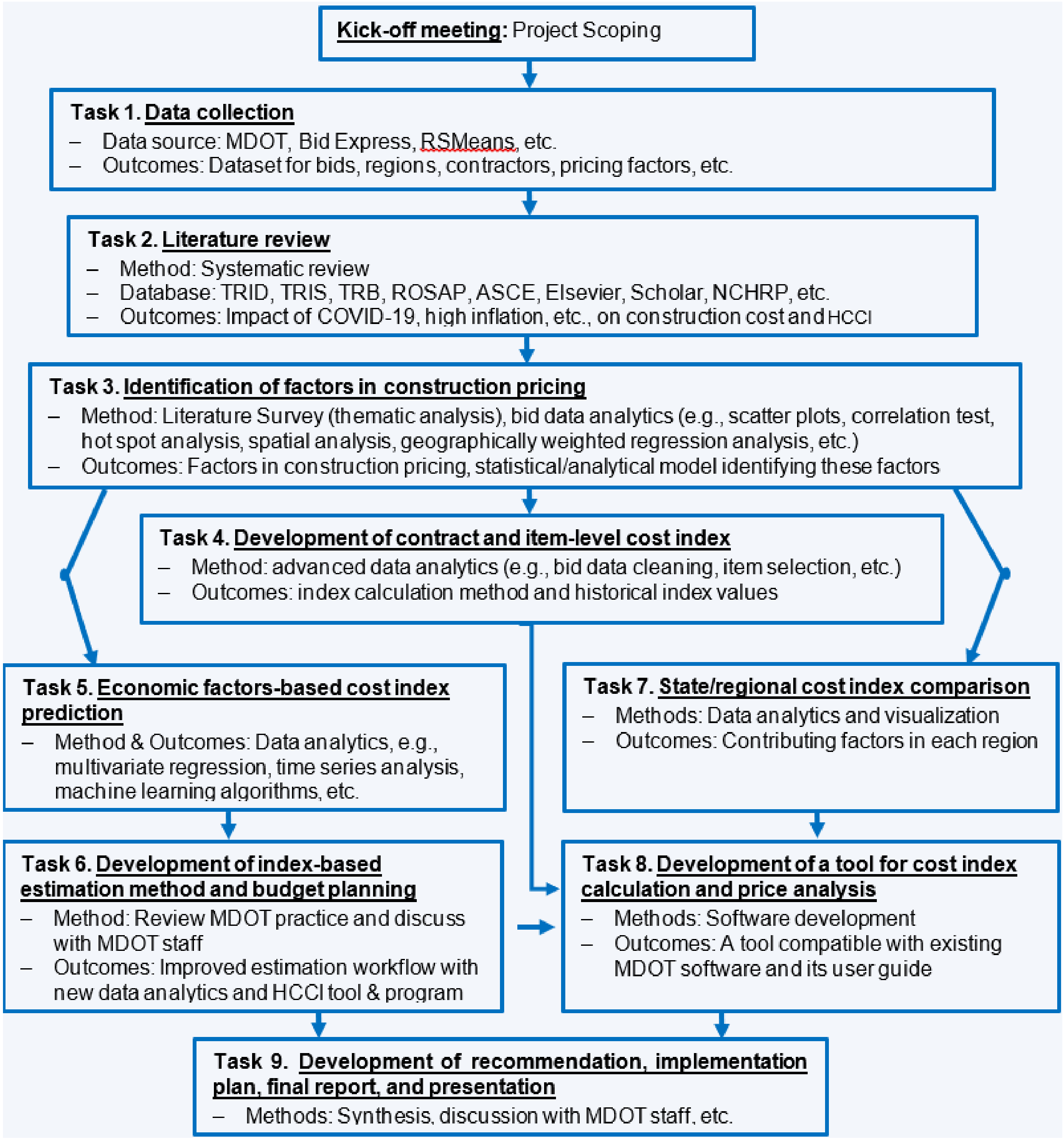

Figure 1. Summary of Research Tasks

1.3 ORGANIZATION OF THE REPORT

The report is structured into six core chapters, each addressing a key aspect of construction cost estimation and budget planning, from identifying construction pricing factors to implementing index-based estimating and budgeting strategies.

Chapter 2 (Identification of Factors in Construction Pricing of Pay Items) introduces the challenges faced by DOTs in estimating construction costs and underscores the importance of accounting for dynamic factors in cost management and then provides a comprehensive review of the key factors influencing construction pricing. It quantitatively examines economic, market, and project-specific conditions, highlighting their impact on the cost estimates.

Chapter 3 (Development of Contract and Item-Level Cost Index) explores the need for a more granular cost index at both the contract and item levels. The chapter proposes a more detailed index calculation method tailored to individual contracts and pay items. Given this, the chapter outlines the structure of the Michigan Highway Construction Cost Index (MHCCI) and discusses the relationship between contract-level indices and broader statewide indices, setting the foundation for advanced cost estimation methods.

Chapter 4 (Economic Factor-Based Cost Index Prediction) focuses on the development of predictive models for the MHCCI based on economic and market conditions. It outlines the limitations of traditional cost index forecast methods, such as relying solely on historical MHCCI data. It demonstrates the use of advanced forecasting techniques to predict future HCCI values by accounting for inflation, economic trends, and unforeseen events.

Chapter 5 (Index-Based Estimation and Budget Planning) explores how historical and forecasted cost indices can be applied to improve cost estimation and budget planning processes. It details the practical steps involved in integrating index-based methods into project development, including revisions to MDOT’s project scoping manual. It emphasizes how such indices can better reflect cost trends and improve the accuracy of the bid-based estimation method for EE. Two contract examples are used to demonstrate the new estimation method.

Chapter 6 (State and Regional Cost Index Comparison) compares MHCCI across different regions, highlighting regional differences in factors affecting MHCCI. By examining regional economic conditions and comparing index trends across MDOT regions, this chapter provides insights into the underlying factors leading to the regional index differences. It emphasizes the importance of understanding these variations for more precise cost estimation.

Finally, Chapter 7 (Recommendations and Conclusions) consolidates the key findings and offers practical recommendations for improving cost estimation and budget planning practices. It highlights the importance of adopting construction pricing factors, contract and item-level indices, and index predictive models to improve budgeting and financial planning. The chapter concludes with insights into how the adoption of these advanced methodologies can lead to more accurate and reliable cost estimates, ultimately improving project delivery and resource management for MDOT and similar agencies.

2. IDENTIFICATION OF FACTORS IN CONSTRUCTION PRICING OF PAY ITEMS

2.1. INTRODUCTION

Given the importance of its accuracy, cost estimating has attracted a considerable amount of effort from both academia and industrial professionals. In the highway construction industry, FHWA (2004) provided cost estimating guidelines and introduced three estimating methods: bid-based approach, actual cost estimating, and combination approach. Recently, FHWA (2021) published new cost-estimating guidelines with the fourth method, i.e., risk-based estimating. Among these, actual cost estimating is believed to generate higher accuracy; however, it is time-consuming and demands a significant workforce. Niedzwecki (2006) and the WMU research team (Liu et al. 2022) surveyed state DOTs to identify the best practice for preparing EE. However, no compelling evidence was found to support the use of the actual cost/combination estimating approach. Alavi and Tavares (2009) also reviewed the cost estimation practice of Montana DOT and provided recommendations in terms of estimating procedures. This effort primarily focuses on the overall procedures and structure of DOTs. The impact of various estimating methods (e.g., bid-based approach and actual cost estimating) on the accuracy of DOT's estimate and their implementation guide and cost-effectiveness are not reported. At present, **the bid-based approach** is the most common estimation method among state DOTs (PM NJ.gov, 2019; Liu et al., 2022).

It is worth noting that the bid-based approach relies on applying historically-awarded unit bid prices of pay items and item quantities of a new project for cost estimation. Its accuracy essentially depends on historical unit bid prices and new quantities of pay items. However, state DOTs experience various challenges in accurately pricing pay items in bid-based estimation. It is partially due to the fact that the collected unit bid prices sometimes do not reflect the 'true' cost of the pay items in the case of uncommon items or differing site conditions. For example, two identical culverts could have different unit bid prices based on the depth of fill or the difficulty of construction access. Also, contractors often adjust the unit bid prices based on market competition and their bidding strategies, such as front-end loading. This bidding practice leads to outliers in the unit bid prices of pay items. Some researchers proposed various algorithms for price data cleaning to estimate more accurately and identify the factors that affect the unit prices. For example, Baek and Ashuri (2018; 2019) explored the random parameters model to determine the variability of asphalt line items. Cao et al. (2017; 2018) used ensemble machine learning to predict the unit prices of resurfacing projects. Alternatively, other researchers reported many algorithms for labor and material cost estimation. One example by Faghih and Kashani (2018) is to forecast construction material prices better using a vector error correction model. Farooghi and Shahandashti (2021) proposed an estimation method for labor wages in transportation construction. Ilbeigi et al. (2014; 2015; 2016; 2017) developed several algorithms for asphalt price estimation, such as generalized autoregressive conditional heteroscedasticity and time-series analysis.

In addition, the construction industry is inherently complex, influenced by a myriad of variables such as material costs, labor availability, project conditions and location, and market conditions. Each of these factors can significantly affect pricing (see Figure 2), yet they are often inadequately accounted for in traditional bid-based estimating methods. However, understanding the impact factors in construction pricing is crucial for improving the accuracy and reliability of cost estimates.

It could lead to an in-depth understanding of cost dynamics and more robust estimating frameworks that not only increase accuracy but also improve decision-making for project planning and execution. Furthermore, a comprehensive analysis of these factors can contribute to the development of innovative estimation techniques, such as machine learning algorithms, that leverage data to adjust pricing models dynamically, thus addressing the limitations of existing methods.

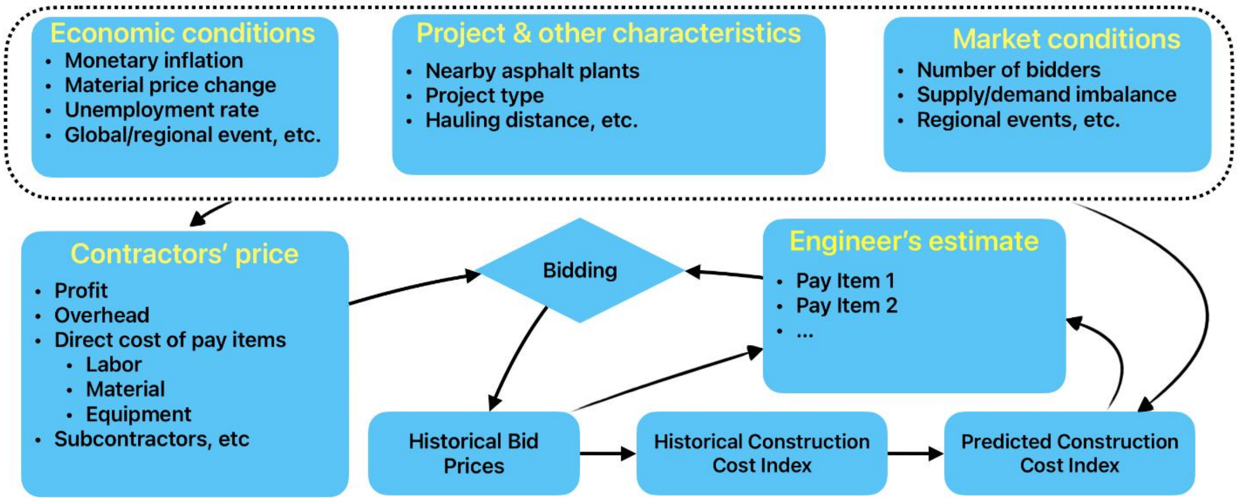

Figure 2. Interaction among HCCI, economic and market conditions, and construction cost

This chapter aims to identify the impacts of pricing factors, e.g., COVID-19 and periods of high inflation on construction costs of pay items. To achieve this, a comprehensive **literature review** related to economic conditions and other conditions affecting construction costs was conducted and compiled. Following this, various **data analytics** were applied to quantitively understand various impact factors on pricing of construction pay items.

2.2. METHODOLOGY

Figure 3 illustrates the two-step method of identifying the factors in construction pricing of pay items. The research begins with **Potential Factor Identification**, which compiles a comprehensive list of potential influence factors in construction costs, i.e., the price of pay items. This is done through a literature review using the PRISMA method in this step. This step gathers relevant studies, articles, and reports, and then draws a list of potential impact factors from Publications.

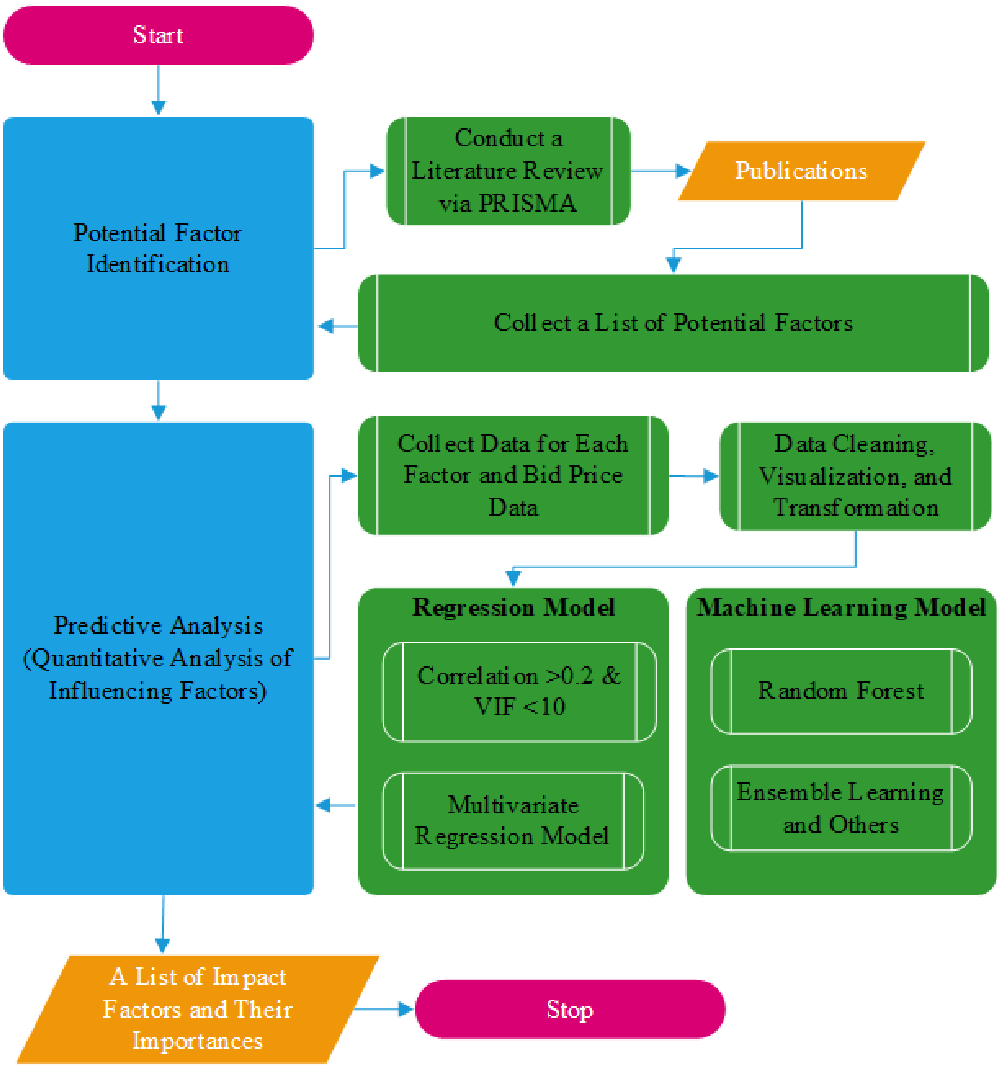

Figure 3. Methodology for Identifying the Construction Pricing Factors.

Alongside the identification of potential factors, relevant data is collected for each factor and unit prices of pay items. The collected data undergoes cleaning and transformation to prepare it for analysis. The process moves to predictive/quantitative analysis, involving two main modeling techniques. A **Multivariate Regression Model** is employed to explore the relationships between impact factors and outcomes, i.e., unit bid prices of pay items. For the regression model, Pearson Correlation and Variance Inflation Factor (VIF) analysis are used to select impact factors among the complied list and eliminate multicollinearity. Various machine learning techniques, such as **Random Forest**, **Ensemble Learning**, and others, are applied to analyze the data from a non-linear perspective and improve predictive relationships. The final outcome of this process is **A List of Impact Factors and Their Importance**, which will provide insights into the construction pricing.

2.3. IDENTIFICATION OF POTENTIAL PRICING FACTORS IN CONSTRUCTION

A comprehensive literature review was undertaken to elucidate the current state-of-the-art and state-of-practice in construction pricing and the impact of COVID-19. It could provide qualitative insights into the most influential factors affecting construction costs. This review laid the foundation for later tasks, such as correlation and pricing analysis. Leveraging the best practices in literature, the WMU team documents any future recommendations for dealing with pandemics such as COVID-19 and, most importantly, how state DOTs can ensure accurate cost estimates by accounting for factors such as pandemics and inflations. With COVID-19 being a recent event, the team understands that due diligence is needed when reviewing related literature to ensure that only reliable information is adopted.

2.3.1 Literature Search

The literature scans are to uncover numerous articles, research papers, reports, and presentation materials documenting construction cost and budget planning. The team also gathers reports and articles detailing the effects of COVID-19 and high inflation on construction costs. Several repositories such as *TRID, FHWA TRIS, TRB, ROSAP, NCHRP, and Scopus* were included to obtain state-of-the-art practice. The specific search terms included: "Unit Price," "Project Cost," "Bid Price," "Pay Item Price," "Bid Cost," "Cost Estimation," "Cost Estimate," "Cost Estimating," "Pricing Factors," "COVID/ Pandemic", and "Economic Factors." These keywords were used to identify the publications in the areas of Highway Construction and Cost Estimation. They were combined using the 'OR' operator to search the literature in the Title, Abstract, and Keywords sections of the aforementioned repositories. The search period was set from 2007 to 2023. The initial search resulted in **631** initial publications in **Scopus** and **248 in TRID**. After filtering for the English language, **606** results remained. Further exclusion of irrelevant subject areas, such as Medicine, reduced the count to 587. A manual review of publication titles and abstracts was performed to ensure relevance to the targeted research area. The manual selection further narrowed the final number of relevant sources to **392**.

2.3.2 Systematic Review

Following the literature search, the team manually reviewed the 392 publications to extract key insights and determine potential impact factors related to highway construction costs. Each paper was carefully examined to identify recurring themes, methodologies, and findings that could contribute to the understanding of cost drivers in highway construction projects. Factors such as GDP, unemployment rate and so forth were specifically noted as they appeared throughout the literature. A brief discussion of these papers, along with an analysis of the extracted factors, is presented in the following sections. These discussions are presented under two sections, namely, Factors in Construction Pricing and COVID-19 Impact.

2.3.2.1 Factors in Construction Pricing

Construction pricing is influenced by a complex array of economic, social, and industry-specific factors. Understanding these variables is critical for accurate cost estimation and budget planning. Among the key factors are 1) administrative disbursements, 2) unemployment rate, 3) gross domestic product (GDP), 4) building permits, 5) gas prices, and others. Some of these factors have been extensively studied to reveal their specific impact on construction pricing, providing valuable insights for better forecasting and financial planning in the industry. For example, Cao et al. (2017; 2018) conducted a **Boruta feature analysis** for factor identification with the aim of predicting the unit prices of resurfacing highway projects. **Twenty factors** were identified from a comprehensive list of 57 related variables, and they consist of project county, terrain, region, duration, quantity, total amount, length, number of bidders, number of nearby asphalt plants, monthly asphalt volume, county-based construction firms, average weekly wage, unemployment, and so forth. Further, **Mahdavian** et al. (2021) used a pool of **69 potential** variables to predict the unit price of 60 cost items in highway construction. Generally, the factors can be categorized into two groups, namely: 1) external factors and 2) internal factors. For example, economic conditions are one of the external factors, including monetary inflation, critical material price change, and local and/or global events. Their study applied **various modeling techniques**, such as <u>*random forest regression, ridge regression, Bayesian ridge regressing, and decision trees*</u>, to select these potential factors for each item in the targeted 60 pay items. Following this, the recursive feature elimination was used to prioritize the importance of the identified factors. Then, a scoring function was employed to determine the best features for each cost item. With the selected independent variables, the linear models are superior to the non-linear models for six types of highway expansion projects, with an accuracy of 92.52%.

Ilbeigi et al. (2016) used multivariate regression analysis to explore how the **twenty-one** potential explanatory factors affect the prices of asphalt items. The factors were identified via a literature review and expert interviews. Some examples include 1) project duration in days, 2) item quantity, 3) total bid price, 4) the ratio of the total price of the asphalt line item over the total bid price of the project, 5) the number of bidders, 6) current asphalt cement price index, 7) historical asphalt cement price index, 8) project location, 9) PAC eligibility, 10) number of projects in a specific region, 11) total annual amount of a specific region, 12) total annual quantity of asphalt mixtures in the region, 13) number of projects in other regions, 14) total annual amount of other regions, and 15) total annual quantity of asphalt mixtures in other regions. The results revealed that factors such as the asphalt cement price index, item quantity, and total bid price could contribute to the variations in the bid prices, while the other factors did not have a significant statistical relationship.

Alternatively, **Baek and Ashuri (2018; 2019)** identified two tiers of variables contributing to the unit price variability of asphalt line items. The first tier consists of project characteristics, supply sources for critical materials, and price adjustment clauses. The second tier is global and external conditions, such as local market and macroeconomic conditions. **Forty-eight factors** were investigated, while **fourteen of these factors** were concluded to be explanatory factors for the price variations of asphalt line items, including, but not limited to, 1) item quantities, 2) the number of asphalt plants, 3) contract amount, 4) state-specific asphalt cement price index, 5) PPI for construction machinery manufacturing, 6) GDP, 7) crude oil prices, 8) ratio of bid item, 9) pavement length, and so forth. On this basis, **random parameters model** was applied to explain the variability of asphalt line items in their study. Market conditions are another critical factor in construction pricing. For example, the competition level in the market is usually considered by contractors in their pricing and bidding. In common sense, higher competition could lead to lower prices and costs.

Internal factors refer to construction materials, labor, and equipment. In this respect, Onayev et al. (2022) found that labor and material price and shifts in demand for higher-quality roadways have a higher impact on highway construction prices than such factors as market concentration, urban vs. rural roadway mileage, and relative spending on maintenance and rehabilitation. Many endeavors were also made to establish methods to estimate the unit prices of these construction resources more accurately. For example, IIbeigi et al. (2016) explored four typical time series models to forecast asphalt cement prices. All four models, including Holt Exponential Smoothing (ES), Holt-Winters ES, Autoregressive Integrated Moving Average (ARIMA), and seasonal ARIMA, were proven to have a higher accuracy than the Monte Carlo simulation. It is worth noting that these models are univariate time series models and cannot consider the explanatory variables for the price forecast. Alternatively, Shiha et al. (2024) established an ANN model between macroeconomic indicators and the prices of construction materials, e.g., steel and cement. Seven and six were selected from nine indicators through **correlation analysis** with a six-month time lag for steel and cement prices, respectively. These indicators are CPI, PPI, unemployment rate, GDP, foreign reserves, exchange rate, and lending rate. The forecast models produce an acceptable MAPR of 4% to 11%. More recently, Wang et al. (2022) used CPI, lending rate, tender price index, average daily wages, and stock market index as inputs for deep neural networks in an attempt to estimate early-stage total building construction cost. Their main objective is to improve the preliminary cost estimate rather than the unit price of cost items in the construction estimate, material unit price, and the construction cost index in other studies.

Construction cost also varies across regions, as it significantly correlates with geographical location (Zhang et al., 2014). For this reason, Baek (2018) explored the **spatial correlations** between construction costs and geographical areas. Notably, the **geographical areas** in their study are represented by many external factors, such as the number of **nearby asphalt plants**, the hauling distance between quarry and asphalts plants, NHCCI, the number of bidders, and so forth. A similar finding, i.e., a strong correlation between **the index values and geospatial locations**, was also reported by Migliaccio et al. (2009), Migliaccio et al. (2013), Zhang et al. (2014), and so forth. T**he WMU research team** (Liu et al., 2020) also found that the MHCCI values experienced different trends across different regions. A question needed to be addressed, i.e., how will the geographical variability of economic and market conditions in Michigan affect the construction cost and the cost index? An in-depth understanding of this question could lead to better project planning and cost management across MDOT regions, which will be explored in Chapter 6.

2.3.2.2 COVID Impact

In contrast, the impact of **regional and global events** on the project cost is less explored. One attempt is to understand the effect of **natural disasters** on transportation construction projects, (Baek, 2018). In this effort, a cumulative sum control chart is proposed to monitor the bid price change of pay items induced by natural disasters, especially hurricanes. Cheng and Wilmot (2009) reported that Louisiana HCCI in hurricane-impacted areas significantly increased after hurricane Katrina and Rita and decreased after two quarters; however, the non-hurricane-impacted areas experienced a decline right after the hurricane. These studies shed light on the price variation in a local or regional event but do not apply to global events such as pandemics. The COVID-19 pandemic, which was announced by the World Health Organization (WHO) on March 11, 2020, disrupted the supply chain severely, among other impacts. The impact of COVID-19 varied among different industries. According to the US Bureau of Labor Statistics (BLS), price increases for inputs to construction and goods industries were much larger during the pandemic than those for inputs to services industries (BLS 2021). The cost inflation for construction materials was observed throughout the pandemic and continues to be challenging. Florence et al. (2021) reported the impact of Pandemic on construction prices based on the report from a survey, analyzing published statistical data, and conducting in-depth interviews. In general, **labor shortages**, **project delays**, **supply chain disruptions**, **and safe management measures** lead to an increase in construction costs. Adepu et al. (2024) also conducted a literature review and questionnaire survey to reveal the contributing factors for the construction cost escalations during the Pandemic. The identified factors include ***labor, material cost, inflation, health measures, insurance cost and so forth***. Alternatively, Wang et al. (2022) used deep neural networks to assess the impact of economic factors on construction cost estimation. They found that factors such as the consumer price index (CPI), stock market indicators (HSI-Close), and tender price indexes were the most influential. These factors are closely related to the economic environment, which changes due to events like the COVID-19 pandemic. To evaluate the pandemic's impact on construction costs, it is essential to analyze pandemic-related factors like labor availability and wage fluctuations, material price changes, inflation, and other economic indicators. By examining these factors, researchers can better understand how the pandemic affects construction pricing and cost.

2.3.3 Summary of Potential Pricing Factors

Leveraging the comprehensive literature review, various potential pricing factors in construction are collected in Figure 4. The factors are grouped into five categories, each representing a different aspect influencing construction costs. This figure highlights that macroeconomic conditions account for the largest category of factors identified in the study, followed by project characteristics and market factors. Region-specific attributes and client/policy considerations represent a smaller portion of the factors. While the distribution does not indicate that any one category is the most influential, it emphasizes the broad range of factors that need to be considered, with a focus on the quantity of factors identified within each category.

- **Macroeconomic (62)**: This category, occupying the largest portion of the chart, indicates that macroeconomic factors are the most contributors to construction cost estimation. These factors can include overall economic conditions, inflation rates, monetary policies, and economic growth.
- **Market Factors (33)**: Market factors, represented by a sizeable portion, refer to elements such as supply and demand dynamics, material and labor costs, market competition, and availability of resources.

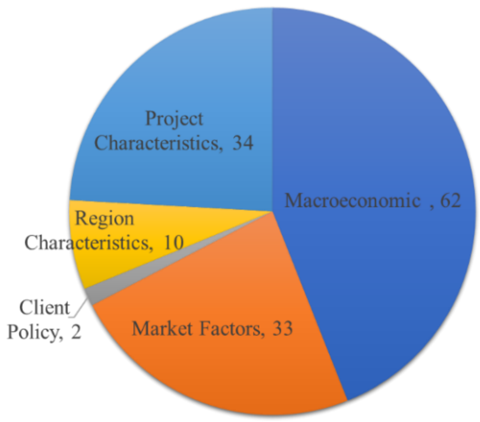

Figure 4. Distributions of Pricing Factors

- **Region Characteristics (10)**: This smaller segment indicates that regional characteristics play a role in cost estimation. Factors can include local economic conditions, geographic considerations, regional regulations, and local labor market conditions.
- **Client/Policy (2)**: The smallest portion of the chart, this category represents the influence of client-specific requirements and policies. This can involve client expectations, funding availability, policy changes, and regulatory impacts.
- **Project Characteristics (34)**: This segment shows that characteristics specific to the construction project itself are also substantial factors. These characteristics can include project size, complexity, design specifications, and project duration.

The specific factors within the "Macroeconomic" category are shown in Figure 5, and they represent the largest group of factors identified in the study, comprising 62 in total. These factors play a crucial role in construction cost estimation, reflecting the broad influence of economic conditions on pricing dynamics. They cover a range of economic variables such as market prices (e.g., house pricing, gold prices, fuel price index), labor indices (e.g., skilled labor index, average weekly wage), policy impacts (e.g., laws and policies, interest rates), and specific industry metrics (e.g., NHCCI, material price index). This detailed enumeration highlights the complexity and multi-faceted nature of macroeconomic influences on construction costs, demonstrating the extensive range of variables that must be considered for comprehensive cost estimation and analysis.

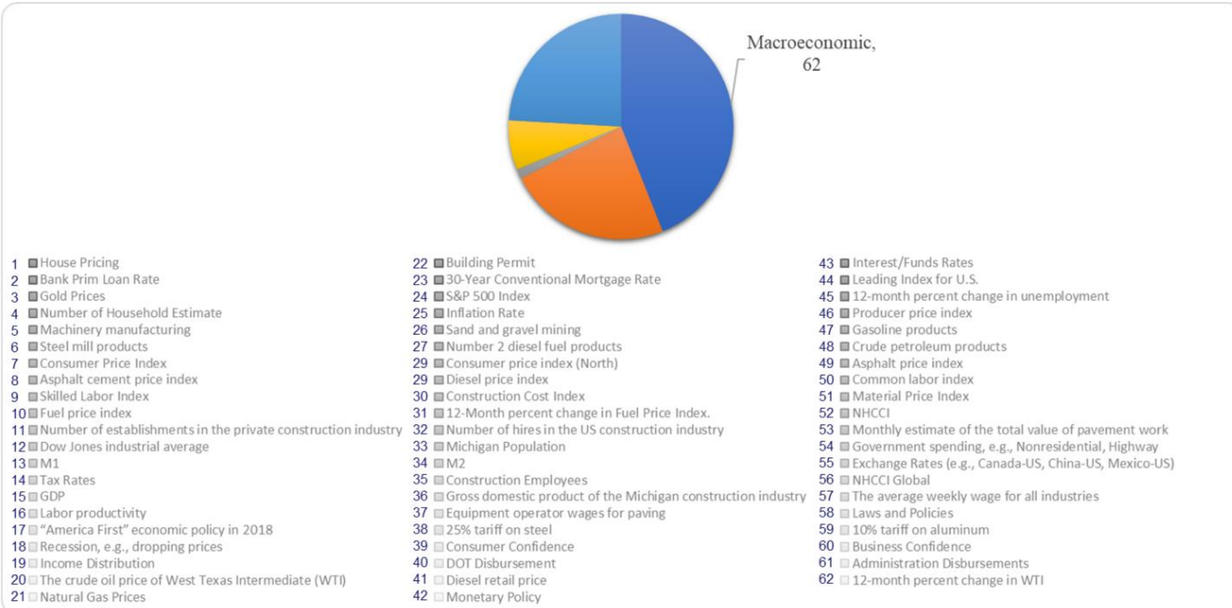

Figure 5. Macroeconomic Factors

The "Market Factors" category includes 33 factors, as shown in Figure 6. They cover a range of influences from local and regional construction metrics, such as the number of contracts and contract values in specific areas, to broader economic indicators like housing market indices and the Architecture Billings Index (ABI). Factors like seasonality, market competition, and transportation costs also play significant roles. This comprehensive enumeration underscores the diversity of market-driven elements that impact construction costs.

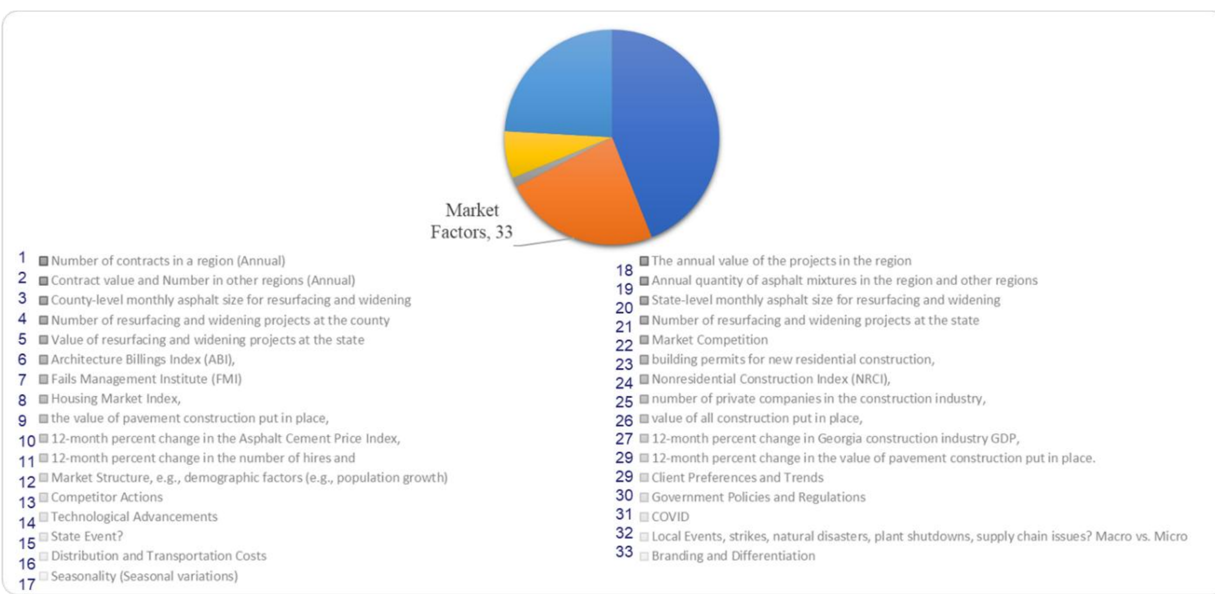

Figure 6. Market Factors

The project-related factors include 34 factors (see Figure 7). These factors cover various aspects of construction projects, such as the type of project, contract details, size, location, and logistical considerations. For example, factors like the number of bidders, contract descriptions, hauling distances, and material-intensive elements all play crucial roles in determining construction costs.

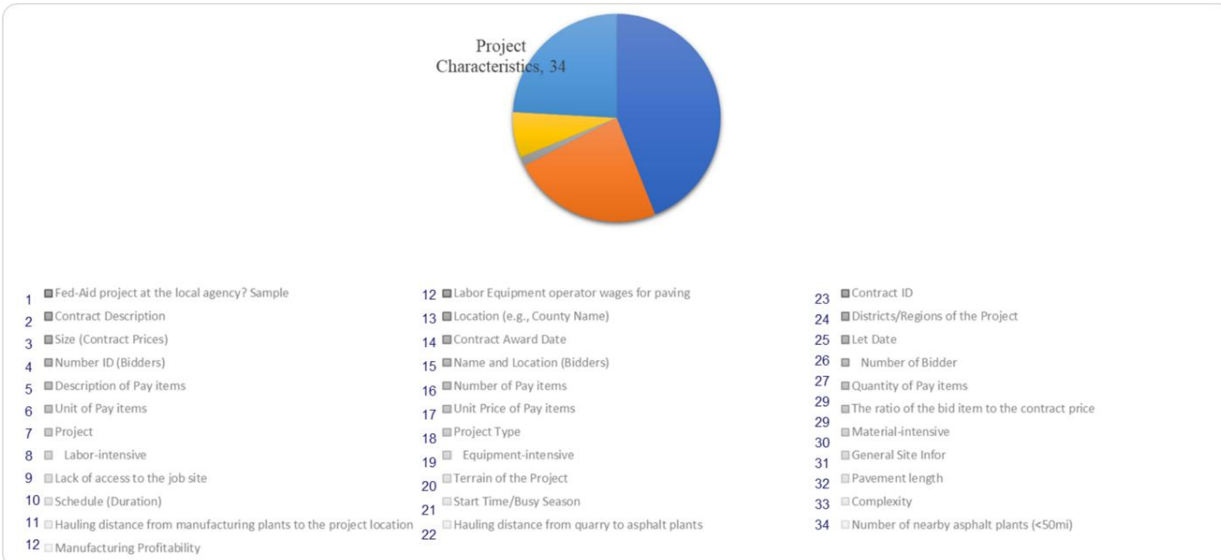

Figure 7. Project Characteristics

The region and policy-related factors include 12 factors, as shown in Figure 8. Region-related factors include labor costs (e.g., prevailing wages in construction), location and logistics, federal funding, and market structure. Policy-related factors involve client-driven aspects such as price adjustment clauses and the right of way.

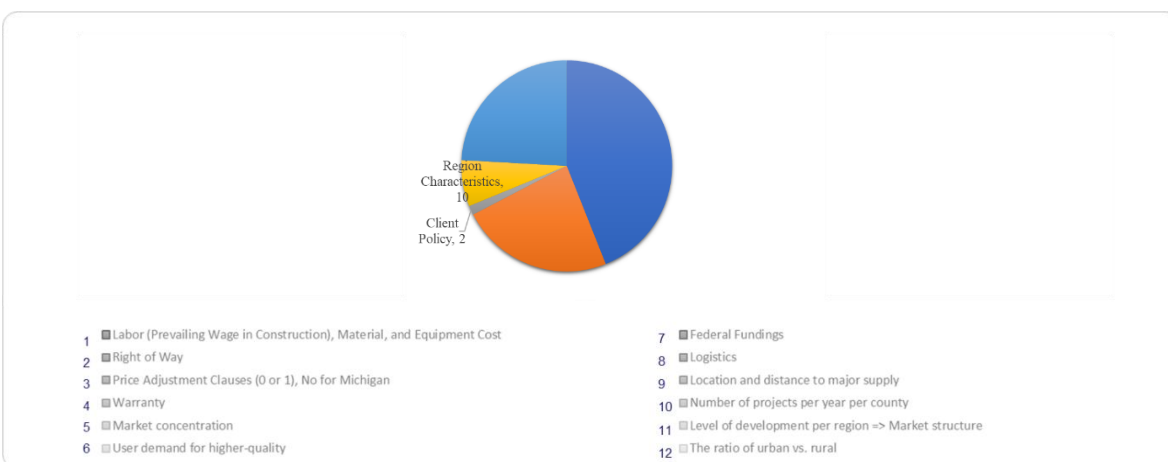

Figure 8. Region Characteristics and Policy

2.4. QUANTITATIVE ANALYSIS OF INFLUENCING FACTORS ON 'UNIT BID PRICE'

One of the primary objectives is to identify the key factors influencing unit bid prices of pay items using **quantitative evidence**. Various data analytics steps were used to achieve accurate and reliable results. This section presents the quantitative analysis for construction pricing based on the factors identified from the literature. **Unit bid price refers to the price per unit of measurement for a specific item or service in a construction project, which is critical for determining the overall construction cost.** Figure 9 illustrates the structure of the pricing analysis for Michigan highway construction costs, with a focus on two key approaches to analyzing prices: unit bid price at the contract level and monthly-averaged prices. Monthly averaged prices are unit bid prices that are weighted by the item quantity for each month. The right side of the diagram represents how construction costs are broken down by Contracts, Projects, and individual Pay Items. For each pay item, two crucial data points are captured: the Unit Bid Price and the Quantity.

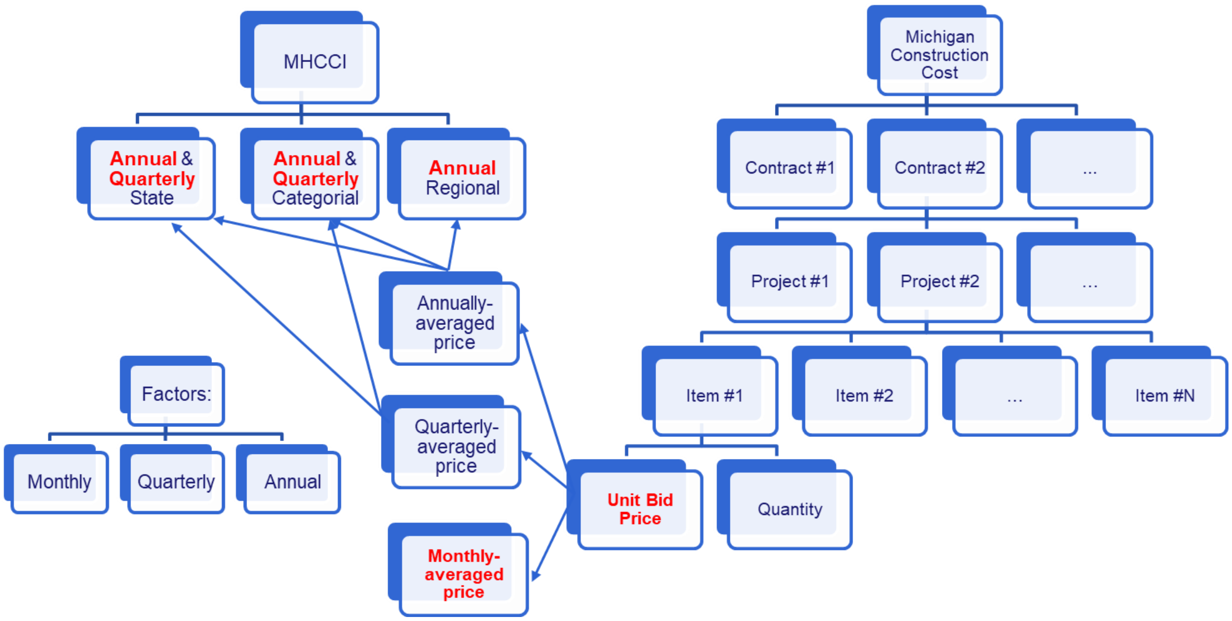

Figure 9. Construction Pricing Analysis: Contract and Monthly Price

The pricing analysis was conducted in two distinct ways: 1) **Unit Bid Price for Each Contract** and 2) **Monthly Averaged Prices**. The Unit Bid Price analysis for Each Contract focuses on the unit bid price at the contract level. For each contract, the unit bid price of each pay item was analyzed to understand how specific factors, such as project size, location, and complexity, influence the pricing of individual items. This granular level of analysis provides insights into how cost variations occur between different contracts and the factors that drive these variations. This is crucial for identifying how specific project characteristics, such as the scope of work, location, or contractor competition, influence bid prices and, ultimately, project costs.

Monthly-Averaged Price analysis aggregates the unit bid prices of pay items over multiple contracts at the monthly level. By aggregating bid prices over time, this analysis captures broader trends in construction costs and provides a higher-level view of how factors such as seasonality, material price fluctuations, and market conditions affect prices on a month-to-month basis across multiple contracts. This analysis helps understand how external factors like inflation, material shortages, or economic cycles impact pricing at a more macro level.

2.4.1 Overview of Pricing Analysis Steps

Figure 3 illustrates the process of quantitative pricing analysis, beginning with data collection from multiple sources for the factors identified in the literature review. After gathering the relevant data, data preprocessing and feature engineering were conducted, where the data was visualized using pair plots to explore relationships among factors. A rigorous data cleaning process was undertaken to ensure the accuracy and reliability of the data, especially bid price data. This involved the removal of outliers and irrelevant data points that could skew the results. Feature engineering techniques are then applied to transform raw data into meaningful features, addressing skewed variables and scaling all features to a similar range. Additionally, multicollinearity is checked using the Variance Inflation Factor (VIF), and features with VIF greater than ten are removed for regression models to ensure a robust model.

Following preprocessing is the modeling and evaluation phase, where predictive models such as linear, random forest, multivariate regression, and machine learning models are applied. The results of these models are evaluated by comparing the actual values to the predicted values, ensuring accuracy and reliability. Ensemble learning is also employed to improve predictions by combining multiple models, and the importance of each factor in construction pricing is analyzed. Several statistical tests were used to validate the findings and ensure that the observed relationships were statistically significant.

Finally, result interpretation and reporting are concluded, where the outcomes of the models are interpreted to prioritize the key factors influencing construction costs. These findings are then summarized and reported. This structured approach ensures a thorough analysis, combining both statistical modeling and domain-specific knowledge to achieve reliable results. A detailed description of each step is presented in the following subsections.

2.4.2 Data Collection for Pricing Analysis

The data used for this research was collected from multiple sources, providing a comprehensive foundation for analyzing the various factors influencing construction costs. The primary source of data was the **bid data** from the MDOT, offering detailed insights into construction costs over the past **14 years (i.e., 2010-2023)**. This dataset offered detailed information on construction pay items associated with each design-bid-build construction contract that MDOT awarded during this period. The data includes not only the unit prices and quantities of various bid items but also essential contract attributes such as contract size and work type. The **unit price** herein refers to the price per unit of a specific pay item in a construction contract. This price was used for the Unit Bid Price analysis for Each Contract.

- Major Pay Items and “5010002 Cold Milling HMA Surface”

The research goal was to gain a deeper understanding of how various pricing factors influence the unit bid prices of pay items. The MDOT construction specification defines thousands of pay items, with some used more frequently and contributing significantly to the overall construction cost, while others are used less often. As a result, this research focused on the most significant items within the dataset. Two key criteria were applied to identify the major items. First, the item's cost percentage of the awarded amount of a contract was considered. Items whose cost amount constituted more than 1% of the total awarded contract amount were classified as major items, representing 15% of the items in the dataset. Second, the frequency of use was also used, focusing on items that had been awarded in at least 28 contracts over the past fourteen years. At least 28 contracts and a 1% cost percentage correspond to the 0.85 quantile in the dataset. This criterion ensured that the analyzed items were not only significant in cost but also commonly used. Using these criteria, a total of 272 significant items were identified.

To ensure that all relevant items were considered, feedback from MDOT's Research Advisory Panel (RAP) regarding the identified pay items was sought. This is to determine if there were any additional items that MDOT wanted to investigate further, specifically on their pricing factors. Based on the feedback, a total of 294 items for detailed investigation were finalized. Table 1 presents the distribution of the selected pay items by item category, illustrating how the items are distributed across all item categories. These items form the core of the pricing analysis, and their detailed list is provided in Appendix A.

Table 1. Selected Pay Items for the Pricing Analysis

Category	Number of items
Bases	15
Bridges & Special Struc. + Struc. Steel	40
Drainage Features	14
Earthwork	16
Electrical Construction, Sign	54
HMA Pavements	32
Others	25
PCC Pavements	21
Pavement Marking	31
Structural Concrete Work	19
Temporary Traffic Control	27
Total	**294**

Given the substantial number of selected pay items, this report presents the analysis procedure using item number **5010002, which pertains to Cold Milling HMA Surface**. This case example serves as a detailed example, illustrating the pricing analysis and demonstrating the tangible impact of the findings on cost estimations. By showcasing this specific example, how the analytical approach directly applies to pricing of construction pay items can be highlighted. The summarized results for all selected pay items are provided in Appendix A for reference.

- Data for Pricing Factors

In addition to the MDOT bid data, supplementary data was gathered from **public agency websites**, including federal and state databases. These sources provided information on broader **economic indicators**, **market dynamics**, **wage metrics**, and **construction activity** trends, complementing the MDOT dataset. Collecting data from diverse sources allowed for a more thorough analysis by incorporating both **project-specific** data from MDOT and **broader economic and market factors** from public agencies. **141 potential factors** that could impact construction pricing and cost estimation were initially identified (see Figure 4). However, due to data availability, data for **80 factors** (see Table 2) were collected and included in the analysis. The remaining factors were excluded from the analysis due to a lack of accessible or reliable data sources.

To offer a more granular approach to understanding the various drivers of construction costs, the 80 factors were grouped into more specific categories (see Table 2), such as **Economic Indicators**, **Price Indexes and Commodities**, **Wage Metrics**, and **Market Indicators**. This detailed breakdown allows for **better precision** in identifying the specific contributors to cost fluctuations, such as material price changes or labor market conditions. By separating factors into more distinct groups, decision-makers can make **more informed, targeted decisions** that address the exact areas of concern, whether it's rising commodity prices or increasing competition. Additionally, it improves **risk management**, as it allows for early identification of risks related to market conditions, contract complexity, or vendor performance. Ultimately, this approach provides a more **comprehensive understanding** of construction cost dynamics, ensuring that strategies can be designed to mitigate specific risks.

Table 2. Potential Factors Affecting Construction Cost and Their Category

Category	Variable/Factor	Category	Variable/Factor	Category	Variable/Factor
Economic Indicators	M2_Supply_Bil	Machinery and Equipment PPI	Const_Equip_PPI	Contract complexity-related Factors	Num of Items
	M1_Currency_Bil		Const_Mach_PPI		CONTRACT DESCRIPTION
	SP500_Index		PowerCrane_PPI		
	DowJones_Avg	Metals and Other Commodities	Const_Materials_PPI	Market-related Factors	TOTAL_AMOUNT_PER_YEAR_PER_STATE
	FFR_Rate		FabMetal_PPI		TOTAL_AMOUNT_PER_YEAR_PER_REGION
	CPI_Inflation		SteelMill_PPI		TOTAL_AMOUNT_PER_YEAR_PER_COUNTY
	MortgageRate_30Yr	Energy and Consumer Price Indexes	CPI_Northeast		TOTAL_AMOUNT_PER_QUARTER_PER_COUNTY
	ABI_Index		CPI_FuelOil_USAvg		TOTAL_AMOUNT_PER_MONTH_PER_COUNTY
	US_Consumer_Conf		CPI_Energy_12MChg		TOTAL_AMOUNT_PER_QUARTER_PER_REGION
Employment Metrics	Const_Emp_Thou		CPI_Gasoline_12MChg		AWARDED_AMOUNT
	MI_Const_Emp_Thou		NaturalGas_PPI		TOTAL_AMOUNT_PER_QUARTER_PER_STATE
	MI_Const_Emp_ Earnings_Thou		CPI_Energy_US		TOTAL_AMOUNT_PER_MONTH_PER_REGION
	Unemployment_Pct	Construction Spending and Activity	NonResConst_Spend		TOTAL_AMOUNT_PER_MONTH_PER_STATE
	Const_Unemployment_Pct		HighwaySpend_Mil	Competition-related Factors	Number_Bidders
Fuel and Oil Prices	DieselFuel_PPI		Household_Est_Thou		NUM_CONTRACTS_PER_YEAR_PER_COUNTY
	US_Diesel_Price		Const_Avg_Earn		NUM_CONTRACTS_PER_QUARTER_PER_COUNTY
	US_Gasoline_Price		TotalConst_Spend		NUM_CONTRACTS_PER_MONTH_PER_COUNTY
	MI_Gasoline_Price		ResConst_Spend		NUM_CONTRACTS_PER_YEAR_PER_REGION
	Gasoline_PPI		NewRes_Building_Permits		NUM_CONTRACTS_PER_MONTH_PER_REGION
	Oil_Price_Barrel		MI_Building_Permits		NUM_CONTRACTS_PER_QUARTER_PER_REGION
	WTI_Oil_Price		Const_Avg_Hrs		NUM_CONTRACTS_PER_QUARTER_PER_STATE
Construction Materials	ColdSteel_Bar_PPI	Wage Metrics	TranspWare_AvgEarn		NUM_CONTRACTS_PER_MONTH_PER_STATE
	Concrete_PPI		TotalPrivate_AvgEarn		NUM_CONTRACTS_PER_YEAR_PER_STATE
	ReadyMix_Concrete_PPI		ENR_Labor_Index	Geographical Factors	DISTRICT
	Asphalt_PPI		Const_Avg_HrlyEarn		PRIMARY COUNTY
	HotSteel_Bar_PPI	Time-related Factors	YEAR	Vendor	REFVENDOR_NM
			MONTH_NUM	Item Specifics	ITEM_QUANTITY

2.4.3 Monthly Averaged Unit Bid Price Analysis

It should be noted that **monthly averaged unit bid prices** are the quantity-weighted average unit bid prices for specific pay items across multiple contracts within a given month.

2.4.3.1 Pair Plot and Spearman Correlation

The **data** was **visualized** using various tools, one of the most effective being the **pair plot**. The pair plot provides a clear and concise way to visualize relationships between multiple variables by plotting each variable against monthly unit bid prices in the dataset. This tool is particularly useful in identifying **potential correlations** between features, trends, and patterns within the data. It allows us to visually inspect the **distribution** of each variable and identify any **linear or non-linear relationships** that might exist between pairs of variables. Furthermore, the pair plot helps detect **outliers** or unusual data points, which could skew the results of the subsequent analysis if left unaddressed. By generating these pair plots, we gained an intuitive understanding of how various features interact with each other and monthly averaged unit bid prices, serving as a valuable first step in refining the data for further analysis.

Following this, **Spearman correlation** was applied to the dataset. Spearman correlation is a non-parametric measure of rank correlation, which assesses how well the relationship between two variables can be described using a **monotonic function**. The Spearman correlation was selected because, unlike the Pearson correlation, it does not assume that the relationship between variables is **linear** or that the data follows a **normal distribution**. Spearman correlation is particularly suited for the pricing analysis because many variables do not exhibit linear relationships and may be influenced by **outliers** or **non-normal distributions**. By using Spearman correlation, **both linear and non-linear relationships** between variables can be identified, offering a more flexible and accurate understanding of the data's structure. In the Spearman test, the coefficients range from **-1 to 1**, where values closer to 1 indicate a strong positive correlation, and those near -1 suggest a strong negative correlation. Accompanying **p-values** are included to assess the statistical significance of these correlations. Table 3 shows Spearman correlation results. They are explained along with their pair plot below.

Table 3. Spearman correlation between monthly averaged unit bid prices and impact factors

Variable/Factor	Spearman Rank Correlation Coefficient	Spearman Rank p-value
YEAR	0.5	0
MONTH_NUM	0.14	0.087
M2_Supply_Bil	0.5	0
M1_Currency_Bil	0.5	0
SP500_Index	0.47	0
DowJones_Avg	0.47	0
FFR_Rate	0.25	0.001
CPI_Inflation	0.24	0.003
MortgageRate_30Yr	0.04	0.575
ABI_Index	0.03	0.755

Variable/Factor	Spearman Rank Correlation Coefficient	Spearman Rank p-value
US_Consumer_Conf	-0.1	0.232
Const_Emp_Thou	0.52	0
MI_Const_Emp_Thou	0.49	0
MI_Const_Emp_Earnings_Thou	0.49	0
Unemployment_Pct	-0.45	0
Const_Unemployment_Pct	-0.48	0
DieselFuel_PPI	-0.06	0.475
US_Diesel_Price	-0.1	0.215
US_Gasoline_Price	-0.14	0.104
MI_Gasoline_Price	-0.18	0.032
Gasoline_PPI	-0.18	0.029
Oil_Price_Barrel	-0.19	0.027
WTI_Oil_Price	-0.2	0.019
ColdSteel_Bar_PPI	0.51	0
Concrete_PPI	0.5	0
ReadyMix_Concrete_PPI	0.5	0
Asphalt_PPI	0.46	0
HotSteel_Bar_PPI	0.28	0
Const_Equip_PPI	0.5	0
Const_Mach_PPI	0.49	0
PowerCrane_PPI	0.47	0
Const_Materials_PPI	0.5	0
FabMetal_PPI	0.45	0
SteelMill_PPI	0.28	0
CPI_Northeast	0.5	0
CPI_FuelOil_USAvg	0.13	0.09
CPI_Energy_12MChg	0.02	0.794
CPI_Gasoline_12MChg	-0.01	0.874
NaturalGas_PPI	-0.15	0.06
CPI_Energy_US	-0.16	0.043
NonResConst_Spend	0.51	0
HighwaySpend_Mil	0.51	0
Household_Est_Thou	0.5	0
Const_Avg_Earn	0.49	0
TotalConst_Spend	0.49	0
ResConst_Spend	0.47	0
NewRes_Building_Permits	0.44	0
MI_Building_Permits	0.26	0.001
Const_Avg_Hrs	0.17	0.03
TranspWare_AvgEarn	0.51	0
TotalPrivate_AvgEarn	0.51	0
ENR_Labor_Index	0.51	0
Const_Avg_HrlyEarn	0.5	0
ITEM_QUANTITY	-0.05	0.517

- Time-related: 2 factors

Figure 10 shows the influence of **time-related factors** on construction pricing. Time is a critical driver in construction cost dynamics, and here **pair plots are** utilized to graphically represent this relationship. The **first plot** provides a yearly overview from **2010 to 2023**, highlighting price fluctuations over years, which likely capture broader **macroeconomic trends** and **cyclical industry patterns**. The **second plot** offers a more granular view, showcasing the **monthly analysis**. This allows us to observe potential **seasonal variations** or **short-term market adjustments**, giving a finer understanding of time-sensitive price shifts.

The correlation between **BID_PRICE** and **YEAR** is **moderately positive**, with a coefficient of **0.50**, suggesting that as time progresses, bid prices tend to increase. The associated p-value is very low, indicating that this correlation is statistically significant. These visual plots are indispensable and offer a clear, immediate understanding of how **time impacts construction costs**.

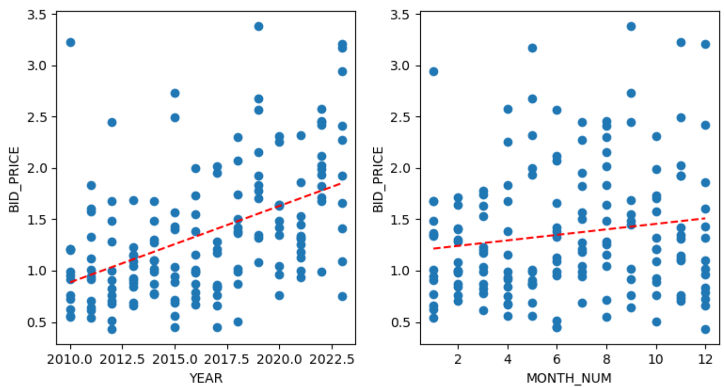

Figure 10. Pair Plot: Time-related Factors and Monthly Bid Price

- Economic Indicators: 9 factors

Figure 11 visually highlights **patterns and trends** between economic factors and monthly bid pricing over time. The indicators like the **S&P500** and **Dow Jones** exhibit **moderate positive correlations** with bid prices, suggesting construction costs tend to rise with the stock market. In contrast, the **US_Consumer_Conf** shows a **weak negative correlation**, indicating a slight inverse relationship that warrants further investigation. Notably, factors like the **FFR Rate** and **CPI Inflation** have **low correlations** but **significant p-values**, meaning they may still offer important insights when included in predictive models.

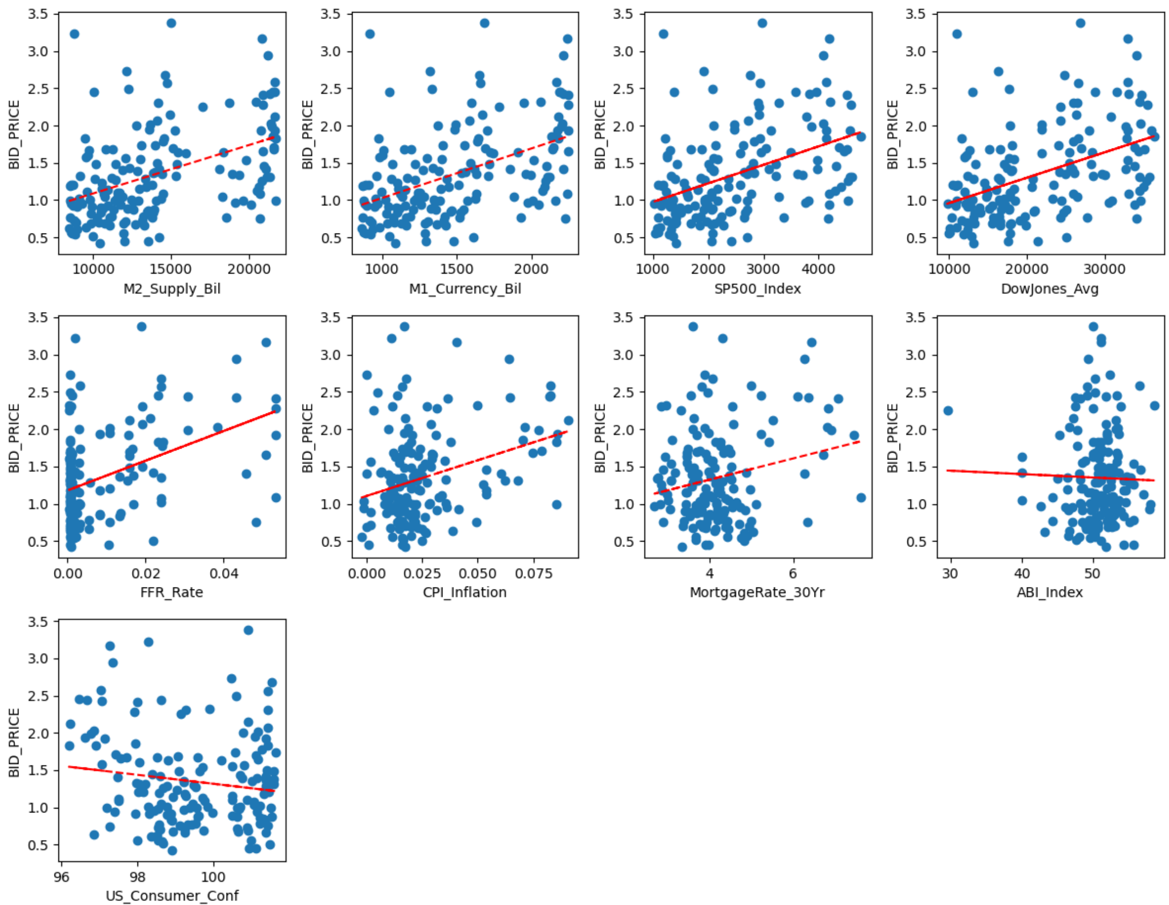

Figure 11. Pair Plot: Economic Factors and Monthly Bid Price

- Employment Metrics: 5 factors

Five employment-related factors are plotted against the bid price to reveal trends and correlations within the data. Figure 12 show how each employment metric interacts with bid prices, providing insights into how labor market conditions may influence construction costs. For example, the last two plots suggest a trend where construction prices decrease as **unemployment rates** rise, possibly reflecting the principle that higher unemployment can reduce labor costs, lowering construction expenses.

The correlation between **'Const_Emp_Thou'** and bid prices is **moderately positive** (0.52), indicating that as construction employment rises, labor demand may drive up construction costs. Conversely, the **'Unemployment_Rate'** shows a **moderately strong negative correlation** (-0.45), reinforcing the visual trend that higher unemployment is associated with lower construction costs. The **p-values** for these correlations are low, indicating that these relationships are statistically significant. These insights allow the incorporation of labor market dynamics into the predictive models, enhancing the accuracy of construction cost forecasts. However, it's important to note that **correlation does not imply causation**, and these relationships may be influenced by other factors not captured in these plots.

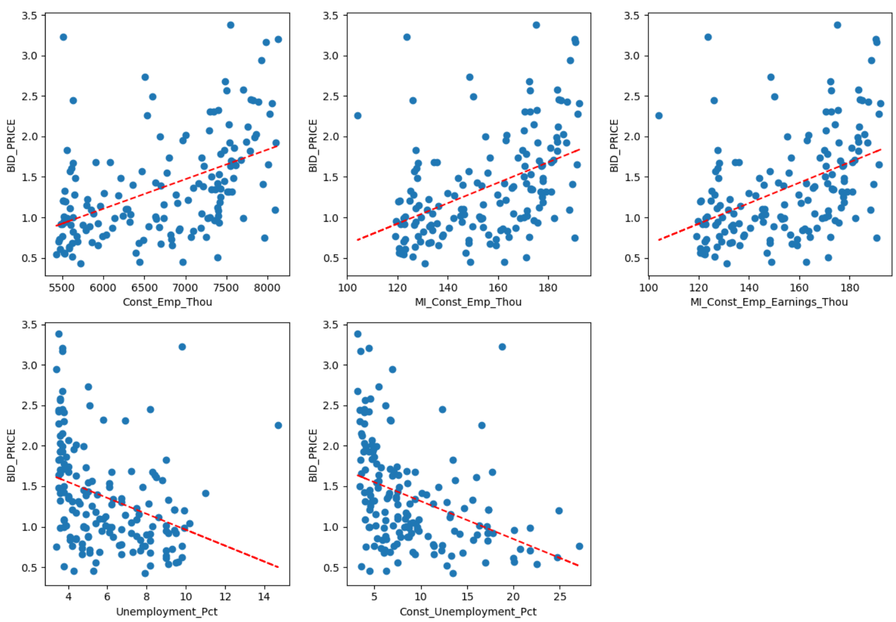

Figure 12. Pair Plot: Employment Metrics and Monthly Bid Price

- Price Indexes and Commodities: 24 factors

From the scatter plots (Figure 13-Figure 17), the dispersion of data is observed, which suggests that changes in these commodity prices may align with fluctuations in unit bid price, though no clear linear trend is evident. This indicates that, for example, the relationship between fuel prices and unit bid prices may be mediated by other factors or could vary over time.

The coefficients are relatively low, indicating **weak correlations** between fuel and oil prices and unit bid prices. For example, **DieselFuel_Price** has a correlation coefficient of **-0.06**, and **WTI_Oil_Price** shows **-0.20**, both suggesting very weak negative relationships with the unit bid price. However, the associated p-values are significant (less than 0.05), indicating that while these correlations are weak, they are statistically consistent and unlikely to be due to chance. This suggests that while fuel and oil prices do influence unit bid prices, they are not dominant factors on their own. Their effects may be **subtle or indirect**, possibly impacting other areas such as **transportation costs** or **machinery operation**.

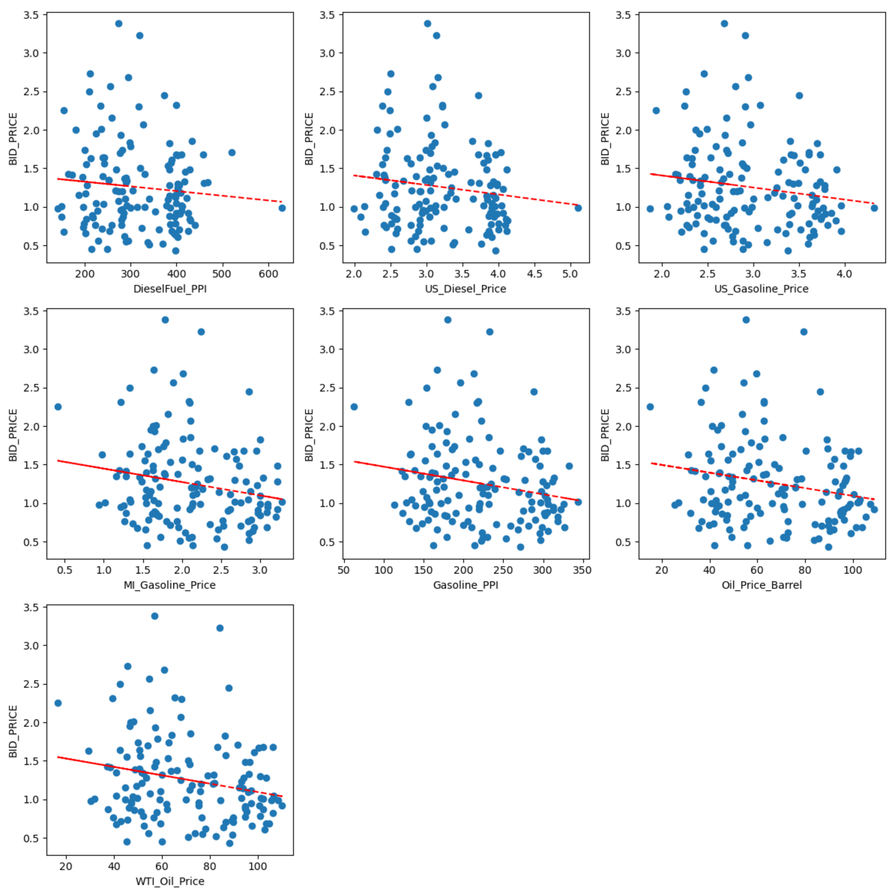

Figure 13. Pair Plot: Fuel and Oil Prices and Monthly Bid Price

The ColdSteel_Bar_PPI exhibits a strong positive correlation of 0.51 with unit bid prices, suggesting that increases in the price of cold steel bars are associated with higher unit bid prices. This correlation may reflect the essential role that steel plays in construction projects, as fluctuations in steel prices can directly impact overall project expenses. Similarly, the Concrete_PPI and ReadyMix_Concrete_PPI both demonstrate positive correlations of 0.50. These findings indicate that rising prices in concrete materials are likely to drive up unit bid prices, reinforcing the importance of concrete as a fundamental component in many construction projects. The Asphalt_PPI shows a slightly lower, yet still significant, positive correlation of 0.46 with unit bid prices. This suggests that variations in asphalt prices can also contribute to changes in construction costs, particularly in road and highway projects where asphalt is a primary material.

Finally, the HotSteel_Bar_PPI has a correlation of 0.28, which, while weaker than the others, still indicates a positive relationship with unit bid prices. This correlation may point to the influence of hot-rolled steel bars in certain construction applications, although its impact is less pronounced compared to cold steel and concrete. All of these factors have p-values of 0.000, indicating that the observed correlations are statistically significant. Understanding these relationships is crucial, as they allow stakeholders to anticipate how fluctuations in material prices may affect overall construction costs.

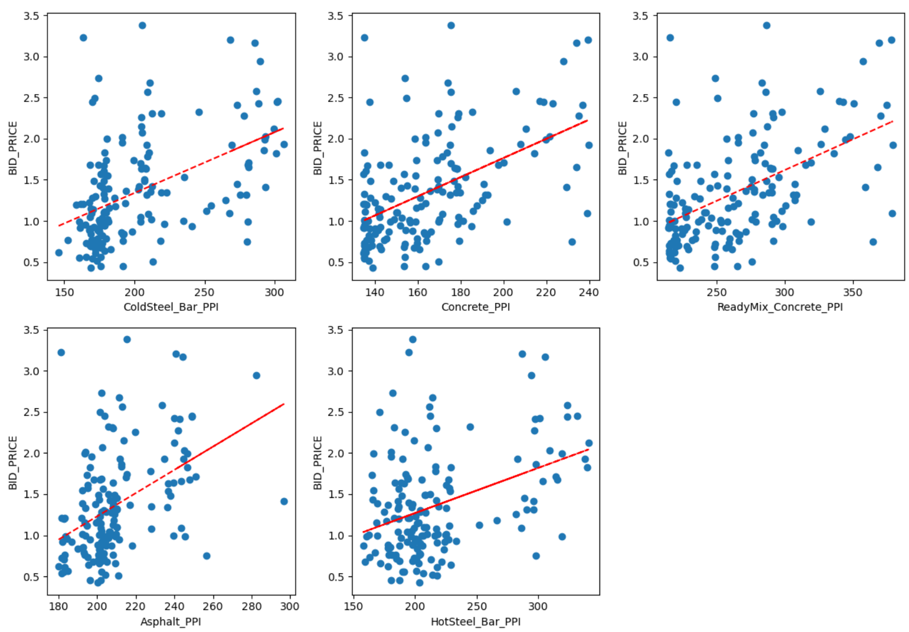

Figure 14. Pair Plot: Construction Materials and Monthly Bid Price

The **Const_Equip_PPI** shows a strong positive correlation of **0.50**, indicating that increases in the price of construction equipment are associated with higher unit bid prices. This relationship highlights the importance of equipment costs in determining overall project expenses, as equipment often represents a significant portion of construction costs, especially for large-scale or infrastructure projects. Similarly, the **Const_Mach_PPI** demonstrates a positive correlation of **0.49**, suggesting that rising prices for construction machinery have a direct impact on unit bid prices. This correlation underscores the influence of machinery costs on construction pricing, particularly in projects that require heavy equipment use. Lastly, the **PowerCrane_PPI** has a positive correlation of **0.47** with unit bid prices, indicating that fluctuations in power crane costs also play a role in shaping overall construction costs. While this correlation is slightly lower than the others, it still highlights the relevance of specialized equipment, such as cranes, in influencing unit bid prices.

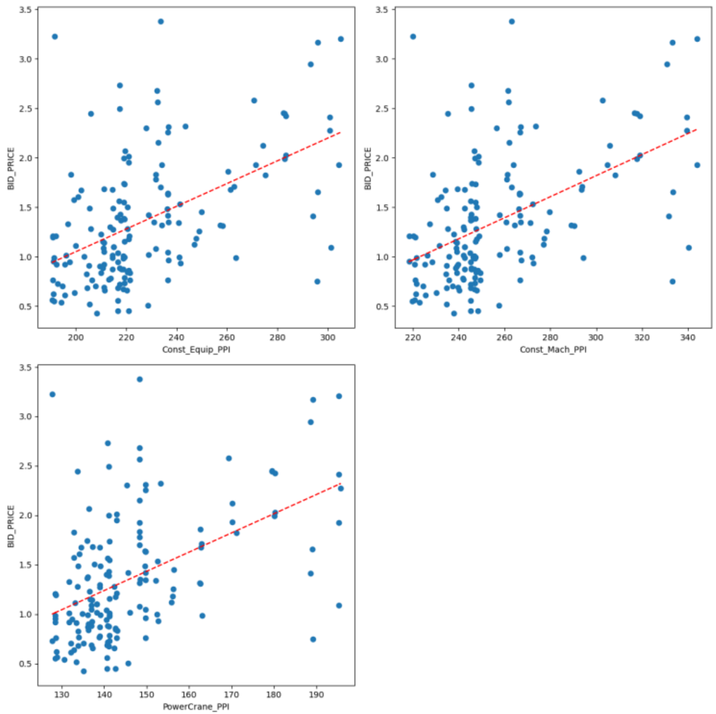

Figure 15. Pair Plot: Machinery and Equipment PPI and Monthly Bid Price

The Const_Materials_PPI shows a strong positive correlation of 0.50, indicating that increases in the prices of construction materials are closely linked to higher unit bid prices. This highlights the significant role that general material costs play in influencing overall construction project expenses, as material costs are a fundamental driver of bid pricing in construction.

Similarly, the FabMetal_PPI demonstrates a positive correlation of 0.45 with unit bid prices. This suggests that rising prices for fabricated metals, which are commonly used in construction, contribute directly to increases in construction costs. Given the widespread use of metal components in structural applications, this correlation reflects the impact of metal prices on project budgets.

Lastly, the SteelMill_PPI exhibits a weaker, but still positive, correlation of 0.28 with unit bid prices. Although the correlation is less pronounced compared to other materials, it still indicates that fluctuations in steel mill product prices, such as beams and plates, can affect construction costs. Steel is a key material in many construction projects, particularly in infrastructure, where its cost fluctuations can influence overall bid pricing.

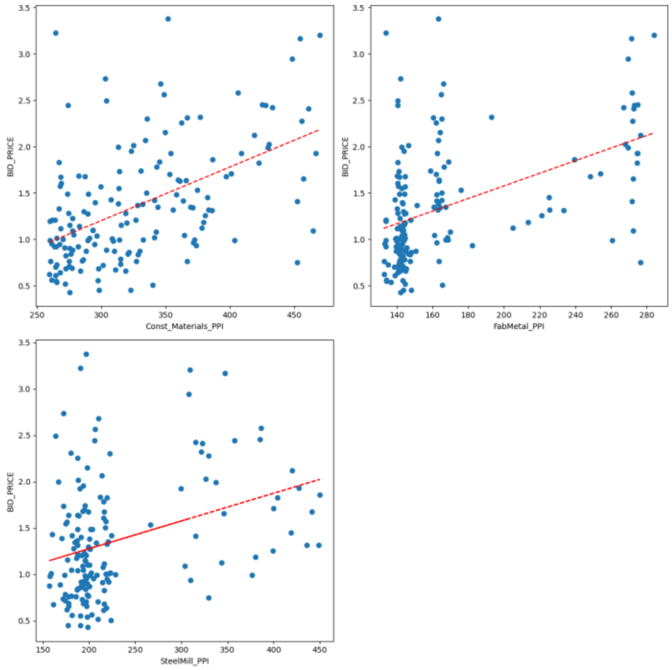

Figure 16. Pair Plot: Metals and Other Commodities and Monthly Bid Price

The analysis of **Consumer Price Index (CPI) and energy-related price indexes** reveals mixed correlations with the bid price. The **CPI_Northeast** exhibits a strong positive correlation of **0.50**, indicating that increases in the overall cost of living and inflation in the Northeast region are associated with higher unit bid prices in Michigan. This suggests that regional inflationary pressures can have a notable impact on construction costs, particularly in areas where labor and material prices might be influenced by broader economic conditions.

The **CPI_FuelOil_USAvg** has a weaker positive correlation of **0.13**, with a p-value of **0.09**, indicating that while there is some relationship between average fuel oil prices across the U.S. and unit bid prices, it is not statistically significant. This suggests that fuel oil prices may have a limited direct impact on construction costs but could still influence project budgets under certain conditions.

The **CPI_Energy_12MChg** shows a minimal correlation of **0.02**, with a p-value of **0.794**, indicating no meaningful relationship between changes in energy prices over the past 12 months and unit bid prices. Similarly, the **CPI_Gasoline_12MChg** exhibits a near-zero correlation of **-0.01**, with a p-value of **0.874**, further suggesting that short-term gasoline price fluctuations have little to no direct effect on unit bid prices.

In contrast, the **NaturalGas_PPI** displays a moderate negative correlation of **-0.15**, with a p-value of **0.06**. This suggests that as natural gas prices increase, unit bid prices may decrease slightly, though this relationship is on the cusp of statistical significance. This could reflect the indirect impact of natural gas prices on construction costs, particularly in terms of energy consumption during project execution.

Finally, the **CPI_Energy_US** shows a slightly stronger negative correlation of **-0.16**, with a statistically significant p-value of **0.043**. This suggests that rising energy prices at the national level may be associated with a modest decrease in unit bid prices, potentially due to reduced construction activity during periods of high energy costs or other mitigating factors that offset direct cost increases.

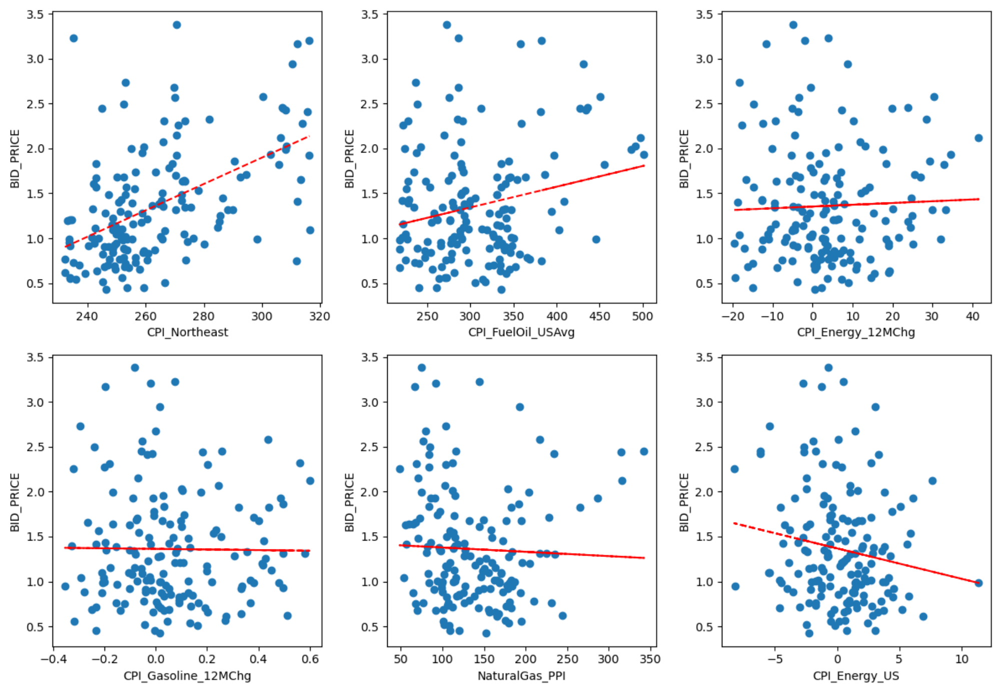

Figure 17. Pair Plot: Energy and Consumer **Price Indexes** and Monthly Bid Price

- Construction Spending and Activity: 9 factors

Moving forward, the impact of **construction spending and activity** on construction pricing is explored by analyzing nine key factors. The scatter plots in Figure 18 visualize each factor in relation to the bid price, providing empirical insights into how levels of spending and construction activity influence costs. The trend lines on the plots suggest varying degrees of **positive correlation** between these factors and unit bid prices, helping us understand the role of economic activity in shaping construction costs.

A closer examination of the **Spearman rank correlation coefficients** reveals the strength of these relationships. For instance, both **'NonresConst_Spend'** and **'HighwaySpend_MI'** have coefficients of **0.51**, indicating that increases in non-residential construction spending and highway expenditures are **moderately associated** with higher unit bid prices. This suggests that as construction activity expands, particularly in these sectors, demand and costs rise accordingly. Similarly, **'Household_Est_Thou'** shows a correlation of **0.50**, implying that as the number of households increases, so do construction prices, possibly driven by higher demand for residential development.

On the other hand, **'MI_Building_Permits'** displays a weaker correlation of **0.26**, suggesting that while building permits are positively correlated with construction costs, they are a less significant predictor compared to other spending and activity metrics. Despite the varying strengths of these correlations, all factors exhibit **p-values significantly below 0.05**, confirming that these relationships are **statistically significant** and not likely to occur by chance.

By understanding these correlations, **macro-level economic and activity indicators** can be better integrated into the predictive models, improving the accuracy of the construction pricing forecasts. These insights offer valuable guidance for stakeholders to anticipate **market trends** and allocate resources more efficiently. Moving forward, these factors will be incorporated into **complex models** that forecast construction pricing dynamics, informing **strategic decision-making** and **financial planning**

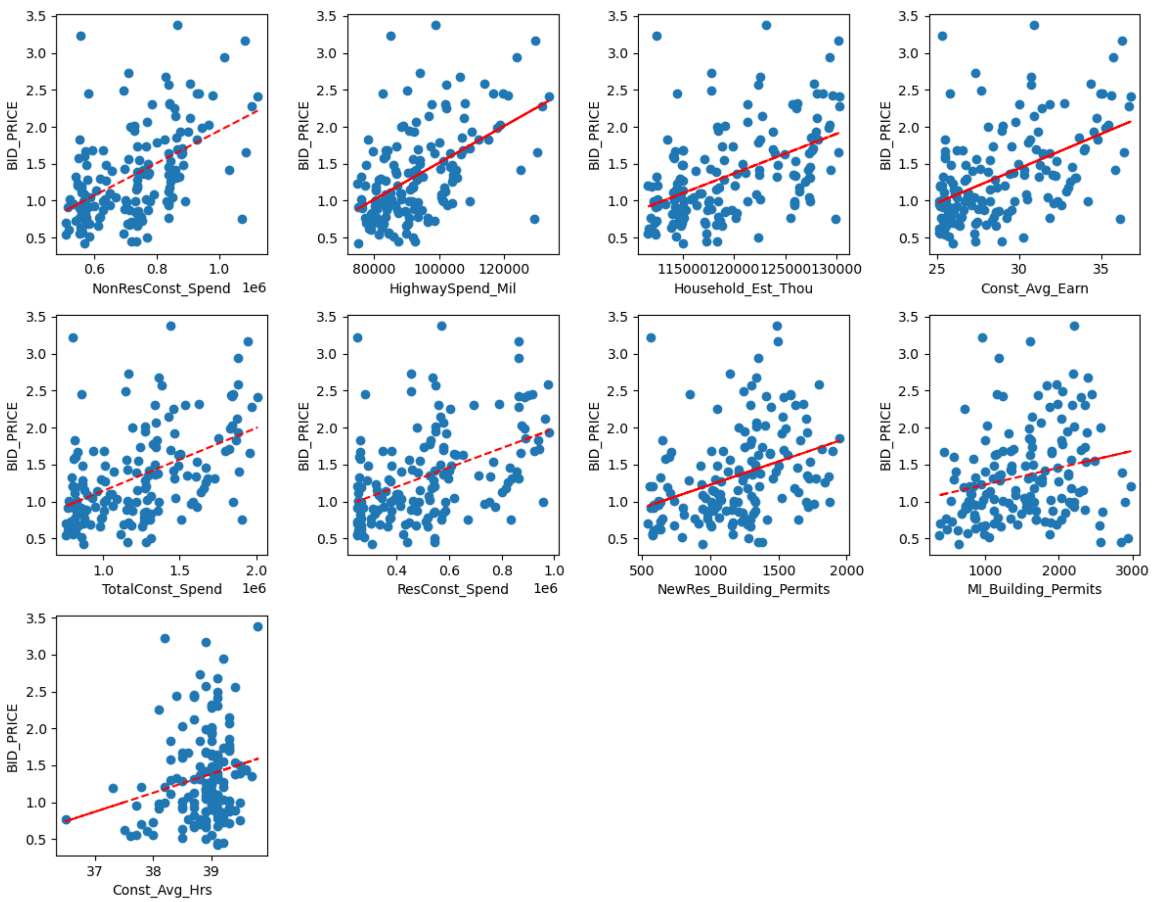

Figure 18. Pair Plot: Construction Spending and Activity and Monthly Bid Price

- Wage Metrics: 4 factors

Labor-related earns and price indexes reveals significant positive correlations with unit bid prices, highlighting the importance of labor costs in construction pricing. The **TranspWare_AvgEarn** exhibits a strong positive correlation of **0.51**, indicating that increases in the average earnings for workers in transportation and warehousing are associated with higher unit bid prices. This suggests that higher wages in the logistics and transport sectors, which are critical for material movement and supply chain efficiency in construction projects, directly influence construction costs.

Similarly, the **TotalPrivate_AvgEarn** also demonstrates a positive correlation of **0.51**, indicating that rising average earnings in the private sector have a strong impact on construction unit bid prices. As labor constitutes a significant portion of construction expenses, this relationship underscores the effect of general wage increases in the broader economy on project costs.

The **ENR_Labor_Index** also shows a positive correlation of **0.51**, further reinforcing the relationship between labor cost trends and unit bid prices. This index tracks labor cost changes specifically within the construction industry, and its strong correlation suggests that as labor costs increase, construction pricing rises in tandem.

Lastly, the **Const_Avg_HrlyEarn** shows a strong correlation of **0.50**, indicating that increases in the average hourly earnings of construction workers are closely linked to rising unit bid prices. This reflects the direct impact of wage increases on project costs, particularly in labor-intensive construction activities.

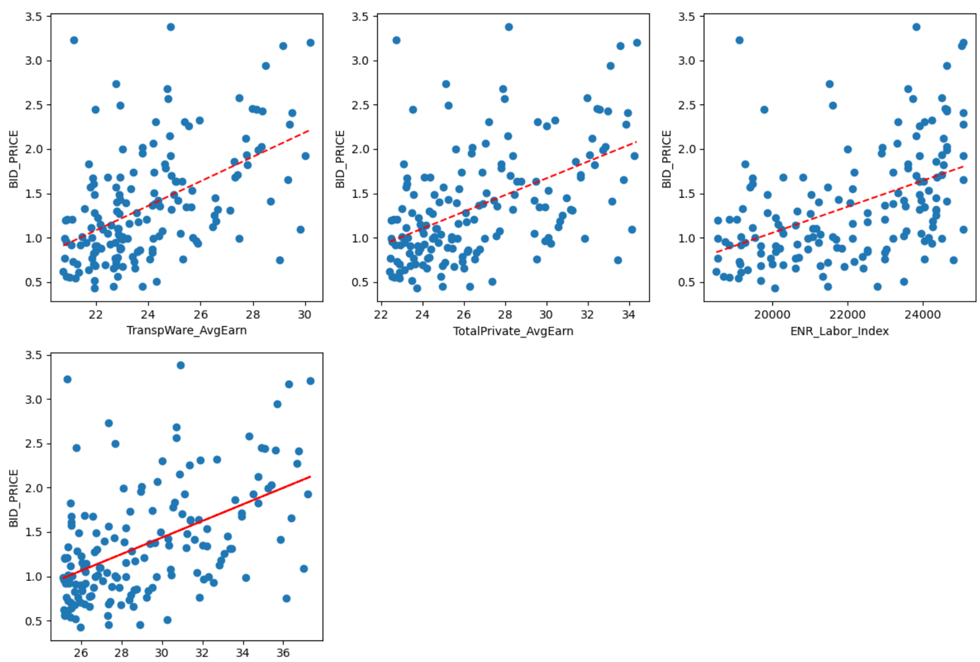

Figure 19. Pair Plot: Wage Metrics and Monthly Bid Price

- Item Specifics: 1 factor

The **monthly ITEM_QUANTITY** reveals a weak negative correlation of **-0.05** with unit bid prices, and the p-value of **0.517** indicates that this relationship is not statistically significant. This suggests that there is no meaningful relationship between the quantity of items and the unit bid prices in this dataset.

The weak and statistically insignificant correlation implies that variations in the quantity of items **within a month** do not have a noticeable impact on the monthly bid price. This could mean that other factors, such as material costs, labor rates, or economic conditions, play a much more dominant role in shaping monthly unit bid prices than the sheer volume of items in a given month.

Given these results, monthly **ITEM_QUANTITY** does not appear to be a significant predictor of monthly unit bid prices in this context, and its influence on construction costs may be minimal compared to other factors analyzed. This insight helps focus attention on more relevant drivers of bid price changes, refining cost estimation models to prioritize the most impactful variables.

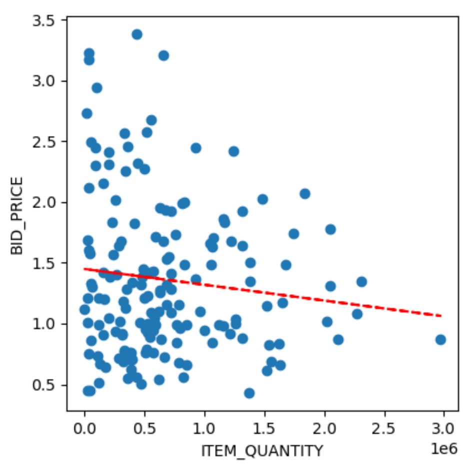

Figure 20. Pair Plot: Quarterly Quantity and Monthly Bid Price

2.4.3.2 Data Transformation

Another critical preprocessing step in the quantitative analysis is the transformation and scaling of highly skewed variables or features to ensure they fall within a similar range, facilitating better performance in predictive models. Transformation addresses the non-normality of the data, while scaling ensures that all variables contribute equally to the learning process of machine learning algorithms. This is done to ensure that the underlying assumptions of many predictive algorithms, particularly their reliance on normally distributed input data, are met.

The histograms in Figure 21 visualize the distribution of the monthly unit bid prices before and after transformation. These visualizations demonstrate the effectiveness of transformation techniques in normalizing the distributions, making them more symmetrical and aligned with the normal distribution. Again, normalization is necessary because many algorithms, such as linear regression or decision trees, can struggle with non-normally distributed data, leading to poor model performance. By transforming the data, the distribution can be improved, making it suitable for further analysis.

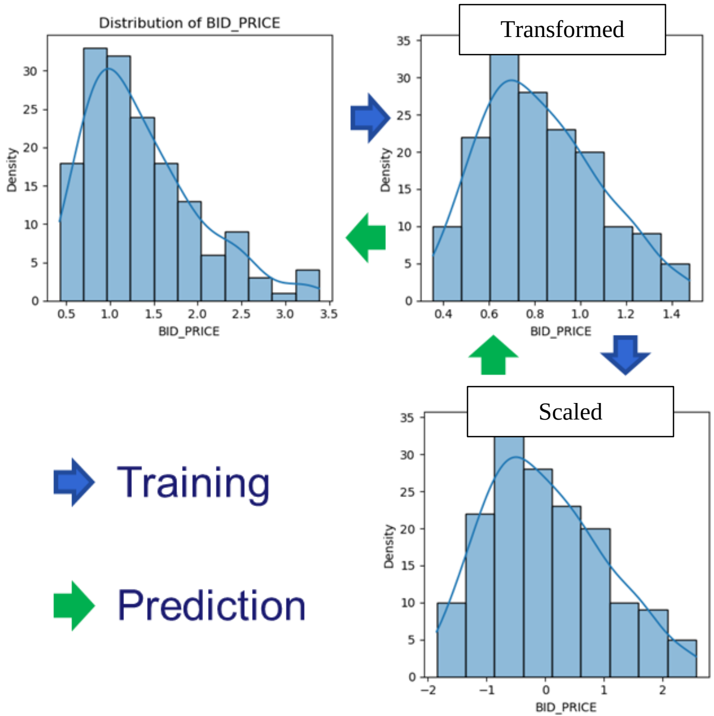

Figure 21 Data Transformation: Example of Monthly Unit Bid Price

Several features are listed in Table 4, alongside their skewness and kurtosis values before transformation. Skewness measures the asymmetry of the distribution, while kurtosis measures the "tailedness," or how much of the data is in the tails versus the center. A normal distribution has skewness and kurtosis values close to zero, and the transformation process is designed to adjust these values closer to this ideal. The general rule of thumb for determining when to apply a transformation to address skewness is based on the skewness value. That is, **if skewness is less than -1 or greater than 1**: The distribution is **highly skewed**, and transformation is usually recommended. A kurtosis value near zero indicates a shape close to a normal distribution. A low kurtosis value indicates light tails or lack of outliers. For example, the 'FFR_Rate' feature had a pre-transformation skewness of 1.88, which was significantly reduced after one transformation. This indicates that the distribution is more aligned with the normal distribution post-transformation, improving the performance of predictive algorithms.

In addition to transformation, scaling is applied to ensure that all features are within a similar range. This is important because features with larger ranges can disproportionately influence the learning process, causing the model to place more importance on these features. The values are standardized, ensuring a level playing field for all features during the model training, as shown at the bottom in Figure 21.

Table 4. Feature Transformation

Feature	skewness	kurtosis
FFR_Rate	1.88	2.70
SteelMill_PPI	1.71	1.82
PowerCrane_PPI	1.59	1.88
FabMetal_PPI	1.57	0.92
CPI_Inflation	1.57	2.00
Asphalt_PPI	1.50	2.96
MortgageRate_30Yr	1.37	1.92
Const_Mach_PPI	1.34	1.12
HotSteel_Bar_PPI	1.27	0.59
BID_PRICE	1.26	1.57
Const_Unemployment_Pct	1.25	0.98
ITEM_QUANTITY	1.24	1.53
Const_Equip_PPI	1.19	0.81
ColdSteel_Bar_PPI	1.14	0.01
DieselFuel_PPI	1.10	1.77
HighwaySpend_Mil	1.09	0.83
NaturalGas_PPI	1.06	1.55
Concrete_PPI	1.02	0.34
Const_Avg_Hrs	1.61	4.30
ABI_Index	1.84	7.49

In summary, by transforming and scaling the data, a solid foundation for building effective predictive models and identifying pricing factors is created. These preprocessing steps are essential for improving the accuracy and reliability of the unit bid price forecasts that will be generated by machine learning algorithms. The transformed and scaled data is fed into sophisticated algorithms to model construction pricing with enhanced precision, ensuring better unit bid price estimations.

2.4.3.3 Factor Analysis via Predictive Modelling

Multivariate regression model

Feature/Factor Selection: After transforming the collected data for unit bid prices and pricing factors, the Spearman correlation was recalculated to select features for the regression model. The criteria for feature selection were that the correlation coefficient must be greater than 0.2. The threshold of 0.2 for the correlation coefficient was chosen to strike a balance between including meaningful relationships and avoiding overfitting. A correlation coefficient of 0.2, while not extremely strong, suggests a moderate relationship between the predictor variables and the unit bid price, which can still provide useful predictive power without including weak or irrelevant features.

Additionally, multicollinearity was addressed by using the Variance Inflation Factor (VIF), which measures how much a predictor is correlated with other variables in the model. When multicollinearity occurs, it can distort coefficient estimates in a regression model. A common practice is to remove variables with a VIF greater than 10, as they may introduce redundancy and instability, negatively impacting model performance. Addressing multicollinearity improves the model's stability and ensures that predictions for construction pricing are both accurate and interpretable.

Table 5 displays various features and their corresponding VIF scores. For instance, 'Asphalt_PPI' has a VIF of 17.2, exceeding the recommended threshold and indicating a high correlation with other predictors. To improve model accuracy and interpretability, it would be advisable to remove or combine 'Asphalt_PPI' with other features to reduce multicollinearity. In this study, 'Asphalt_PPI' is closely related to the pay item 5010002, Cold Milling HMA Surface. On the other hand, features like 'ITEM_QUANTITY' and 'CPI_Energy_US' have much lower VIF scores (2.2 and 4.5, respectively), indicating minimal multicollinearity, and they can remain in the model without concern.

Table 5. Variance Inflation Factor: Monthly Pricing Factor/Features

Features	Coefficient	VIF
ITEM_QUANTITY	-0.05	2.2
CPI_Energy_US	-0.16	4.5
Const_Avg_Hrs	0.17	5.9
ABI_Index	0.03	6.4
MI_Building_Permits	0.26	8.9
Asphalt_PPI	0.46	17.2

With the reduced list of pricing factors, the data was used to fit the regression model. Table 6 presents the OLS regression results for modeling **unit bid prices** based on several predictor variables.

- **Coefficient (Coef)**: Represents the estimated impact of each variable on the bid price. For example, **ITEM_QUANTITY** has a coefficient of **-0.1934**, indicating that an increase in item quantity tends to decrease unit bid prices, while **Asphalt_PPI** has a positive coefficient (**0.2622**), suggesting that higher asphalt prices increase unit bid prices.
- **Standard Error (Std Err)**: Indicates the uncertainty in each coefficient estimate. Smaller standard errors imply more precise estimates.
- **t-Value**: Measures the significance of each predictor in relation to unit bid prices. Larger absolute values suggest stronger evidence of a relationship.
- **p-Value**: Variables with p-values below 0.05, such as **ITEM_QUANTITY** (p-value = **0.012**) and **Asphalt_PPI** (p-value = **0.022**), are statistically significant and contribute meaningfully to predicting unit bid prices. Other variables, such as **CPI_Energy_US** and **MI_Building_Permits**, have higher p-values, suggesting they are not significant in this model.

- **95% Confidence Interval**: Provides a range within which the true effect of each variable is expected to lie. For example, **Asphalt_PPI** has a confidence interval of **[0.038, 0.486]**, meaning the confident ia 95% that its effect on unit bid prices lies within this range.

In short, **ITEM_QUANTITY** and **Asphalt_PPI** are the most significant predictors of unit bid prices, with statistically significant p-values. Other variables like **CPI_Energy_US** and **ABI_Index** do not have statistically significant effects, suggesting that their relationship with unit bid prices is weaker or less clear. The model's **R-squared** value of **0.153** suggests that about 15.3% of the variation in unit bid prices is explained by the model. While this indicates that other factors not captured in the model may influence unit bid prices, the statistically significant predictors provide valuable insights for understanding key cost drivers in construction pricing.

Table 6. OLS Regression Results for Bid Price Estimation

Variable	Coefficient (Coef)	Std. Error (Std Err)	t-Value (t)	p-Value (P>|t|)	95% Confidence Interval [0.025, 0.975]
Constant (Intercept)	-0.1026	0.077	-1.325	0.188	[-0.256, 0.051]
ITEM_QUANTITY	-0.1934	0.076	-2.555	0.012	[-0.344, -0.043]
CPI_Energy_US	-0.1128	0.075	-1.5	0.137	[-0.262, 0.036]
Const_Avg_Hrs	0.0703	0.092	0.765	0.446	[-0.112, 0.253]
ABI_Index	-0.085	0.079	-1.077	0.284	[-0.241, 0.072]
MI_Building_Permits	0.0872	0.083	1.048	0.297	[-0.078, 0.252]
Asphalt_PPI	0.2622	0.113	2.32	0.022	[0.038, 0.486]

<u>Random forest model</u>

In addition to the multivariate regression model, a **Random Forest** model was implemented to further explore the predictive power of the variables. The Random Forest model is a robust method that leverages multiple decision trees to improve prediction accuracy. The model was trained using the same dataset, where the target variable was **BID_PRICE** and the independent variables included **all features/factors**. Random Forest models are well-known for their ability to handle large numbers of features without overfitting. It naturally evaluates the importance of each feature during training. By considering all features, the model identifies which variables contribute the most to predictions, helping assess their relevance without the need for pre-selection. This can lead to more accurate and unbiased rankings of feature importance compared to manual selection. Unlike linear models, Random Forest is not significantly affected by multicollinearity because it randomly selects a subset of features for each tree split. Therefore, including all features does not risk model instability or inflated importance of correlated predictors, as the algorithm effectively reduces their impact during the process.

To train the model, the dataset was split into training and testing sets, using an 80/20 ratio. The Random Forest algorithm was then applied to the training data, with hyperparameters such as the number of trees (estimators) and maximum tree depth being optimized through cross-validation to ensure the model's generalizability. Figure 22 shows the results of the Random Forest prediction for unit bid prices. It is divided into two main sections: the top graph shows the Actual (blue) vs. Predicted Values (orange), and the bottom graph presents the Residuals vs. Predicted plot. While the model captures general trends, it struggles with more extreme variations, such as around observations 20 and 25. The model's Mean Squared Error (MSE) is 0.45, and its R-squared (R^2) is 0.13, **meaning it explains only 13% of the variance, indicating limited predictive accuracy**. The bottom graph shows residuals (prediction errors) against predicted values. Ideally, residuals should scatter around zero. Here, larger deviations indicate the model occasionally underpredicts or overpredicts unit bid prices.

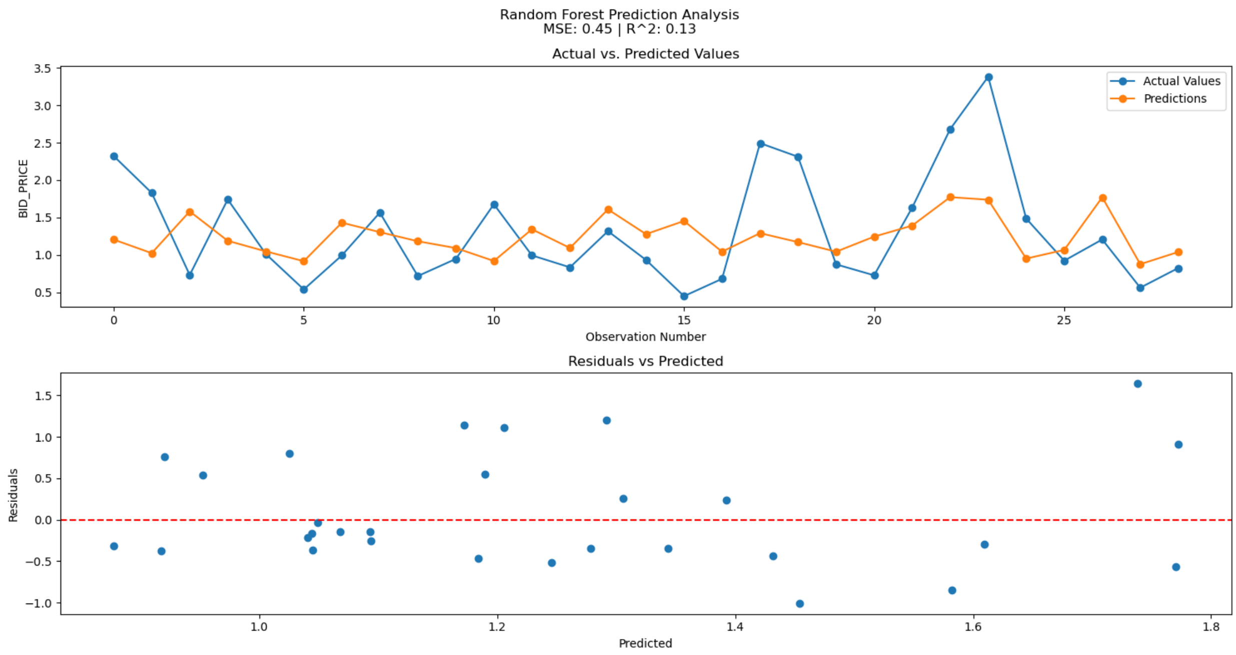

Figure 22. Random Forest Prediction: Monthly Bid Price

Figure 23 displays the feature importance scores from the Random Forest model, highlighting the variables that have the greatest influence on predicting unit bid prices. **Const_Unemployment_Pct** and **ITEM_QUANTITY** are the two most important predictors contributing significantly to the model's performance. This suggests that unemployment rates within the construction sector and the quantity of items in a month have the largest impact on unit bid prices. **HighwaySpend_Mil**, **MI_Building_Permits**, and **NaturalGas_PPI** also rank highly, indicating that highway spending, building permits, and natural gas prices are key factors influencing monthly unit bid prices. Other material-related factors like **ColdSteel_Bar_PPI** and **Asphalt_PPI** show moderate importance, reinforcing their influence on unit bid prices, especially in material-heavy construction projects. Variables such as **US_Consumer_Conf**, **SP500_Index**, and **CPI_Energy_12MChg** have very low importance, suggesting limited direct impact on unit bid prices in this model. The results highlight the significance of labor market conditions (unemployment rates) and item-specific factors (monthly quantity) in determining unit bid prices. Additionally, public spending and material prices play a crucial role, while broader economic indicators such as consumer confidence and stock market indexes appear to have less influence on monthly unit bid prices of 5010002 Cold Milling HMA Surface.

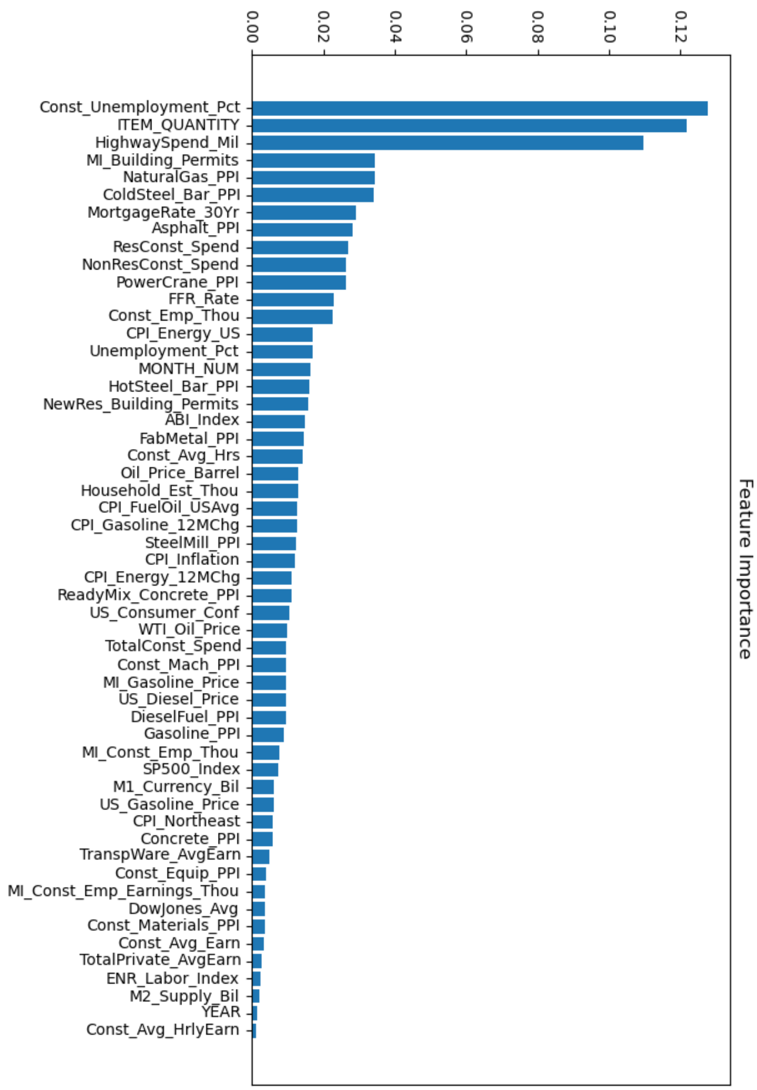

Figure 23. Feature Importance by Random Forest Model

Ensemble Learning model

An **Ensemble Learning model** was implemented using a **StackingRegressor** to improve the predictive accuracy of monthly unit bid prices. Stacking is an ensemble technique that combines the predictions of multiple base models, and then uses a final estimator to make the overall prediction, leveraging the strengths of different algorithms for enhanced performance.

The ensemble model utilized several estimators:

- **RandomForestRegressor**: A random forest model with 100 estimators, no maximum depth, and a minimum of 10 samples per split, providing robustness by averaging multiple decision trees.

- **SVR (Support Vector Regressor)**: Applied with a regularization parameter (C=1.0), epsilon=0.1, and a scale kernel to capture nonlinear relationships between predictors and unit bid prices.
- **GradientBoostingRegressor**: With 100 estimators, a learning rate of 0.1, and a maximum depth of 5, this model incrementally improves predictions by correcting errors from previous iterations.
- **DecisionTreeRegressor**: A decision tree model without depth restrictions but requiring a minimum of 10 samples per split, helping to reduce overfitting.
- **KNeighborsRegressor (KNN)**: A K-Nearest Neighbors model with 5 neighbors and uniform weights to capture local data trends by comparing new points with the nearest observed data.
- **AdaBoostRegressor**: An adaptive boosting model with 50 estimators and a learning rate of 1.0, which adapts to previous errors by adjusting model weights dynamically.
- **ExtraTreesRegressor**: With 10 estimators and a maximum depth of 10, this model introduces randomness to capture complex relationships.
- **Ridge Regression**: A linear model with L2 regularization (alpha=10.0) to mitigate multicollinearity and overfitting issues.
- **Lasso Regression**: A Lasso model with L1 regularization (alpha=0.001), useful for feature selection by reducing less important feature coefficients to zero.
- **MLPRegressor**: A multi-layer perceptron (MLP) neural network with 100 neurons in a single hidden layer, using ReLU activation and the Adam solver to model complex nonlinear relationships.

The predictions from these models were aggregated by a **LinearRegression** model as the final estimator, combining the outputs of all base models to produce the final prediction. The model was trained using 10-fold cross-validation (**cv=10**) to ensure robustness and prevent overfitting.

Figure 24 presents the results of the **Ensemble Learning: Stacking Prediction**, with two graphs visualizing the model's performance. The model achieves a **Mean Squared Error (MSE)** of **0.40** and an **R-squared (R^2)** of **0.23**, meaning the model explains **23%** of the variance in unit bid prices. This is an improvement over the Random Forest model (which had an R^2 of 0.13), suggesting better overall performance in capturing bid price trends. While the residuals are centered around zero, there are some noticeable deviations, particularly for higher predicted values, indicating that the model might still struggle to predict extreme price variations accurately. Overall, the ensemble model enhances prediction accuracy and provides a more stable forecasting tool for bid price estimation, though there is still room for refinement.

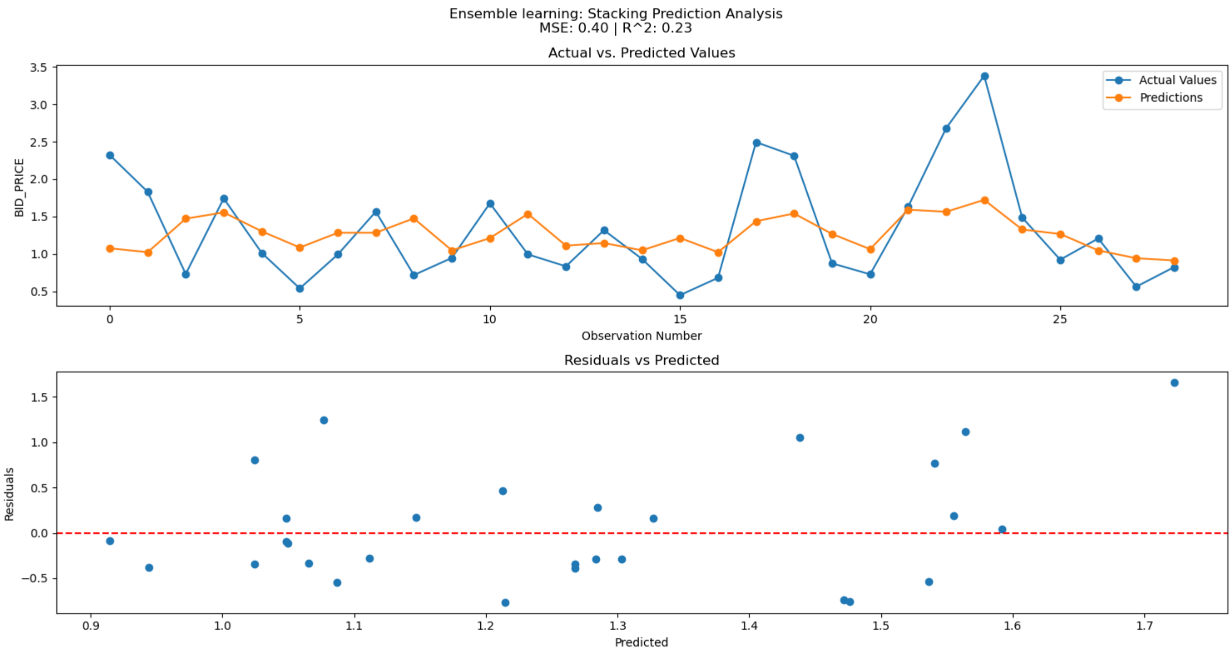

Figure 24. Ensemble Learning Prediction: Monthly Bid Price

Figure 25 shows the **feature importance ranking** from the Ensemble Learning model, highlighting which variables had the greatest influence on predicting unit bid prices. **Asphalt_PPI**: The most important variable, with an importance score of around **0.30**, suggesting that changes in asphalt prices significantly impact unit bid prices. **ITEM_QUANTITY**: The second most important feature with a score of **0.25**, indicating that the quantity of items plays a substantial role in determining the bid price of 5010002 Cold Milling HMA Surface. **Building_Permits**: Contributes moderately to the model, showing its relevance to predicting unit bid prices. **Const_Avg_Hrs**, **CPI_Energy_US**, and **ABI_Index** have lower importance scores, implying they have less influence on the predictions compared to other factors. When comparing this ranking with the Random Forest model, several key differences and similarities arise:

- **Asphalt_PPI** and **ITEM_QUANTITY** are highly important in both models, but **Asphalt_PPI** takes the lead in the ensemble model, whereas **Const_Unemployment_Pct** was more prominent in the Random Forest model.
- **Building_Permits** ranks higher in the ensemble model, suggesting that this factor plays a more critical role in the combined model than it did in Random Forest.
- **Const_Avg_Hrs** and **CPI_Energy_US** maintain moderate importance in both models, but their rankings are slightly higher in the ensemble model compared to Random Forest.

Asphalt_PPI and **ITEM_QUANTITY** are consistently significant across both models, emphasizing their critical role in construction pricing of *5010002 Cold Milling HMA Surface*. The focus on these variables can be particularly useful for estimating 5010002 Cold Milling HMA Surface. **Building_Permits** appear more influential in the ensemble model, suggesting that broader economic and regulatory factors, like construction permits, may have an indirect but notable effect on construction costs. The Ensemble Learning model, which aggregates predictions from multiple algorithms, seems to highlight different interactions between factors compared to the Random Forest model. This suggests that combining various models allows for a more balanced view of the underlying data relationships.

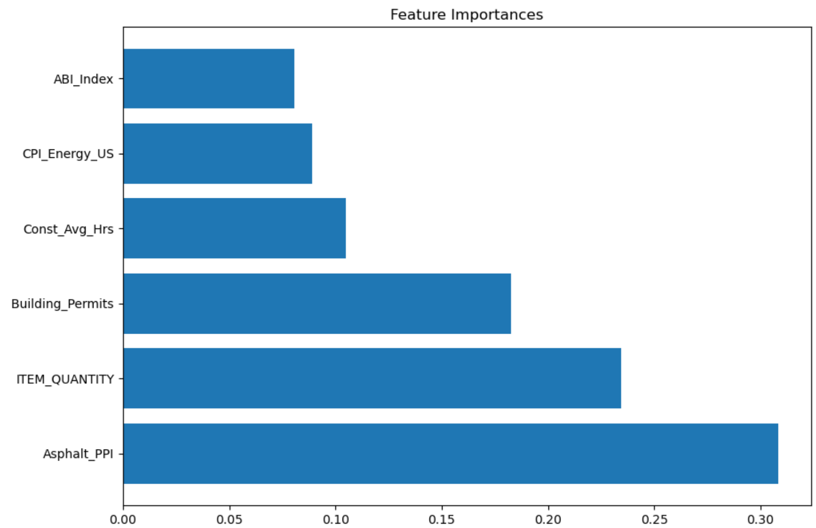

Figure 25. Feature Importance by Ensemble Learning

In conclusion, while both models point to similar key predictors, the Ensemble Learning model highlights **Asphalt_PPI** and monthly item quantity as the most dominant factor.

2.4.4 Contract-Level Unit Bid Price Analysis

Contract-level unit Bid Price analysis focuses on the unit bid price of pay items at the contract level.

2.4.4.1 Pair Plot and Spearman Correlation

The analysis followed a similar procedure to the Monthly Averaged Unit Bid analysis. It began with a pair plot visualization and Spearman correlation analysis. The pair plot helps visualize relationships between variables, allowing for a quick assessment of potential correlations and patterns. Spearman correlation, on the other hand, measures the strength and direction of monotonic relationships between variables, which helps identify significant predictors for further analysis. Table 7 presents the Spearman Rank Correlation Coefficients and p-values of impact factors and contract unit bid prices. They are explained as below:

Strong Positive Correlation:

- **ITEM_QUANTITY** at the contract level has a strong negative correlation with BID_PRICE (-0.52) and a significant p-value (0.000). This suggests that as the quantity of items increases, the bid price tends to decrease significantly.

Table 7. Spearman Correlation for Contract Unit Bid Price

Variable/Factor	Spearman Rank Correlation Coefficient	Spearman Rank p-value
BID_PRICE	1	0
YEAR	0.28	0
MONTH_NUM	0.07	0.007
TOTAL_AMOUNT_PER_YEAR_PER_STATE	0.25	0
TOTAL_AMOUNT_PER_YEAR_PER_REGION	0.23	0
TOTAL_AMOUNT_PER_YEAR_PER_COUNTY	0.2	0
TOTAL_AMOUNT_PER_QUARTER_PER_COUNTY	0.18	0
TOTAL_AMOUNT_PER_MONTH_PER_COUNTY	0.16	0
TOTAL_AMOUNT_PER_QUARTER_PER_REGION	0.14	0
AWARDED_AMOUNT	0.14	0
TOTAL_AMOUNT_PER_QUARTER_PER_STATE	0.14	0
TOTAL_AMOUNT_PER_MONTH_PER_REGION	0.12	0
TOTAL_AMOUNT_PER_MONTH_PER_STATE	0.11	0
DISTRICT	0.13	0
PRIMARY COUNTY	0.05	0.09
Num of Items	0.28	0
CONTRACT DESCRIPTION	0.11	0
ITEM QUANTITY	-0.52	0
Number_Bidders	0.16	0
NUM_CONTRACTS_PER_YEAR_PER_COUNTY	0.12	0
NUM_CONTRACTS_PER_QUARTER_PER_COUNTY	0.1	0
NUM_CONTRACTS_PER_MONTH_PER_COUNTY	0.1	0
NUM_CONTRACTS_PER_YEAR_PER_REGION	-0.01	0.631
NUM_CONTRACTS_PER_MONTH_PER_REGION	-0.03	0.299
NUM_CONTRACTS_PER_QUARTER_PER_REGION	-0.04	0.139
NUM_CONTRACTS_PER_QUARTER_PER_STATE	-0.07	0.007
NUM_CONTRACTS_PER_MONTH_PER_STATE	-0.07	0.006
NUM_CONTRACTS_PER_YEAR_PER_STATE	-0.09	0.001
REFVENDOR_NM	0.26	0

Moderate Positive Correlation:

- **Num of Items** (0.28) and **YEAR** (0.28) both show positive correlations with BID_PRICE and have significant p-values (0.000), suggesting that over time and with more items in a contract, unit bid prices increase slightly.
- **AWARDED_AMOUNT** (0.14), **TOTAL_AMOUNT_PER_YEAR_PER_STATE** (0.25), and **TOTAL_AMOUNT_PER_YEAR_PER_REGION** (0.23) show moderate

positive correlations with BID_PRICE and have highly significant p-values (0.000). This implies that higher awarded amounts and larger total contract amounts are associated with higher unit bid prices.
- **Number_Bidders** (0.16) shows a slight positive correlation with BID_PRICE, indicating a marginal increase in unit bid prices with more bidders.
- **DISTRICT** (0.13) shows a weak positive correlation with BID_PRICE, though it is statistically significant.

Weaker Correlations:

- Several variables, including **TOTAL_AMOUNT_PER_MONTH_PER_REGION** (0.12), **TOTAL_AMOUNT_PER_MONTH_PER_COUNTY** (0.16), and **NUM_CONTRACTS_PER_YEAR_PER_COUNTY** (0.12), show weak but significant correlations, indicating that these factors still have some influence on unit bid prices but to a lesser extent.

Statistically Insignificant Variables:

- **PRIMARY COUNTY** has a correlation of 0.05 and a higher p-value (0.09), indicating that its influence on BID_PRICE is weak and not statistically significant.
- **NUM_CONTRACTS_PER_YEAR_PER_REGION** (p-value of 0.631) and **NUM_CONTRACTS_PER_MONTH_PER_REGION** (p-value of 0.299) have very weak correlations with BID_PRICE and are not statistically significant, suggesting little to no relationship.

Negative Correlations:

- **NUM_CONTRACTS_PER_YEAR_PER_STATE** (-0.09), **NUM_CONTRACTS_PER_QUARTER_PER_STATE** (-0.07), and **NUM_CONTRACTS_PER_MONTH_PER_STATE** (-0.07) all exhibit weak negative correlations with BID_PRICE, but they are statistically significant. This implies that the number of contracts per state may inversely affect unit bid prices.

Overall, the data suggests that unit bid prices are influenced by a variety of factors, with item **quantity, year, and total amounts per year per region/state** having the most notable correlations. However, several contract-related variables show weaker or insignificant correlations, suggesting the need for further analysis to explore their full impact on bid pricing. The following section presents the pair plot for all the features, providing a visual overview of their relationships.

- Market Indicators: 10 factors

In Figure 26, there are general positive trends. The data points for AWARDED_AMOUNT show significant scatter, indicating variability in how total amounts affect the bid price. This suggests that while larger total amounts tend to correlate with higher unit bid prices, there are other contributing factors that influence the final bid price. The AWARDED_AMOUNT plot shows a clearer linear relationship compared to other variables, suggesting that higher awarded amounts are more consistently associated with higher unit bid prices. Overall, the scatter plots confirm that there is a positive relationship between total project amounts and unit bid prices, but the strength of the correlation varies across different time frames (year, quarter, month) and geographic scales (state, region, county). The awarded amount appears to have the strongest relationship with bid price, while the total amount at the monthly or county level shows a weaker relationship, indicating that larger-scale or longer-term totals are more influential in determining unit bid prices.

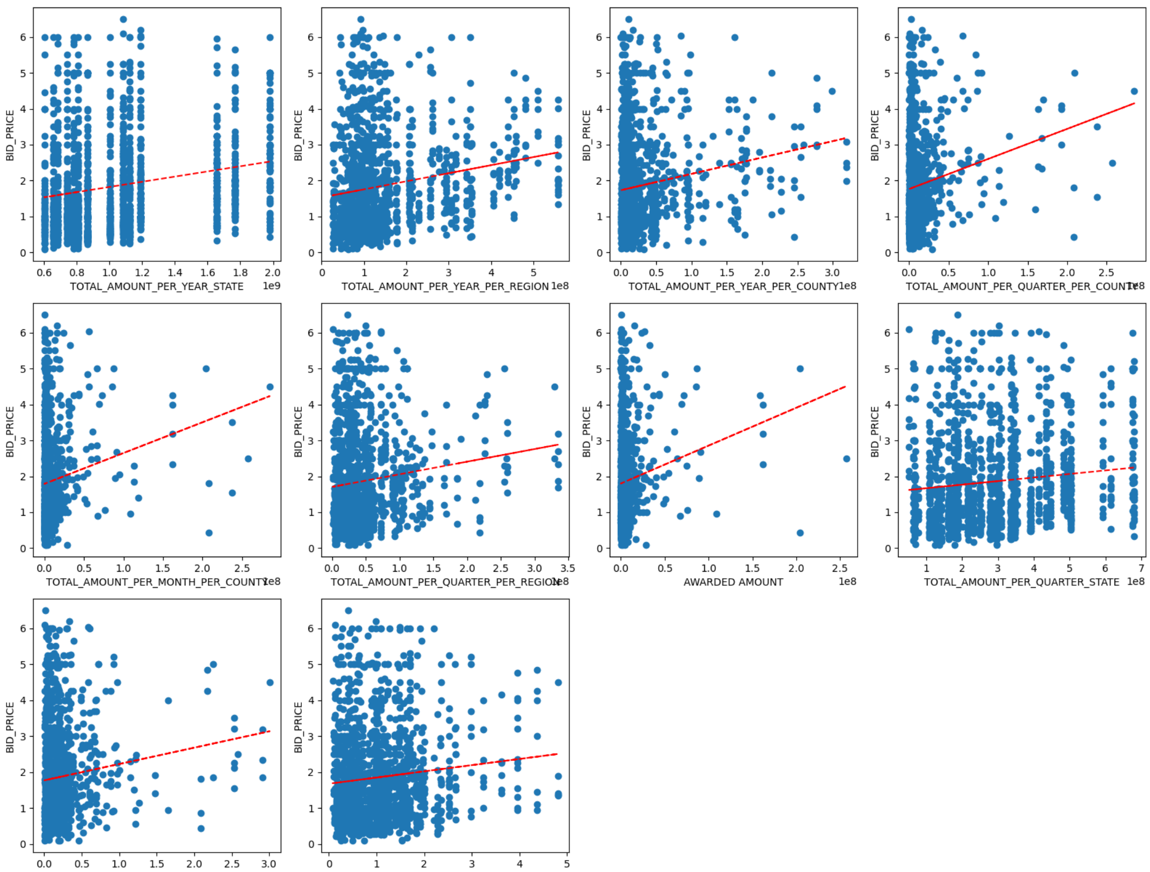

Figure 26. Pair Plot: Market Indicators and Contract Bid Price

- Geographical Indicators: 2 factors

As shown in Figure 27, the data points are scattered across each district (1–7), with notable variation within each district, suggesting that while there may be a general upward trend, unit bid prices can vary significantly within individual districts. The positive slope suggests that in some districts, unit bid prices tend to increase slightly, but the wide distribution of points indicates that the district itself is not a strong predictor of bid price on its own. The regression line for **Primary County** is almost flat, suggesting that there is no clear linear relationship between bid price and county. The data points are heavily scattered, showing significant variation in unit bid prices across different counties. This suggests that the primary county where the construction project is located does not strongly influence the bid price.

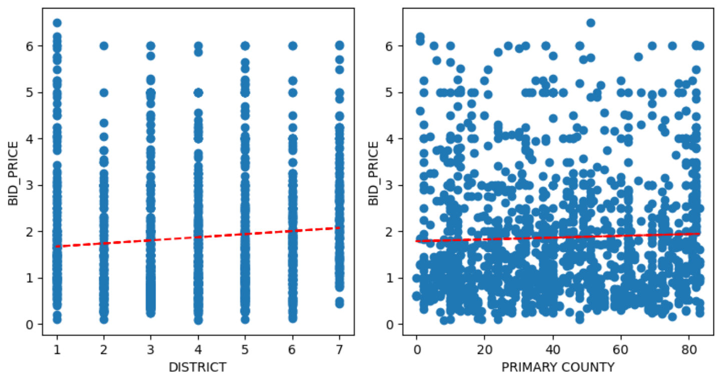

Figure 27. Pair Plot: Geographical Indicators and Contract Bid Price

- Contract Complexity: 3 factors

Figure 28 displays three scatter plots, each illustrating the relationship between **BID_PRICE** and three variables: **Num of Items**, **CONTRACT DESCRIPTION**, and **ITEM QUANTITY**. Red regression lines in each plot represent the general trend of these relationships. Contracts with a higher number of items may tend to have higher unit bid prices, likely due to the complexity and scope of work involved in managing multiple items. The regression line for Contract Description or Work Type is almost flat, indicating a weak relationship. This suggests that CONTRACT DESCRIPTION has little to no significant effect on the bid price, at least when considered in isolation. The third plot shows a clear negative correlation between ITEM QUANTITY and BID_PRICE. The downward slope of the regression line suggests that as the quantity of items increases, the bid price tends to decrease. This could reflect economies of scale, where larger quantities of items lead to a reduction in the per-unit price of those items.

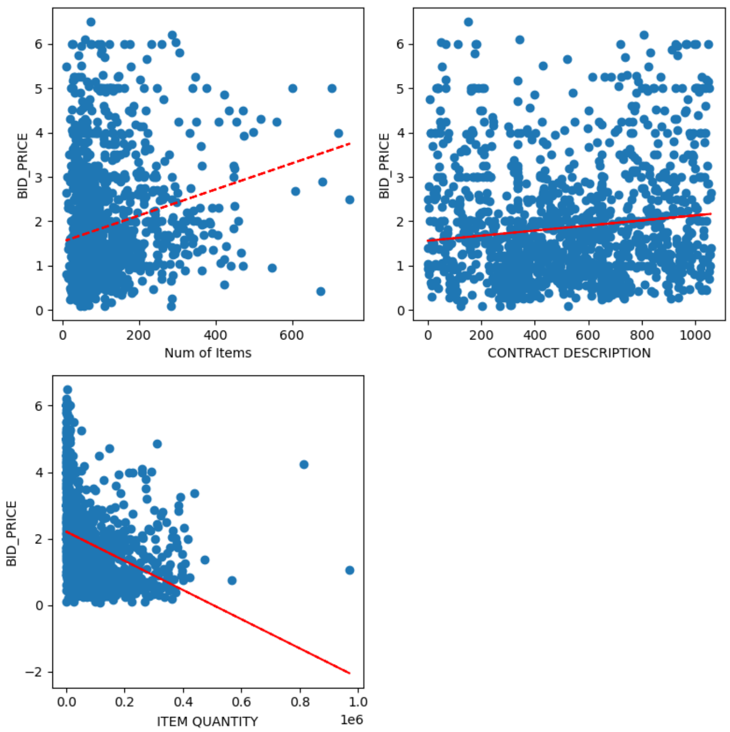

Figure 28. Pair Plot: Contract Complexity and Contract Bid Price

- Competition Metrics: 10 factors

Figure 29 displays scatter plots illustrating the relationships between **BID_PRICE** and several variables related to the number of contracts and bidders. The red regression lines indicate the trends for these relationships. The Number of Bidders and the number of contracts per year or quarter at the county level are positively correlated with BID_PRICE, implying that increased bidding activity may drive up prices. A positive correlation between Number of Bidders and BID_PRICE might seem counterintuitive at first, as increased competition is typically expected to drive prices down. Some other circumstances (e.g., project complexity or market conditions) can lead to a positive relationship between Number of Bidders and BID_PRICE.

In contrast, at the regional and state levels, the number of contracts (monthly, quarterly, or annually) shows weak to negative correlations with BID_PRICE, potentially suggesting that market saturation or competition at higher levels may lead to slightly reduced unit bid prices.

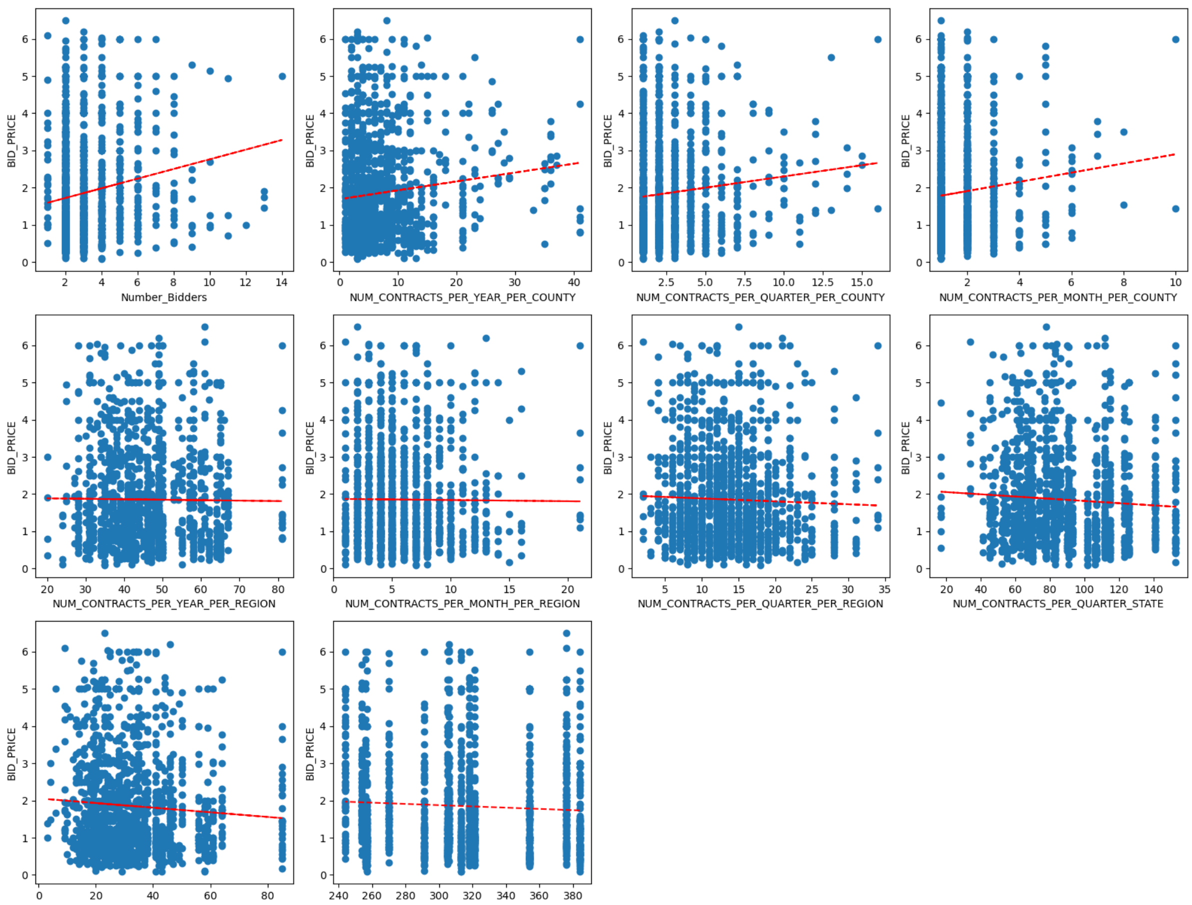

Figure 29. Pair Plot: Competition Metrics and Contract Bid Price

- Vendor Metrics: 1 factor

The positive correlation between **REFVENDOR_NM** (the bidder ID) and **BID_PRICE** indicates that as the vendor ID increases, the bid price tends to rise slightly, which is also observed in Figure 30. If higher REFVENDOR_NM values correspond to newer bidders, the positive correlation between REFVENDOR_NM and BID_PRICE could suggest the following: 1) Newer contractors might have less experience, leading to higher costs due to inefficiencies or uncertainties in estimating project expenses and 2) Newer vendors may not be as well-versed in optimizing bids to be competitive, potentially leading to overestimated costs. However, this trend is not strong (as seen from the spread of data points), so while a general upward trend exists, it may not hold across all instances.

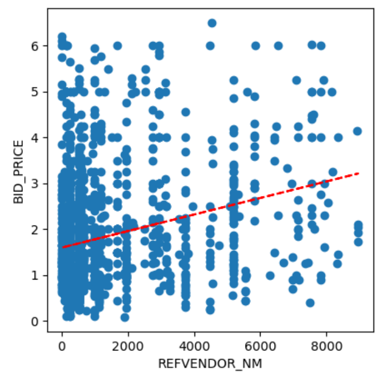

Figure 30. Pair Plot: Vendor Metrics and Contract Bid Price

2.4.4.2 Factor Analysis via Predictive Modelling

With the insights gained from both the pair plot and Spearman correlation, the feature set was refined, and variables were prioritized for more detailed analysis and modeling.

Multivariate regression model

Table 8 shows the OLS regression results, offering key insights into the factors influencing unit bid prices in construction projects. **R-squared** = **0.538** and **Adjusted R-squared** = **0.527** indicate that the model explains about 53% of the variance in unit bid prices. While moderate, there is room for improving the model by considering additional factors. The **F-statistic** of **49.70** (P-value = **1.56e-159**) shows the model is statistically significant overall, with the predictors combined having a meaningful relationship with unit bid prices. **YEAR**: Positive and highly significant (coef = **0.2953**, P-value = **0.000**), suggesting unit bid prices increase over time. **ITEM_QUANTITY**: Negative impact (coef = **-0.1070**, P-value = **0.000**), indicating larger item quantities lead to lower prices, likely due to economies of scale. **Number of Items** and **Number of Bidders**: Both negatively impact unit bid prices, reflecting that more competition and variety reduce costs. Several predictors, including **AWARDED_AMOUNT** and **REVFENDOR_NM**, show little influence on unit bid prices, as indicated by their high P-values. **Model Diagnostics** suggest that the residuals deviate slightly from a normal distribution, but the model remains robust for practical purposes.

Table 8. OLS Regression Results for Bid Price Estimation

Variable	coef	std err	t	P>|t|	[0.025	0.975]
const	-0.0148	0.021	-0.713	0.476	-0.055	0.026
YEAR	0.2953	0.042	6.956	0	-0.212	0.379
MONTH_NUM	0.0379	0.022	1.67	0.095	-0.006	0.082
AWARDED_AMOUNT	-0.025	0.034	-0.73	0.466	-0.093	0.042
DISTRICT	-0.0671	0.033	2.013	0.044	-0.132	0.002
ITEM_QUANTITY	-0.107	0.027	-3.864	0	-0.16	-0.054
Num of Items	-0.0842	0.038	-2.242	0.025	-0.158	-0.011
Number_Bidders	-0.0832	0.038	-3.936	0	-0.126	-0.04
REVFENDOR_NM	0.0294	0.023	1.29	0.197	-0.015	0.074
NUM_CONTRACTS_PER_MONTH_PER_COUNTY	0.0539	0.033	1.614	0.107	-0.012	0.119
NUM_CONTRACTS_PER_MONTH_PER_REGION	0.0306	0.042	0.476	0.634	-0.062	0.102
TOTAL_AMOUNT_PER_MONTH_PER_REGION	0.0199	0.042	0.476	0.634	-0.072	0.112
NUM_CONTRACTS_PER_MONTH_STATE	-0.0868	0.045	-1.923	0.055	-0.176	0.003
TOTAL_AMOUNT_PER_MONTH_STATE	0.0167	0.037	0.457	0.648	-0.088	0.122
NUM_CONTRACTS_PER_QUARTER_PER_COUNTY	-0.0068	0.051	-0.133	0.894	-0.108	0.094
NUM_CONTRACTS_PER_QUARTER_PER_REGION	-0.0417	0.051	-0.82	0.412	-0.142	0.058
TOTAL_AMOUNT_PER_QUARTER_PER_REGION	-0.0335	0.044	-0.764	0.445	-0.12	0.054
NUM_CONTRACTS_PER_QUARTER_STATE	0.035	0.041	0.86	0.39	-0.046	0.145
TOTAL_AMOUNT_PER_QUARTER_STATE	0.0397	0.041	0.978	0.328	-0.119	0.04
NUM_CONTRACTS_PER_YEAR_PER_COUNTY	-0.0357	0.044	-0.808	0.419	-0.122	0.051
NUM_CONTRACTS_PER_YEAR_PER_REGION	0.0492	0.043	1.138	0.256	-0.134	0.132
TOTAL_AMOUNT_PER_YEAR_PER_REGION	0.052	0.041	1.272	0.204	-0.036	0.145
NUM_CONTRACTS_PER_YEAR_STATE	0.0841	0.035	2.377	0.018	0.015	0.154
TOTAL_AMOUNT_PER_YEAR_STATE	-0.017	0.048	-0.356	0.722	-0.111	0.077

Ensemble Learning model

Figure 31 presents the results from the **Ensemble Learning: Stacking Prediction Analysis.** The **MSE (Mean Squared Error)** is **0.37**, indicating the average squared difference between actual and predicted values. Lower MSE values reflect better prediction accuracy. The $\mathbf{R^2 = 0.63}$ shows that the model explains 63% of the variance in the unit bid prices, indicating a strong fit and significant improvement compared to previous models (e.g., Multivariate regression model). The graph demonstrates that, while the model captures the general trend of the actual values, there are still some instances where the predicted values deviate from the actual prices, especially at more extreme points. The residuals are fairly well distributed, though there are some deviations for higher and lower predicted values. The spread of residuals indicates that the model is generally unbiased but could still improve in predicting extreme values. Overall, this ensemble method demonstrates that combining multiple models into a stacked framework provides a better prediction performance compared to single models.

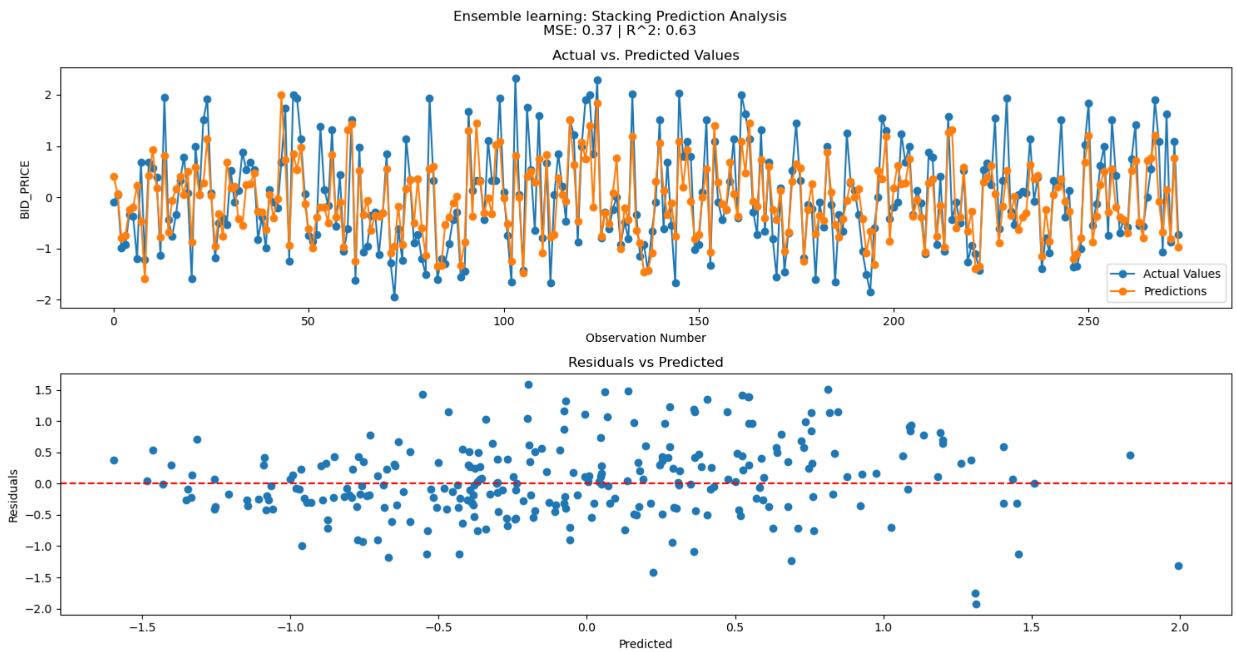

Figure 31. Ensemble Learning Prediction: Contract Unit Bid Price

This feature importance in Figure 32 provides insights into which variables have the most significant impact on predicting unit bid prices. **Item Quantity** has the highest importance score, around **0.40**, indicating it is the most influential factor in determining unit bid prices. This aligns with the understanding that larger quantities typically lead to more competitive or lower unit prices due to economies of scale. This variable also shows substantial importance, with a score around **0.08**, suggesting that the total amount spent annually within a region significantly impacts unit bid prices. This may be related to the allocation of resources and overall demand in specific regions. The **Year** variable has moderate importance (around 0.06), which reflects the trend of increasing unit bid prices over time due to inflation and market changes. Variables such as **Awarded Amount**, **REFVENDOR_NM**, and **Contract Description** have smaller importance scores, but they still contribute to the predictive model. These factors reflect the project's financial scope, the vendor's influence, and the contract's specific details. Several contract metrics, such as **NUM_CONTRACTS_PER_YEAR_STATE** and **NUM_CONTRACTS_PER_MONTH_PER_COUNTY**, have minimal importance. These metrics may not directly affect unit bid prices but still offer context for market activity.

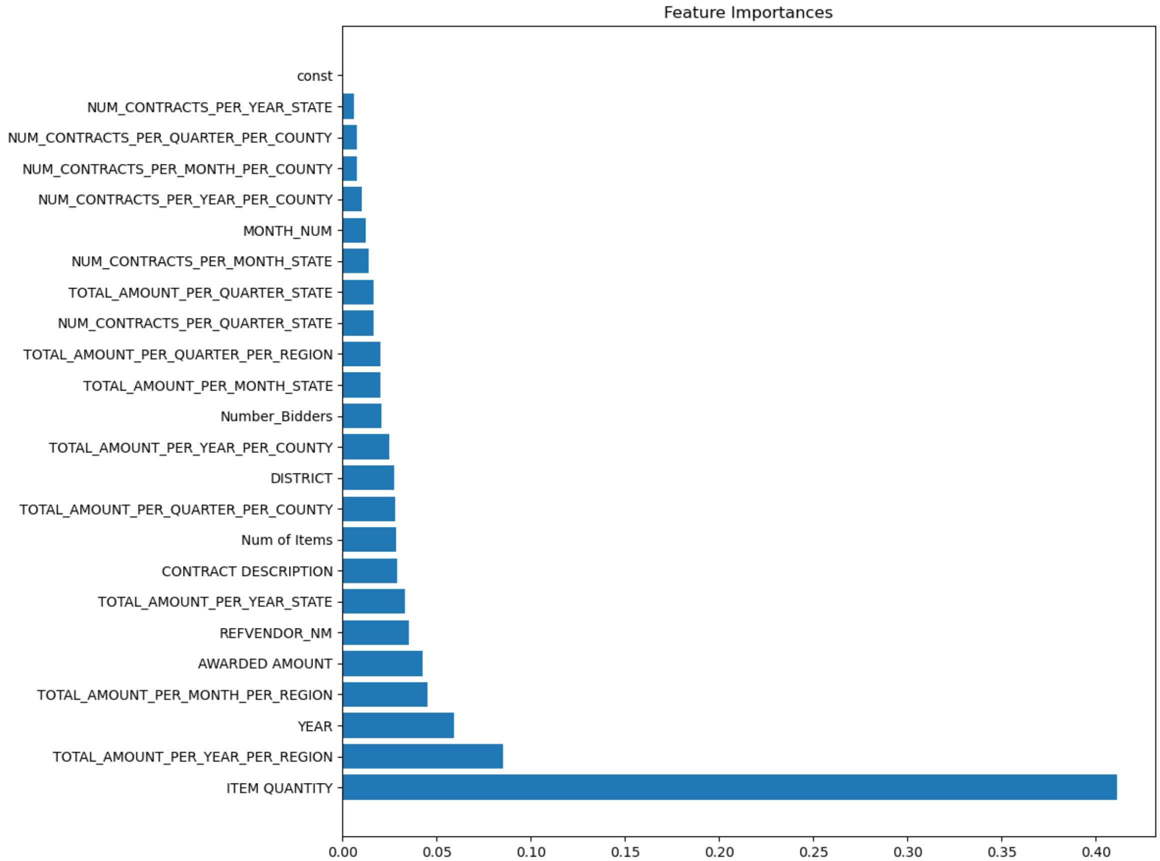

Figure 32. Feature Importance in Contract Bid Price by Ensemble Learning

2.5. CONCLUSION

The analysis of unit bid prices for pay item 5010002, pertaining to **Cold Milling HMA Surface**, provides a comprehensive understanding of the factors influencing both **monthly unit bid prices** and **contract-level unit bid prices**. Through the use of multiple modeling approaches, including **Regression**, **Random Forest**, and **Ensemble Learning**, several important insights were uncovered regarding the dynamics of bid pricing for this specific pay item.

1. Item Quantity as a Major Driver:

Across all models, Item Quantity emerged as the most influential factor in predicting unit bid prices. Larger quantities typically lead to lower unit prices, suggesting that economies of scale play a significant role in determining pricing. This was evident in both contract-level and monthly bid price analyses, where item quantities consistently showed the highest feature importance.

Since item quantity consistently emerged as the most influential factor, cost estimators should account for the economies of scale when estimating unit bid prices. For larger quantities, unit prices are likely to decrease, so estimators should adjust pricing forecasts accordingly. When estimating costs for this item involving substantial quantities, lower unit prices should be anticipated, leading to more accurate and competitive bids.

2. Regional and Time-based Factors:

The models highlighted the importance of Total Amount per Year per Region as a significant predictor, particularly for contract-level unit bid prices. This suggests that the economic conditions and spending patterns within a specific region heavily impact bid pricing. Additionally, the Year variable showed moderate importance, reflecting that unit bid prices generally increase over time due to inflation.

- **Regional adjustments**: In regions with higher spending or increased infrastructure activity, unit bid prices may be higher. Cost estimators should incorporate regional data and trends into their models, using historical unit bid prices from similar regions to adjust their estimates.
- **Time-based adjustments**: Given that unit bid prices tend to rise over time due to inflation, estimators should factor in future cost escalations based on the expected year of the project. Inflation rates, labor costs, and material prices should be included in these projections.

3. Contract-specific Factors:

Contract-specific features, such as the Number of Bidders and the Number of Items in a contract, were found to have a notable impact on contract unit bid prices. More competition (as reflected by the number of bidders) generally drives prices lower, while the complexity of contracts (measured by the number of items) influences bid pricing. Contracts with more items tend to have higher unit bid prices, possibly due to the complexity of managing larger projects.

- **Number of bidders**: Estimators should assess the likely level of competition for a project. Projects with more bidders are expected to have lower unit bid prices, so estimates might be adjusted downward in highly competitive markets.
- **Number of items**: Contracts with a greater number of items typically have higher unit bid prices. This may be due to the complexity of managing larger, multifaceted contracts. For projects with numerous pay items, estimators should consider slightly higher unit prices to account for the increased complexity and coordination required.

4. Economic Indicators and Regional Spending:

While economic indicators like CPI Energy and Asphalt PPI were considered, they had a relatively moderate impact on monthly unit bid prices. However, regional spending patterns, such as the Total Amount per Year per Region, showed substantial influence on pricing, indicating that macroeconomic factors related to regional project budgets are key in driving unit bid prices.

5. COVID Impact:

Factors most closely related to the pandemic are those that were directly affected by economic disruptions, labor market changes, material price volatility, and fiscal policy responses. Specifically, employment metrics, commodity and fuel prices, economic indicators, and market spending patterns reflect the pandemic's significant impact on the construction industry and therefore on unit bid prices for items like 5010002 (Cold Milling HMA Surface). Specific data evidence related to the impact of the pandemic on the bid price of Pay Item 5010002 (Cold Milling HMA Surface) can be drawn from several key quantitative findings:

Asphalt PPI: Asphalt PPI showed a strong positive correlation with bid prices (correlation coefficient of 0.46), which indicates that increases in asphalt prices were significantly associated with higher unit bid prices for 5010002. During the pandemic, supply chain disruptions and increased demand led to spikes in asphalt prices, which were factored into bids, raising overall costs for items involving asphalt-intensive processes like cold milling.

Construction Employment and Average Earnings: Const_Emp_Thou (construction employment) and MI_Const_Emp_Thou showed moderate positive correlations with unit bid prices (0.52 and 0.49, respectively). This indicates that as construction employment levels increased post-pandemic, labor costs rose due to increased demand for a smaller workforce. Additionally, Const_Avg_HrlyEarn (average hourly earnings) exhibited a strong positive correlation (0.50), reflecting wage inflation in the construction sector during the pandemic. Higher labor costs directly contributed to increased bid prices for 5010002.

Year and CPI Variables: The Year variable displayed a correlation coefficient of 0.50 with bid prices, indicating a trend of increasing prices over time, which accelerated during the pandemic. The correlation with CPI_Northeast (0.50) also highlighted inflationary pressures that were exacerbated by the pandemic, reflecting increased costs for materials, energy, and labor. These time-related factors point to a steady rise in bid prices, with a notable increase during the pandemic period due to heightened inflation.

Total Amount per Year per Region/State: This factor showed moderate positive correlations (around 0.25) with bid prices. The pandemic led to changes in government spending patterns and stimulus measures, which increased the overall spending on infrastructure projects in some regions. This elevated spending drove up bid prices due to increased competition for resources and labor.

Number of Bidders: The Number of Bidders showed a weak positive correlation (0.16), indicating that higher bid prices could also be a result of limited competition or contractors factoring in higher risk premiums. This reflects how market uncertainties led to changes in bidding behavior during the pandemic.

Diesel Fuel PPI and NaturalGas PPI: While DieselFuel_PPI had a weak correlation with bid prices (-0.06), it still showed a statistically significant impact during the pandemic. Rising fuel prices due to supply chain disruptions and market volatility contributed to increased transportation and equipment operation costs, affecting bid prices. Similarly, the NaturalGas PPI had a negative correlation (-0.15), indicating that fluctuations in energy costs had a significant influence on its unit bid price.

6. Differences Between Models:

The Ensemble Learning model, which combines multiple predictive models, demonstrated a higher accuracy in predicting unit bid prices ($R^2 = 0.63$) compared to individual models like Random Forest or OLS. This method emphasized Item Quantity and Total Amount per Year per Region, showcasing the advantage of combining different learning techniques to capture various aspects of the data.

Summary: The results of this study suggest that while traditional economic factors, such as inflation or energy costs, do have some impact on unit bid prices, <u>contract-specific variables (e.g., item quantity, competition, and regional spending) are the primary drivers</u>. These findings emphasize the importance of considering the contract scope and regional economic conditions when estimating and forecasting unit bid prices for pay items like Cold Milling HMA Surface. By using advanced machine learning models alongside conventional regression analysis, stakeholders can improve cost estimations, manage contracts more effectively, and plan better for future infrastructure projects.

3. DEVELOPMENT OF CONTRACT AND ITEM-LEVEL COST INDEX

3.1. INTRODUCTION

Construction projects vary significantly in work type, as well as in the number and type of pay items involved. Some projects may emphasize pavement-related work, while others focus on electrical construction. Consequently, statewide or category-specific HCCI may not accurately reflect price trends for a particular project or contract that spans multiple categories of pay items in a specific region. Currently, no index tracks price changes at the item or contract level, creating a gap in understanding how costs fluctuate for specific contracts or services. A generalized HCCI often fails to capture the true market conditions affecting a particular contract, especially for projects with a diverse mix of pay items. This highlights the critical need to develop an HCCI at both the item and contract levels. Such an index would enable more precise adjustments of historical unit prices, accounting for the unique characteristics of each contract. By implementing a detailed HCCI calculation at these levels, MDOT could more accurately estimate future construction costs based on contract-relevant characteristics. Such HCCI would improve bid-based estimation accuracy by better reflecting the price trends of specific pay items. Furthermore, it would offer MDOT deeper insights into the factors driving price fluctuations in particular construction activities. This could lead to more effective planning, budgeting, and contracting processes.

In this research, new indices at both the **item and contract levels** are proposed. The **item-level index** tracks price changes for individual bid items, calculated quarterly to monitor fluctuations over time. The **contract-level index** aggregates these item-level insights into a specific contract, capturing the unique combination of bid items involved. Unlike broader indices (such as state, regional, or categorical indices), the contract-level index is tailored to the specific mix of items within a contract, providing a more accurate reflection of the costs associated with individual contracts.

Given the existence and proposal of various types of MHCCI, Figure 33 illustrates the structure of MHCCI and their relationships, particularly emphasizing the **contract/item-level index** and its connections to other indices, such as annual and quarterly, state-level indices. On the left of the diagram is **Michigan Highway Construction Cost**, which encompasses all construction costs associated with highway projects. These costs are organized by **contracts**, each of which may consist of multiple **projects**. For each project, there are several **items** (such as pavement or electrical components), each having its own **quantity** and **unit price**. These two attributes (quantity and unit price) form the foundation for the calculation of various indices. **Quarterly and annually averaged prices** refer to quantity-averaged prices that are tracked over different time periods. Based on these prices, an item-level index can be calculated and further aggregated into contract, regional, categorical, and state-level indices. Historical MHCCI values are then derived from historical bidding data, offering a long-term perspective on how construction costs have evolved over time. The contract-level index ties into this historical data, allowing for more detailed cost analysis within individual projects or contracts.

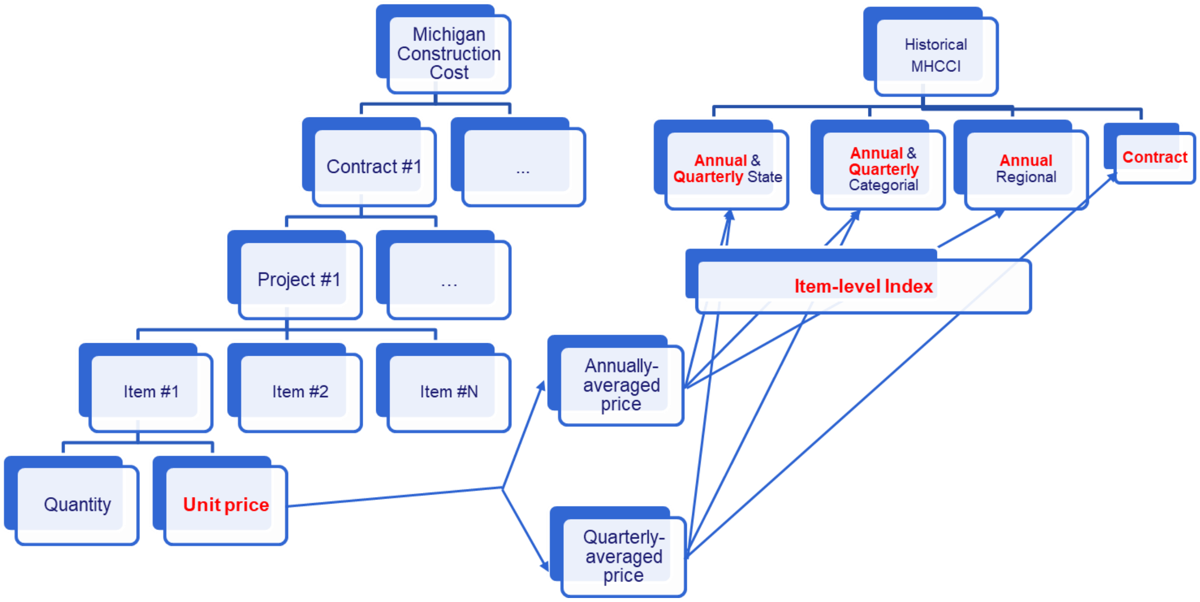

Figure 33. Bid Data and MHCCI Aggregation

3.2. Methodology

Figure 34 illustrates the overall process used to calculate the HCCI at the contract and item levels. The procedure consists of three main steps: **Data Cleaning**, **Bid Item Selection**, and **HCCI Calculation**, which are described in the following subsections.

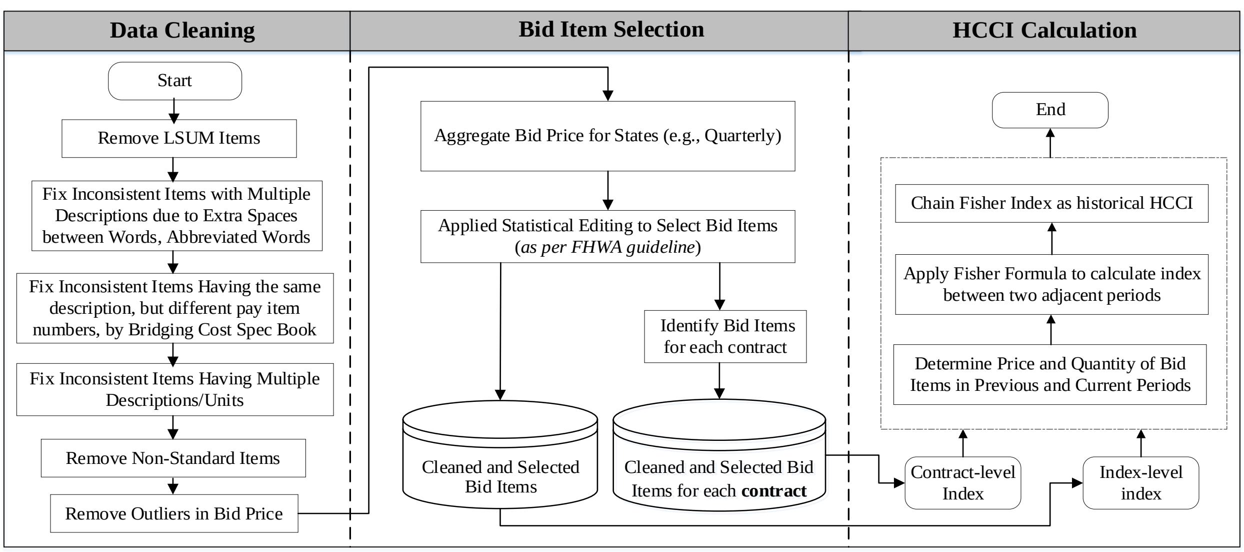

Figure 34. Contract-Level MHCCI Calculation Methodology

3.2.1 Data Cleaning

MDOT provided bid item data from its design–bid–build construction contracts for the period from the first quarter of the 2010 Calendar year to the first quarter of the 2024 Calendar year. The data included attributes such as item quantity, bid price, unit, and item description, among others. Lump-sum and non-standard items were removed due to their lack of statistical relevance. Only bid items from the first low bid were retained for analysis. Additionally, inconsistencies between MDOT pay item code books from 2003, 2012, and 2020 were resolved by either updating descriptions or treating substantially different items as separate entities. Outliers in unit bid prices at the contract level were also removed using various statistical methods, ensuring the dataset was clean and ready for further analysis.

3.2.2 Bid Item Selection

The bid items selected for the HCCI calculation were chosen based on specific criteria to ensure the index accurately reflects changing market conditions. The research team applied a six-step statistical editing process used by the FHWA (FHWA, 2017), which included selecting items with lagged observations and those with unit bid prices for at least eight quarters. Outliers in aggregated prices were adjusted using averages from non-outlier observations, and items with extreme price or quantity variations were excluded. This statistical editing was applied to aggregated prices to ensure a representative set of bid items.

Once the appropriate bid items were identified through the six-step editing process, only the items included in the specific contract under analysis were selected for calculating the contract-level HCCI. This approach ensures that the index accurately reflects the costs relevant to the contract's scope of work. By focusing on the contract-specific items, the HCCI calculation avoids distortions from unrelated bid items, leading to a more precise measurement of cost changes for that particular contract.

3.2.3 HCCI Calculation

The cleaned and selected bid items were used to calculate the contract HCCI. Three widely used formulas—Laspeyres, Paasche, and Fisher price indices—were considered for the calculation. The Fisher price index (See Equation 1), which accounts for the weights of both base and current periods (e.g., item quantities), was applied for the **contract-level index** due to its ability to handle substitutions. The Fisher index values for adjacent periods were chained together to form a continuous time series of contract HCCI values.

$$F(p,q) = \sqrt{\frac{\sum_{j=1}^{N} p_{j,t} \times q_{j,0}}{\sum_{j=1}^{N} p_{j,0} \times q_{j,0}} \times \frac{\sum_{j=1}^{N} p_{j,t} \times q_{j,t}}{\sum_{j=1}^{N} p_{j,0} \times q_{j,t}}} \qquad \text{Eq. (1)}$$

$$I(p) = \frac{p_{j,t}}{p_{j,0}} \qquad \text{Eq. (2)}$$

- $F(p,q)$: The fisher price of a contract

- $I(p)$: The item cost index
- $p_{j,t}$: The price of item **j** in the current time period **t**.
- $p_{j,0}$: The price of item **j** in the base period (time period **0**).
- $q_{j,0}$: The quantity of item **j** in the current time period **t**.
- $q_{j,0}$: The quantity of item **j** in the base period (time period **0**).
- **N**: The total number of items.

A Python-based tool was developed to automate the data cleaning, editing, selection, and calculation of the contract and item-level HCCI on a quarterly basis. Figure 35 illustrates the graphical user interfaces (GUIs) of the prototyped system. The developed tool, as depicted in Figure 35, enables users to select the desired HCCI aggregation level, including options such as the overall state HCCI, regional sub-HCCI, category-specific sub-HCCI, or contract-specific sub-HCCI. All system components are seamlessly integrated using the Python programming language. For detailed instructions on using this tool, please refer to the user guide.

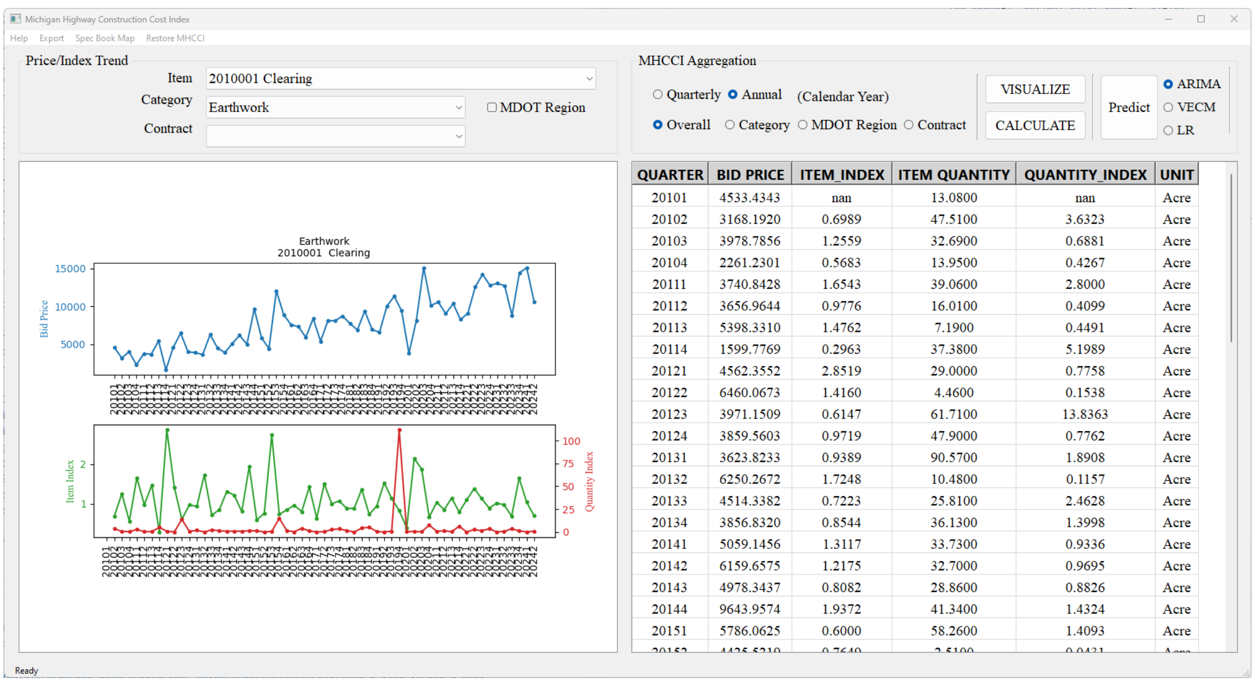

Figure 35. GUIs of the developed MHCCI tool

3.3. Results

3.3.1 Item-level Index

The quarterly item-level MHCCI was calculated for the period spanning from the first quarter of the 2010 calendar year. The base for the MHCCI calculation was set at the first quarter of the 2010 calendar year. Item-level indices were calculated for hundreds of pay items, though this report presents only one example, i.e., **2010001 Clearing**. The full set of item indices can be easily accessed using the developed MHCCI tool. Figure 36 shows the price index trend for the pay item **2010001: Clearing** over time. The index, which tracks the relative changes in cost for clearing activities, fluctuates significantly over this period.

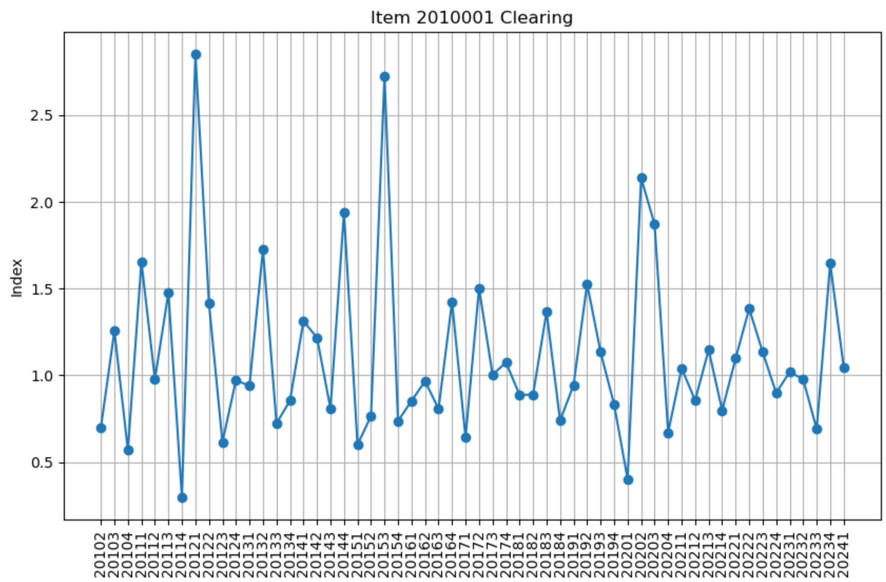

Figure 36. Item-Level MHCCI: example

Key observations include:

- The index demonstrates considerable volatility, with multiple sharp peaks and troughs, suggesting that clearing costs have been subject to considerable variation.
- Several pronounced spikes in the index are visible, with values exceeding 2.5 at certain points, indicating periods of substantial cost increases. Notable spikes occurred in mid-2012, 2015, and early 2020.
- Conversely, there are several instances where the index drops below 0.5, indicating a significant reduction in clearing costs during those quarters. Examples of such drops occur in late 2011, early 2015, and 2020 Q1.
- Despite the fluctuations, the general trend remains irregular without a clear upward or downward trajectory over the long term, suggesting that clearing costs are heavily influenced by external or project-specific factors.

These fluctuations highlight the importance of tracking specific pay items, as the price of clearing activities does not follow a consistent statewide or category-wide trend. An item-level index helps MDOT better understand these cost variations, which may be driven by factors like project location, seasonal demand, or labor availability.

3.3.2 Contract-level Index

Figure 37 displays the calculated cost index trend for three contracts, along with the state-level MHCCI.

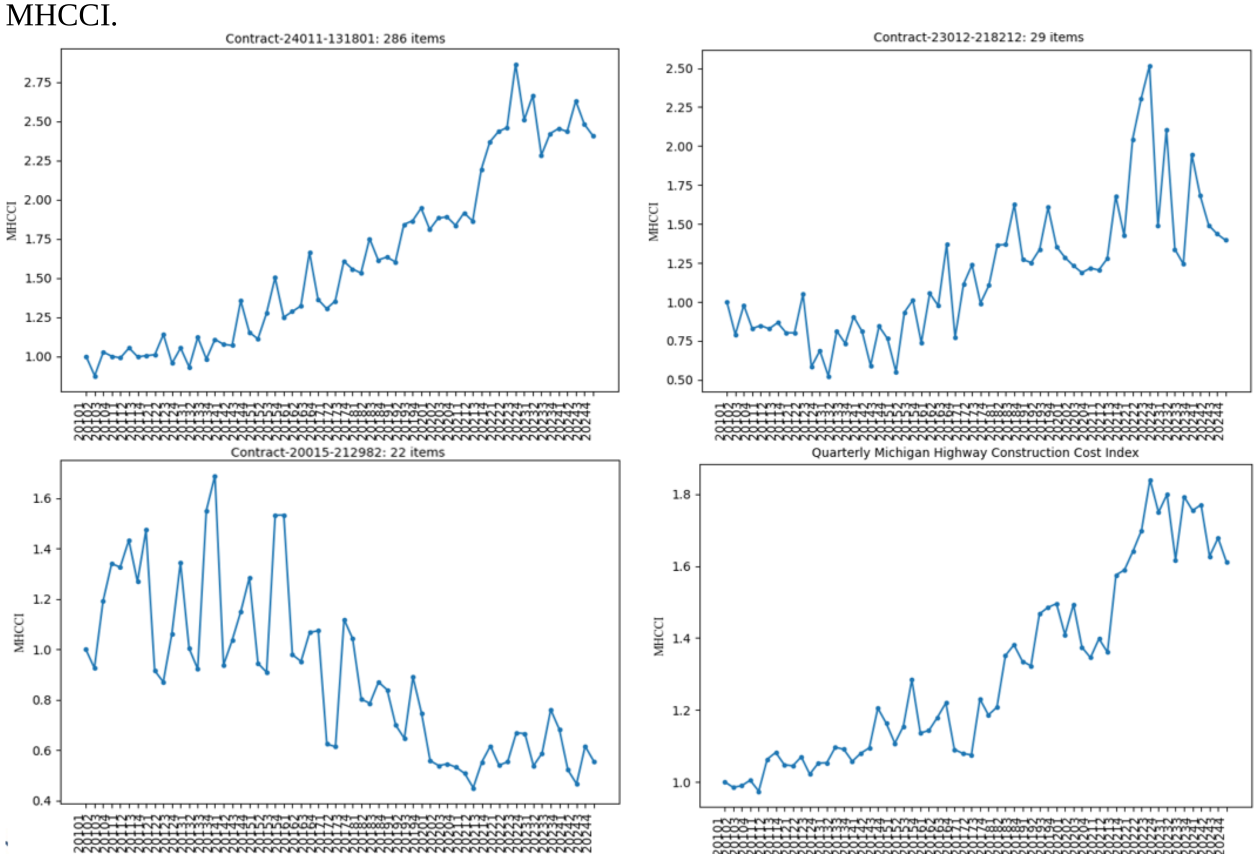

Figure 37. MHCCI: Contract-Level vs. State-Level

State-level MHCCI tracks changes in highway construction costs over this period, starting from a base value close to **1.00** in 2010 Q1 and extending to nearly **1.85** by 2022 Q3. From 2010 Q1 to 2014 Q3, the MHCCI remained relatively stable, with mild fluctuations, hovering around 0.97 to 1.10. This period indicates that highway construction costs experienced minimal increases, suggesting stable market conditions. Factors contributing to this stability could include consistent prices for construction materials, steady labor costs, and a balanced supply-demand scenario in the construction industry. Starting around **2014 Q4**, a more consistent upward movement is observed in the index. The MHCCI gradually climbs to about **1.50** by **2020 Q2**, showing a moderate rise in construction costs. This trend suggests that factors such as economic growth in Michigan, increased investment in infrastructure, and rising prices of construction materials like asphalt, steel, and concrete began to impact overall costs. Additionally, labor costs may have increased due to a tightening labor market in the construction industry. After **2021 Q3**, there is a sharper increase in the MHCCI, which accelerates further toward **2023 Q3**. The index peaks at nearly **1.79** by **2023 Q3**, indicating a dramatic rise in highway construction costs in the most recent years. This significant escalation could reflect broader economic factors, including:

- **Inflation:** General inflation rates may have risen, increasing the cost of goods and services across the board.
- **Supply Chain Disruptions:** Events like the COVID-19 pandemic disrupted global supply chains, leading to shortages of construction materials and driving up prices.
- **Increased Demand:** A surge in infrastructure projects, possibly due to government stimulus packages or renewed focus on infrastructure improvement, increased demand for materials and labor.
- **Labor Shortages:** A scarcity of skilled labor in the construction industry could have led to higher wages, contributing to increased project costs.
- **Material Costs:** Prices for key materials such as concrete and petroleum-based products (like asphalt) may have spiked due to global market fluctuations.

The first graph in Figure 37 shows the contract-level index for **Contract 24011-131801, which** includes 286 items. Its index tracks changes of pay items for this specific contract, starting from 1.00 in the base period and extending to nearly 3.00 within the analysis period. The index shows a clear upward trend, indicating a steady and significant increase in the overall cost of the items associated with this contract over time. The cost index remained relatively stable with mild fluctuations from 2010 to 2014, where it hovered around 1.00 to 1.25. This indicates that construction costs during this period experienced minimal increases. Starting around 2015, a more consistent upward movement is observed, with the index gradually climbing to about 1.85 by 2020, showing a moderate rise in construction costs. After 2020, there is a sharper increase in the cost index, which accelerates further toward 2023Q1. The index peaked at nearly 2.86, indicating a dramatic rise in construction costs in the most recent years. This trend demonstrates the impact of market changes, inflation, and potentially supply chain disruptions on the contract's cost items. The sharp rise in recent years could reflect broader economic factors affecting material and labor costs.

The second graph in Figure 37 represents the index trend for **Contract 23012-218212 with** 29 items. The index starts from a base value of 1.00 and reaches over 2.50 within the period, highlighting significant cost changes for this contract. Initially, from 2010 to around 2016, the cost index fluctuated modestly between 0.52 and 1.05, indicating relatively stable costs for this contract during the early years. Around 2015, a noticeable upward trend began, with the cost index gradually increasing over time, peaking at about 2.50 in mid-2022. This reflects moderate but consistent growth in the costs associated with the contract. After 2022, the cost index experienced a slight decrease, with the most recent data showing an index value of 1.40 at 2024Q4, indicating a substantial decrease in costs toward the end of the period.

Contract-20015-212982's cost index fluctuates, showing variations in the costs associated with the contract items (see the 3rd graph in Figure 37). Initially, the cost index was below 1.00, indicating lower costs compared to the base period. However, this phase is marked by notable volatility, with frequent sharp increases and decreases. A prominent spike occurs around the mid-period, where the index rapidly climbs to approximately 1.65, reflecting a substantial surge in costs. This period of elevated cost levels is characterized by repeated fluctuations, with the index oscillating between 1.25 and 1.65. Following this peak, the cost index enters a steady decline, gradually dropping below 1.00. The downward trend continues, with intermittent fluctuations, reaching a minimum close to 0.50. In the most recent periods shown in the graph, the index remains relatively low, fluctuating between 0.50 and 0.75, without a clear upward recovery. This sustained decline suggests that cost reductions have taken hold, potentially due to shifts in market conditions, material availability, or changes in project execution strategies.

The comparison between the state-level and contract-level MHCCIs (e.g., Contract 23012-218212 and 24011-131801) over the period from **2010 Q1 to 2024 Q4** reveals both similarities and differences:

- **Similarities**: Both indices exhibit overall upward and then downward trends with periods of stability and acceleration, influenced by common external factors like market conditions and economic changes.
- **Differences**: The contract-level MHCCI shows a more pronounced increase in costs, particularly between 2020 and 2023, suggesting that specific project factors can lead to cost escalations exceeding state averages.
- **Contract-Specific Factors Matter**: Individual contracts may experience cost trends that differ significantly from broader state trends due to unique challenges and requirements.

The contract-level index for **20015-212982** shows more fluctuation due to its smaller scope (22 items). While it experiences sharp fluctuations, its long-term trend differs from the state-level index. The contract index peaks around 1.65 before declining and stabilizing at lower levels. It likely reflects unique project challenges or price sensitivities that may not be as pronounced in the broader state-level index. The sharp spike in the contract-level MHCCI suggests that project-specific factors—such as sudden material price hikes or unanticipated complexities—had a significant impact on this particular contract. This spike is more pronounced than what is reflected in the state-level trends. In contrast, the state-level MHCCI showed a significant increase, rising by approximately 60% over the observed period. The index starts around 1.00 and follows an upward trajectory, with periodic fluctuations, reaching a peak above 1.80 before slightly declining. This sustained growth reflects increasing construction costs at the state level. This comparison highlights that while state-level construction costs have seen a substantial rise, individual contract cost trends may deviate due to project-specific factors, market conditions, or material price variations.

3.4.DISCUSSION

The comparison between the **contract-level MHCCI** and the **state-level MHCCI** reveals several key insights that justify the need for a contract-level index in addition to the traditional state-level MHCCI. Both indices serve as valuable and complementary tools for monitoring and managing highway construction costs. The following discussion outlines the reasons why incorporating both indices can significantly enhance project management, cost estimation, and risk mitigation.

3.4.1 Capturing Project-Specific Variability

State-Level MHCCI: The state-level index provides a broad overview of construction cost trends by smoothing out variations across multiple contracts. While this is useful for understanding general cost trends over time, it may obscure significant fluctuations occurring at the contract level.

Contract-Level MHCCI: The contract-level index captures short-term volatility and contract-specific factors that are not visible in the state-level index. For example, as shown in Contract 20015-212982, the drops in the prices of construction pay items can result from contract-specific challenges or market conditions. By monitoring these fluctuations at the contract level, decision-makers can better assess the financial health and risks of individual projects, leading to more accurate budget adjustments.

Justification: A contract-level index provides granular insights into individual contracts that a state-level index cannot. It is particularly useful for tracking contract-specific risks, such as unexpected cost changes in key construction pay items, enabling real-time adjustments that improve financial control and resource allocation.

3.4.2 Addressing Volatility in Construction Pay Item Costs

State-Level MHCCI: By averaging data across multiple contracts, the state-level index tends to smooth out short-term volatility in the prices of construction pay items, offering a more stable trend. However, this can mask critical cost spikes in particular pay items that affect individual contracts at specific times.

Contract-Level MHCCI: In the case of Contract 20015-212982, there were periods of sharp cost increases for specific construction pay items. These spikes may reflect changing market conditions, project-specific challenges, or the timing of purchases for these items. Tracking the cost of construction pay items at the contract level ensures that short-term spikes are captured more accurately.

Justification: A contract-level index helps identify how fluctuations in the prices of construction pay items (e.g., base materials, asphalt, structural components) impact specific contracts. This information allows contract managers to implement cost-saving strategies such as adjusting purchasing schedules, managing inventory, or revising payment terms based on real-time data.

3.4.3 Improved Budgeting and Forecasting Accuracy

State-Level MHCCI: While the state-level index provides a good baseline for estimating future costs on a macro scale, it lacks the level of detail needed for precise forecasting at the contract level. The state-level averages may obscure variations in pay item costs that affect individual contracts.

Contract-Level MHCCI: A contract-level index allows for more accurate budgeting at the project level, particularly for contracts with unique or complex requirements. By accounting for the specific factors that drive cost changes in individual construction pay items, a contract-level index can generate more reliable and dynamic forecasts.

Justification: The contract-level index provides tailored forecasts for individual projects, accounting for specific pay item cost trends. This leads to more precise budget estimates and contingency planning, helping to mitigate cost overruns and ensuring that contracts remain within budget.

3.4.4 Tailored Contract Management Strategies

State-Level MHCCI: While useful for broad contract management strategies across the state, the state-level index doesn't reflect the unique cost dynamics of individual contracts.

Contract-Level MHCCI: The contract-level index offers insights into the specific cost behaviors of a contract, allowing for more tailored management strategies. For instance, if the contract-level index shows significant cost increases in specific pay items, managers can revisit the contract terms to adjust escalation clauses or negotiate better rates for those items.

Justification: The contract-level index enables more flexible and informed contract management. If a project experiences rapid cost increases in key construction pay items, managers can adjust or renegotiate terms before costs spiral out of control, reducing financial risks and improving the likelihood of completing the contract within budget.

3.4.5 Enhanced Risk Management and Mitigation

State-Level MHCCI: The state-level index provides a general sense of construction cost trends and financial risks facing statewide infrastructure projects but lacks the specificity needed to address individual project risks.

Contract-Level MHCCI: The contract-level index identifies risks tied to the cost of specific pay items within individual contracts. For example, the sharp rise in the cost index for Contract 20015-212982 could point to risks associated with the availability or pricing of critical pay items. Early identification of these trends allows for timely interventions to mitigate risks.

Justification: A contract-level index gives project managers early warnings about cost risks that could threaten a project's timeline or budget. This enables the development of targeted risk mitigation strategies, ensuring that projects are more resilient to external market disruptions and internal challenges.

3.4.6 More Responsive Policy and Funding Decisions

State-Level MHCCI: State-level data informs policymakers about general cost trends across the state and helps with infrastructure funding decisions. However, relying solely on state-level data risks over- or underfunding specific contracts that experience higher or lower-than-average cost trends.

Contract-Level MHCCI: A contract-level index allows for more responsive and adaptive funding decisions. When the index reveals significant cost increases in construction pay items, funding can be adjusted quickly to ensure that the project remains financially viable. This ensures that projects with higher cost risks receive adequate resources.

Justification: Incorporating contract-level indices into the funding process ensures a more equitable and efficient allocation of resources. Projects facing greater cost pressures can receive additional funding, while those with more stable costs can proceed without needing further adjustments.

3.5. CONCLUSION

Incorporating a **contract-level MHCCI** alongside the traditional **state-level MHCCI** provides a comprehensive framework for understanding and managing highway construction costs. The **state-level MHCCI** offers a broad view of general cost trends, while the **contract-level MHCCI** delivers detailed insights into individual contracts by tracking the cost of specific construction pay items.

- **Contract-Level Granularity**: Contract-level MHCCI tracks key pay items critical to a project, offering real-time insights into cost fluctuations that affect project budgets.
- **Base Period Tracking**: Establishing a base period for the contract-level MHCCI allows stakeholders to monitor changes over the life of the contract and pinpoint specific periods where significant cost changes occur.

In summary, the **contract-level MHCCI** provides a more **detailed, responsive, and accurate tool** for managing contract-specific costs, particularly when dealing with fluctuating prices of construction pay items. When combined with the state-level MHCCI, this dual-layer approach supports more informed decision-making, risk management, and financial control, leading to more efficient and financially sound project delivery. For example, a contract with more volatility in its cost index would require a higher contingency to account for potential price spikes.

4. ECONOMIC FACTOR-BASED COST INDEX PREDICTION

4.1 INTRODUCTION

Construction cost estimation is a critical process that aims to forecast the expenses likely to be incurred in future construction projects. Traditionally, Departments of Transportation (DOTs) determine the cost of construction items based on historical prices, often looking back over the previous two years to estimate costs for upcoming projects. However, construction costs are not static; they fluctuate over time due to various factors such as inflation. To account for these changes, DOTs typically apply a standard inflation rate of 4% per year from the time of estimation to the start of construction. While this standard rate provides a baseline, it may not accurately reflect actual inflation in construction prices. Alternatively, the HCCI and other consumer product indexes can be used in construction cost management. The WMU research team (Liu et al., 2020; 2021) reported the potential uses of HCCI in managing highway construction costs, including its application in budget planning, price adjustments, and overall cost control. HCCI offers a more precise measurement of historical price changes by tracking cost variations in key construction activities. Hence, DOTs have developed the Highway Construction Cost Index (HCCI) to better capture price changes over time. For example, the WMU research team (Liu et al., 2020; 2021) developed state-specific HCCI for Michigan and Ohio.

Despite its development, HCCI has not been widely or effectively utilized in cost estimation within the highway construction industry. One key limitation is that HCCI primarily reflects historical price trends and past economic or market conditions, without accounting for future changes in the economy, emerging market dynamics, or unforeseen global and local events. As a result, one question regarding the application of HCCI in cost estimation remains unanswered. Can advanced analyses be conducted to forecast the Michigan Highway Construction Cost Index (developed by the WMU team) based on economic conditions? For long-term construction projects, where costs may evolve significantly throughout the project lifecycle, the use of HCCI forecast enables more accurate projections by adjusting estimates to account for future cost escalation at the midpoint of the project's duration (White and Erickson, 2011). This dynamic approach helps ensure that cost estimates remain aligned with market conditions, reducing the risk of under- or overestimating project costs.

Given this, this chapter aims to develop advanced methods for predicting HCCI values based on economic conditions and market trends. This chapter provides a foundation for the subsequent chapters, which will focus on how these predictions can be used to improve cost estimation and budget planning in highway construction projects.

4.2 LITERATURE REVIEW

To enhance the accuracy of MHCCI predictions, a comprehensive literature review on construction cost indices was conducted and is presented in this section. This review helps identify existing methodologies, models, and frameworks that have been applied to predict construction cost indices, such as HCCI. It also provides insight (e.g., gaps and limitations) into best practices and advanced techniques, which can be leveraged to improve future HCCI predictions. The review is structured based on the types of prediction models used in the literature, with a focus on three main categories: **statistical models**, **causal models**, and **machine learning**. The **statistical models** section explores methodologies such as regression analysis, curve fitting, time series analysis, and other traditional statistical approaches. These models rely on historical index data to forecast future trends. For example, the time series analysis leverages historical data to identify patterns and trends over time. These models are widely used due to their simplicity and ease of application but often lack the ability to incorporate complex relationships between external variables. The **causal models** section delves into models that aim to predict the HCCI by identifying and analyzing key economic and market factors that directly influence construction costs and/or HCCI. These models establish cause-and-effect relationships, offering a deeper understanding of the underlying drivers of cost index changes. Finally, the **machine learning** section reviews more advanced techniques, such as Artificial Neural Networks (ANNs) and hybrid models like ARIMA-ANN. These methods can capture complex patterns and nonlinear relationships between the index value and external variables, offering more flexibility and potentially higher accuracy in long-term forecasting.

4.2.1 Statistical Method

Curve fitting and time series analysis are often used to predict construction cost indexes, especially for short-term predictions. For example, Hwang (2011) developed two-time series models such as ARMA (5,5) and VAR (12), for forecasting HCCI. These statistical methods are easy to use; their accuracy may not be sufficient as they fail to describe the relationship between explanatory variables (that may affect future cost behavior) and the cost index, i.e., a lack of explanatory capability. Also, their accuracy often declines for long-term forecasts, although effective for short-term predictions. Alternatively, Ilbeigi et al. (2014) applied Geometric Brownian Motion (GBM) to estimate the asphalt cement price index over time. While GBM is a well-known stochastic model, commonly used for predicting stock prices, its application in construction cost forecasting presents challenges. GBM assumes that future price movements are random and follow a continuous path based on past data trends. However, this assumption may not be held in the construction industry, where costs can be affected by sudden market shifts, supply chain disruptions, or policy changes. Furthermore, GBM does not incorporate factors like economic indicators, inflation, or commodity price trends, limiting its ability to capture the full complexity of cost fluctuations in construction. Kim et al. (2021) combined Linear ARIMA and Nonlinear ANNs to predict city-level CCI. ARIMA, as a linear time series model, is excellent for capturing historical trends, but it struggles with complex, nonlinear relationships inherent in real-world data. On the other hand, ANNs are powerful at detecting nonlinear patterns, but their effectiveness depends on the quality and volume of data available.

4.2.2 Causal Method: Leading Factors for Cost Index

Various other techniques for the HCCI forecast were applied, including an Artificial Neural Network model (Williams, 1994), a multiple regression model (Mill, 2013), and a multiplicative model (Wilmot & Cheng, 2003). One of the early efforts in the HCCI forecast was the identification of leading indicators of the HCCI (Akintoye and Skitmore, 1993). They concluded that the tender index variation could be attributable to several economic factors, such as unemployment level, real interest rate, and manufacturing profitability, in the context of the UK construction industry. In the Artificial Neural Network model by Williams (1994), ***prime lending***

rate, housing starts, and the months of the year were taken as inputs for the CCI prediction. Subsequently, Ng et al. (2000) conducted similar research in Hong Kong, reporting ***interest rates, building costs, and consumer price indexes*** caused significant changes in Hong Kong's tender price index. In the United States, the leading indicators were concluded to be the **1) consumer price index, 2) producer price index, 3) GDP, 4) number of building permits, 5) housing starts, 6) employment levels, 7) money supply, and 8) crude oil price** (Ashuri et al., 2012). In particular, money supply and crude oil prices are revealed to have a long-term relationship with CCI. Given these indicators, Shahandashti and Ashuri (2013) further established Vector Error Correction Models to forecast the Engineering News-Record Construction Cost index. Later, the same research team (Shahandashti and Ashuri, 2016) applied the same method to predict the NHCCI. It is worth noting that their identified leading indicators differed from those for ENR CCI. That is, **crude oil price** and **average hourly earnings** turned out to be leading factors among all other 14 factors, such as ***Consumer price index, Federal funds rate, Unemployment rate, Employment rate in construction, prime loan rate, building permits, money supply, average hourly earnings, Dow jones industrial average, producer price index, housing starts, construction spending, GDP, and GDP implicit price deflators***. The VEC model with NHCCI, average hourly earnings, and crude oil price offer better out-of-sample forecasting. ENR CCI and NHCCI prediction models differ because these indices are designed for private and public construction projects. NHCCI primarily measures the price changes in highway construction so that **the housing starts and Prime loan rate could have less impact on the NHCC**. Another similar attempt is the work by Faghih et al. (2018), who applied a vector error correction model to forecast the short- and long-term price index for construction materials, such as asphalt, cement, and steel. Thirteen explanatory variables were selected from existing economic literature. Different variables were identified for asphalt, cement, and steel, respectively. For example, the **six** explanatory variables for asphalt are CPI, housing starts, PPI, iron ore prices, building permits, and crude oil prices. The **eight** variables for steel prices consist of CPI, industrial gas prices, housing starts, personal income, PPI, iron ore prices, building permits, and crude oil prices. The cement price factors (in total six) include employment rate, GDP, housing starts, the hourly earnings of labor, building permits, and construction spending.

4.2.3 Machine Learning

In recent years, artificial intelligence (AI) has garnered significant attention from both industry and academia for its potential to enhance forecasting accuracy. AI has been applied to a wide array of forecasting applications, particularly in the time series forecasting. Research has demonstrated that AI models can effectively address the noisy and chaotic nature of forecasting challenges (Livieris et al., 2020). Among the various AI models, Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs) have emerged as the leading approaches for time series problems. Cao and Ashuri (2020) notably applied LSTM networks to forecast the Highway Construction Cost Index (HCCI), marking one of the pioneering uses of LSTM in construction engineering. Their study found that LSTM models outperformed traditional time series models in forecasting accuracy. The proposed LSTM model utilized historical HCCI data to make predictions across various time horizons, including short-term, mid-term, and long-term forecasts. For example, the maximum MAPE of LSTM is 18.51%, while the ARFIMA and ARIMA models have MAPEs of 42.38 and 33.37, respectively. However, the model was limited in that it could not incorporate external factors into its forecasts.

Furthermore, the LSTM model was trained and tested on an extensive dataset spanning from 1998 to 2008 (Cao and Ashuri, 2020). However, existing methods for forecasting the construction cost index (CCI) still lack reliability and robustness. In contrast, the model presented in this study is designed to forecast using a smaller dataset. Our approach aims to maintain robust forecast performance despite the reduced data volume, highlighting the adaptability of LSTM networks to different data constraints. By advancing the application of LSTM models in construction cost forecasting, this study contributes to the ongoing efforts to develop more reliable and robust predictive models that can effectively incorporate both historical data and external factors.

In practice, four state DOTs forecast the HCCI for the next five or ten years. For example, using a multiple regression model, Mills (2013) used the regression model to predict the HCCI for CDOT based on macroeconomic and demographic forecasts. It should be noted that their HCCI is still forecasted based on the assumption that **future economic conditions** remain the same as historical conditions. The WMU team also successfully predicted the index values for the next five years based on traditional time series analysis. Yet, the HCCI forecast models must be improved to consider the economic conditions and global events for higher accuracy.

4.3 METHODOLOGY

This research aims to improve the accuracy of HCCI predictions by considering external factors. A comparative analysis of three prediction models—Long Short-Term Memory (LSTM), Vector Error Correction Model (VECM), and Seasonal ARIMA, was conducted. These models were selected based on their strengths in forecasting construction cost indexes. **LSTM**, a type of artificial intelligence model, is well-suited for handling time series data with complex patterns, and it offers superior forecasting accuracy due to its ability to capture long-term dependencies and relationships. **VECM**, on the other hand, excels in capturing long-run equilibrium relationships between variables, making it highly effective for economic forecasting where co-integration exists, such as between construction cost index and macroeconomic factors like crude oil prices or employment levels. **Seasonal ARIMA**, a traditional time series model, is included for its simplicity and effectiveness in handling seasonal patterns in data, making it useful for predicting cost indexes with seasonal fluctuations. It should be noted that seasonal ARIMA is a traditional time series model that uses only time data to generate future cost index predictions, without incorporating external factors. In contrast, both LSTM and VECM are capable of integrating external variables into their predictions, offering more dynamic and comprehensive forecasting. The comparative analysis will assess the forecasting performance of these models across various time horizons, evaluating their robustness and reliability in predicting future cost trends. Key performance metrics such as Mean Absolute Percentage Error (MAPE) will be used to determine the model's effectiveness, ensuring the best method is identified for accurate HCCI forecasting.

Figure 38 provides an overview of the process for predicting the MHCCI**. It includes three steps, namely Explanatory Factor Identification**, **Model Training** and **Evaluation, and Predictive Model Selection** for the final index forecast.

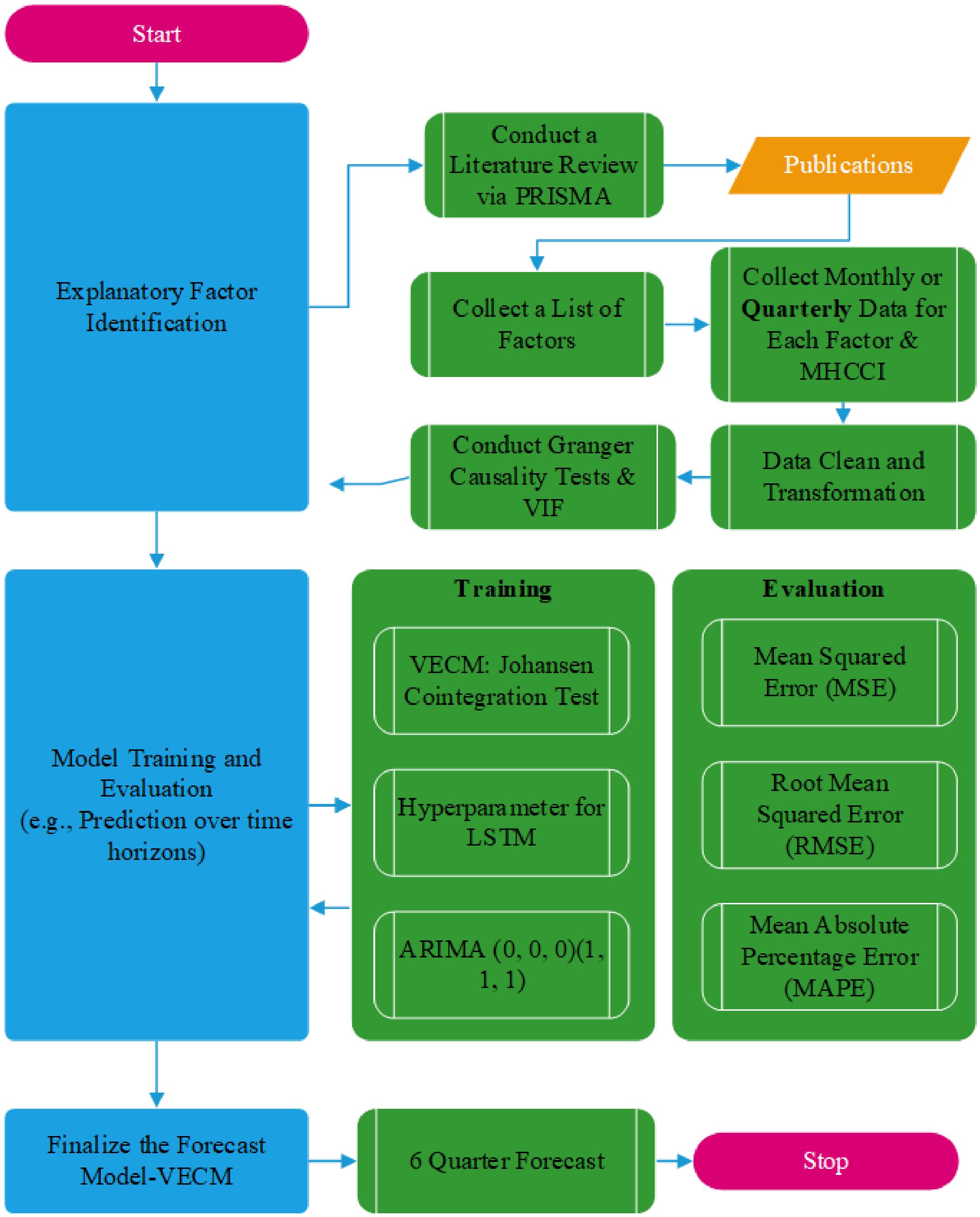

Figure 38. MHCCI Forecast Methodology

1. **Explanatory Factor Identification**: This step involves identifying key factors that influence MHCCI. It starts with conducting a literature review using the PRISMA method, followed by compiling a list of relevant factors. Granger Causality Tests and VIF are then used to determine the most impactful variables for the model.
2. **Model Training and Evaluation**: In this phase, models such as VECM, LSTM, and ARIMA are trained using the identified factors. After training, the models are evaluated using performance metrics like Mean Squared Error (MSE), Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE).

3. **Finalize the Forecast Model**: Based on the evaluation results, the best-performing model (in this case, VECM) is selected for the final forecast, which predicts the MHCCI for a six-quarter period.

These three overarching steps are explained in further detail in the following sub-sections.

4.4 External Factor Identification

The first step is to identify a comprehensive list of potential factors that significantly influence MHCCI. Various studies have identified key economic indicators, such as GDP, inflation rates, construction material costs, and labor market conditions, that can significantly influence cost indices. As such, literature could provide valuable insights into which **factors** can be included in **predictive models** for HCCI. This step is to systematically identify relevant factors through a comprehensive literature review. To ensure a structured and unbiased approach, the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flow diagram was employed to guide the identification and selection of relevant papers, ensuring that the findings related to construction inflation were both reliable and credible.

A systematic search process was then initiated to identify relevant literature (see Figure 39). This began by examining established research repositories, including TRID, FHWA TRIS, TRB, ROSAP, NCHRP, and Scopus, to locate publications focused on cost inflation within the construction industry. The search used targeted keywords such as "Cost Inflation," "Causes of Inflation," "Construction Cost Inflation," "Cost Index," "Highway Construction Cost Index," and "Inflation in Construction." In total, 1,020 articles and reports were collected from three main databases: 730 from Scopus, 216 from the Mendeley library, and 56 from the TRID database. An additional 18 publications were obtained through manual searches of recognized organizations, websites, and published articles. By reviewing this extensive body of literature, we aim to identify robust methodologies, models, and external factors that can be adapted for accurate HCCI predictions, providing the foundation for improved cost estimation and forecasting in highway construction.

All publications were documented, and their citations were managed using Mendeley Reference Manager, which identified and removed 123 duplicates, resulting in a refined database for in-depth screening. An review of the 897 screened publications led to the exclusion of 360 publications published before 2007. The remaining 537 publications were then assessed for eligibility, leading to further exclusions based on the following criteria:

- **462 publications** were excluded as they were deemed "out of scope" due to their lack of direct relevance to the specific research focus or questions. These publications were too broad, context-specific, outdated, or inaccessible. For example, Lawal et al. (2023) developed a computerized simulation-based binomial model (CSBBM) for building investment appraisal, which focused only minimally on inflation and cost estimation, providing insufficient depth for this study. Similarly, Kneebone and Gres (2016) explored the declining need for homeless shelters, attributing it to poverty, but did not sufficiently address inflation causes and effects relevant to this research.

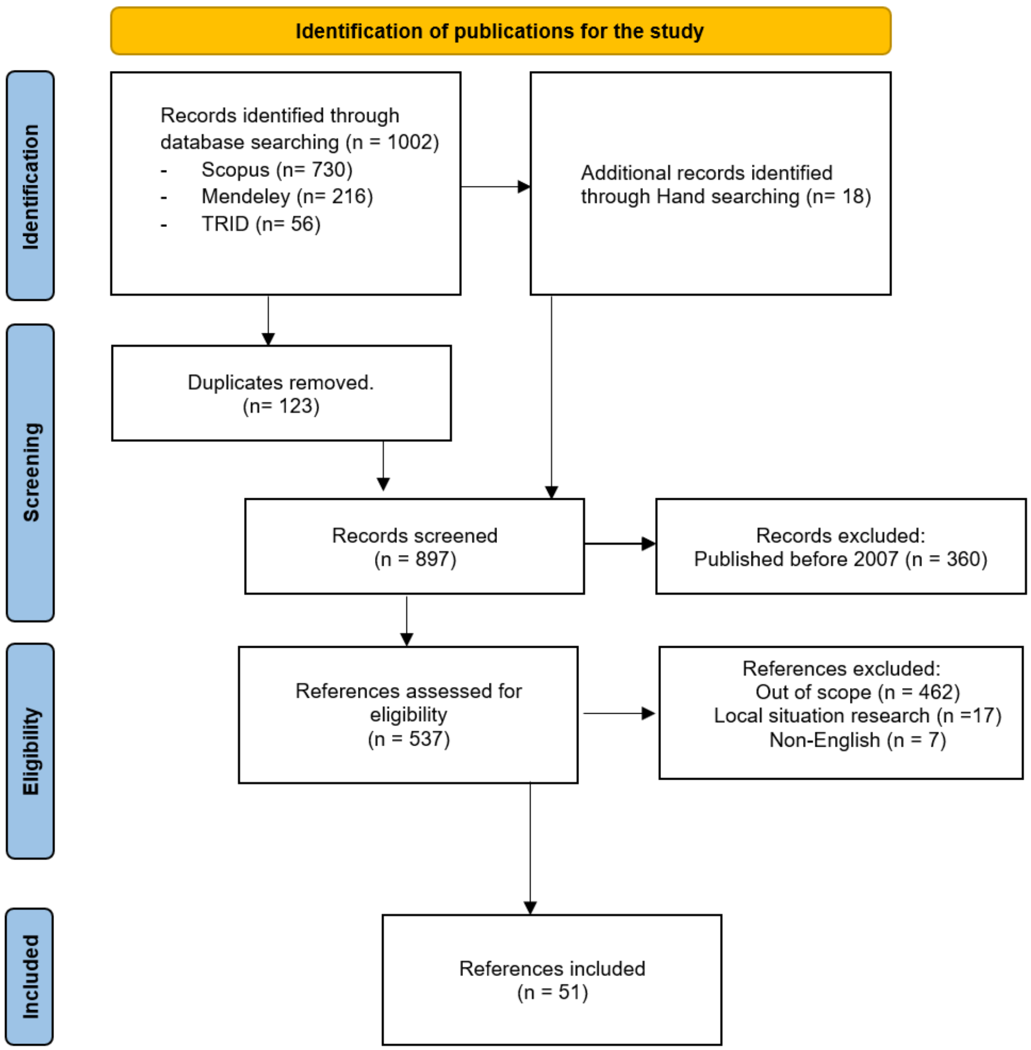

Figure 39. Inflation-related literature search

- **17 publications** were excluded due to their high specificity to particular regions, localities, or contexts, which made it difficult to generalize findings to broader regions.
- **7 publications** were excluded because they were not published in English.

After careful screening, **51 papers** were selected for their relevance and contribution to the study, and these papers are reviewed, and these factors have been identified and gathered into Table 9. As shown in Table 9, various external factors that influence construction cost indices are grouped into six categories: Economic Indicators, Construction Activities, Labor Market, Manufacturing and Materials, Housing and Real Estate, and Seasonal and Temporal Factors. These groupings facilitate a comprehensive analysis of the various elements that impact the cost indices, providing a clearer understanding of the different drivers behind cost variations in the construction sector. The "Count" column indicates the number of publications that have reported the potential of each factor for HCCI predictions. For example, under Economic Variables, **Consumer Price Index (CPI)**, **Producer Price Index (PPI)**, and **Crude Oil Price** are the most frequently cited in literature, each being referenced in **3 publications**.

Table 9. External Factors and Their Categories for HCCI Forecast

Category	**Name**	**Count**
Economic Indicators		
	Consumer price index	3
	Producer price index	3
	GDP	1
	Money supply	1
	Asphalt are CPI	1
	Interest rates	1
	Crude oil price	3
	Personal income	1
	Real interest rate	1
	Prime lending rate	1
Construction Activities		
	Construction spending	2
	Number of building permits	2
	Building costs	1
Labor Market		
	Average hourly earnings	2
	Average hourly earnings Constr.	1
	Unemployment level	1
	Employment Rate	2
Manufacturing and Materials		
	Manufacturing profitability	1
	Iron ore prices	1
	Industrial gas prices	1
Housing and Real Estate		
	Housing starts	3
Seasonal and Temporal Factors		
	The months of the year	1

Economic Indicators: Economic indicators provide a broad overview of the economic climate, and they include the 1) Consumer Price Index (CPI), 2) Producer Price Index (PPI), 3) crude oil prices, real interest rates, prime lending rates, general interest rates, Gross Domestic Product (GDP), money supply, and personal income. These indicators help in understanding inflation trends, economic growth, and overall financial health which directly impact construction costs and index.

Construction Activity Factors: The construction activity group includes factors that directly affect the construction industry. These factors are the number of building permits issued, overall construction spending, and building costs, including the Asphalt Cement Price Index (CPI). These metrics provide insight into the construction activity and construction cost dynamics.

Labor Market: The labor market group includes factors such as employment rate, average hourly earnings (both general and specific to construction) and unemployment levels. These metrics provide insight into the labor availability within the sector.

Manufacturing and Materials: Factors in this group address the production side of the economy and material costs. They include manufacturing profitability, iron ore prices, and industrial gas prices. These elements are essential in assessing the cost of raw materials and manufacturing processes that influence construction material costs.

Seasonal and Temporal Factors: This group includes the months of the year, which accounts for the seasonal variations in construction activities. Seasonal trends can significantly affect construction costs due to changes in labor availability, material supply, and weather conditions.

Housing and Real Estate: Housing starts fall under this category, reflecting the initiation of new residential construction projects. This factor is a vital indicator of the housing market's health and demand, influencing overall construction activity and costs.

4.4.1 Data Preparation and Stationarization

Following the identification of potential factors, the next step involves gathering data for each identified factor and historical MHCCI. The data used in this analysis was sourced from public agency websites. For example, unemployment rates were obtained from the Bureau of Labor Statistics (BLS), the number of building permits from the U.S. Census Bureau, GDP from the Bureau of Economic Analysis (BEA), and the Asphalt Index from the FRED websites. Some raw data, such as monthly economic indicators, were first aggregated into **quarterly data**, similar to MHCCI, by averaging the monthly values to ensure consistency across the dataset. The historical MHCCI values from 2010 to 2023, including both annual and quarterly data, were obtained from the **MHCCI Tool** (Liu et al., 2020). It is important to note that MHCCI values from 2020 onward may vary, as adjustments may have been applied to account for necessary modifications.

The next critical step in developing robust forecasting models is to stationarize the data to remove any trends and ensure stability over time. The Augmented Dickey-Fuller (ADF) test was employed to assess whether each variable in the dataset was stationary, meaning it showed no time-dependent patterns. For variables found to be non-stationary, iterative differencing was applied until stationarity was achieved. The **Python codes were** used to determine which variables became stationary after differencing, producing a clean dataset ready for further analysis. Table 10 tabulates the results from the Augmented Dickey-Fuller (ADF) test, used to determine whether time series data is stationary (i.e., if its statistical properties do not change over time). All variables in the table are stationary, as indicated by the TRUE value under the "Stationary" column. Some variables, such as Unemployment % and Avg Weekly Hours of Construction Employees, are stationary without differencing (Differing = 0), while others required differencing once or more (Differing = 1, 2, or 3) to become stationary. The results revealed that several economic factors required up to five iterations of differencing before achieving stationarity.

Table 10. Stationarizing quarterly MHCCI and explanatory variables

Name	ADF Statistic	p-value	Used lag	Stationary	Differing
Unemployment %	-2.863	0.050	0	TRUE	0
Avg Weekly Hours of Construction Emp	-3.307	0.015	1	TRUE	0
GDP (Billions)	-7.879	0.000	0	TRUE	1
Interest rate (FFR)	-5.230	0.000	8	TRUE	1
Money supply (M2) (Billion)	-3.735	0.004	0	TRUE	1
Oil prices ($/Barrel)	-6.201	0.000	0	TRUE	1
Hot finished steel bars (PPI)	-4.252	0.001	4	TRUE	1
Construction Machinery Manufacturing: Power Cranes, Draglines, and Shovels (PPI)	-3.096	0.027	1	TRUE	1
Number of Building Permits In Michigan	-3.711	0.004	3	TRUE	1
Unemployment in Construction %	-3.444	0.010	3	TRUE	1
Bank Prime Loan Rate %	-4.457	0.000	9	TRUE	1
Housing units starts	-6.892	0.000	1	TRUE	1
MHCCI	-3.027	0.032	11	TRUE	1
Cement, Hydraulic (PPI)	-2.912	0.044	1	TRUE	1
Inflation rate (CPI)	-4.296	0.000	9	TRUE	2
Asphalt (Producer Price Index)	-3.807	0.003	10	TRUE	2
Concrete (PPI)	-3.721	0.004	6	TRUE	2
Ready-Mix Concrete Manufacturing (PPI)	-2.962	0.039	9	TRUE	2
Cold finished steel bars (PPI)	-4.941	0.000	8	TRUE	2
Fabricated Structural Metal Manufacturing (PPI)	-4.307	0.000	11	TRUE	2
Construction equipment (PPI)	-8.119	0.000	1	TRUE	2
Construction Machinery Manufacturing (PPI)	-4.895	0.000	3	TRUE	2
Avg hourly earnings of all emp (Construction)	-8.921	0.000	1	TRUE	2
Construction sand, gravel and crushed stone (PPI)	-4.073	0.001	5	TRUE	2
Total construction spending on highway and streets in US (Millions)	-7.948	0.000	5	TRUE	3

4.4.2 Explanatory Factor Identification via Statistical Analysis

Granger causality tests were performed to identify the directional relationships between the MHCCI and other explanatory variables, thus revealing **cause-and-effect relationships** between variables over different lags. The test helped filter which variables had predictive power over MHCCI. Variables such as GDP, unemployment in the construction sector, oil prices, and producer price indices (PPI) for critical materials like concrete and steel showed significant causality. The Granger Causality results guided the selection of variables for subsequent modeling steps, refining the focus to the most predictive indicators. Table 11 summarized the causality test results. The table is organized by the factors being tested, and each factor has p-values and f-statistics corresponding to 4 different lag periods (lags 1, 2, 3, and 4).

Table 11. Granger causality tests results for quarterly MHCCI and explanatory variables

Factors		Lag 1	Lag 2	Lag 3	Lag 4
Unemployment %	p_values	0.0731	0.1166	0.1806	0.3875
	f_statistics	3.4278	2.3103	1.7496	1.0819
Number of Building Permits In Michigan	p_values	0.5278	0.0886	**0.0290**	0.1034
	f_statistics	0.4071	2.6308	**3.4995**	2.1673
Unemployment in Construction %	p_values	0.4570	0.0698	**0.0362**	0.2455
	f_statistics	0.5665	2.9123	**3.2756**	1.4594
GDP (Billions)	p_values	0.1245	0.0581	0.0640	**0.0000**
	f_statistics	2.4844	3.1340	2.7219	**11.2748**
Intrest rate (FFR)	p_values	**0.0381**	0.0916	0.1892	0.2842
	f_statistics	**4.6699**	2.5919	1.7067	1.3396
Inflation rate (CPI)	p_values	**0.0413**	0.0578	0.1145	0.0601
	f_statistics	**4.5078**	3.1404	2.1718	2.6206
Money supply (M2) (Billion)	p_values	0.2074	0.3258	0.3792	0.5061
	f_statistics	1.6538	1.1644	1.0678	0.8527
Oil prices ($/Barrel)	p_values	**0.0176**	0.0330	0.1014	0.0236
	f_statistics	**6.2465**	3.8299	2.2861	3.4308
Cold finished steel bars (PPI)	p_values	0.0111	0.0342	0.0361	**0.0033**
	f_statistics	7.2370	3.7867	3.2800	**5.3219**
Fabricated Structural Metal Manufacturing (PPI)	p_values	**0.0005**	0.0014	0.0042	0.0015
	f_statistics	**15.0678**	8.2050	5.5583	6.1392
Hot finished steel bars (PPI)	p_values	0.0371	0.0396	0.0408	**0.0056**
	f_statistics	4.7193	3.6038	3.1602	**4.7847**
Construction equipment (PPI)	p_values	0.0972	0.0849	**0.0365**	0.3356
	f_statistics	2.9150	2.6812	**3.2699**	1.2020
Construction Machinery Manufacturing (PPI)	p_values	0.1608	0.1363	**0.0366**	0.3430
	f_statistics	2.0578	2.1315	**3.2653**	1.1839
Total construction spending on highway and streets in US (Millions)	p_values	0.3887	0.4600	0.3578	0.3859
	f_statistics	0.7631	0.7970	1.1215	1.0855
Construction Machinery Manufacturing: Power Cranes, Draglines, and Shovels (PPI)	p_values	0.4944	0.5278	0.1659	0.5584
	f_statistics	0.4775	0.6529	1.8277	0.7650
Avg Weekly Hours of Construction Emp	p_values	0.5511	0.7068	0.9051	0.1737
	f_statistics	0.3627	0.3511	0.1859	1.7421
Bank Prime Loan Rate %	p_values	**0.0364**	0.0858	0.1812	0.3165
	f_statistics	**4.7567**	2.6684	1.7465	1.2507
Housing units starts	p_values	0.5076	0.6855	0.8726	0.2060
	f_statistics	0.4487	0.3824	0.2330	1.6026
	p_values	0.9709	0.1886	0.2148	0.2010

Factors		Lag			
		1	2	3	4
Avg hourly earnings of all emp (Construction)	f_statistics	0.0014	1.7644	1.5902	1.6228
Construction sand, gravel and crushed stone (PPI)	p_values	0.4283	0.0203	**0.0182**	0.1838
	f_statistics	0.6433	4.4500	**3.9735**	1.6961
Asphalt (Producer Price Index)	p_values	**0.0041**	0.0176	0.0657	0.0618
	f_statistics	**9.1358**	4.4578	2.6012	2.4727
Concrete (PPI)	p_values	0.8165	**0.0012**	0.0039	0.0018
	f_statistics	0.0547	**8.4650**	5.6339	5.9185
Ready-Mix Concrete Manufacturing (PPI)	p_values	0.8059	**0.0131**	0.0230	0.0188
	f_statistics	0.0614	**5.0301**	3.7301	3.6331
Cement, Hydraulic (PPI)	p_values	0.1866	0.2990	0.2842	0.1059
	f_statistics	1.8193	1.2573	1.3335	2.1473

- **p-values**: These indicate whether the null hypothesis (that the factor does not Granger-cause the MHCCI) can be rejected. A p-value less than 0.05 suggests a statistically significant relationship.
- **f-statistics**: These test the significance of the relationship between the variable and MHCCI at different lag values. A higher f-statistic indicates a stronger predictive relationship.

Based on the analysis, several factors show significant predictive potential due to their statistically significant p-values across various lags. Key predictors include **GDP (Billions)**, which is highly significant at lag 4, and the **Inflation Rate (CPI)**, showing significance at lags 1, 2, and 4. Additionally, **Oil Prices ($/Barrel)** are significant at lags 1, 2, and 4, while **Cold Finished Steel Bars (PPI)**, **Fabricated Structural Metal Manufacturing (PPI)**, and **Hot Finished Steel Bars (PPI)** exhibit significance across all lag periods. The **Asphalt Producer Price Index (PPI)** and **Concrete (PPI)** are also important, with significance at lags 1 and 2 for Asphalt and lags 2, 3, and 4 for Concrete. Moreover, the **Bank Prime Loan Rate %** is significant at lag 1, further contributing to its predictive value. These factors, with consistently significant relationships over time, provide strong candidates for use in forecasting and predictive modeling.

- GDP (Billions) (lag 4)
- Inflation Rate (CPI) (lags 1, 2, and 4)
- Oil Prices ($/Barrel) (lags 1, 2, and 4)
- Cold Finished Steel Bars (PPI) (all lags)
- Fabricated Structural Metal Manufacturing (PPI) (all lags)
- Hot Finished Steel Bars (PPI) (all lags)
- Asphalt (PPI) (lags 1 and 2)
- Concrete (PPI) (lags 2, 3, and 4)
- Number of Building Permits in Michigan (lags 2 and 3)
- Unemployment in Construction % (lags 2 and 3)

- Interest Rate (FFR) (lag 1)
- Bank Prime Loan Rate % (lag 1)
- Ready-Mix Concrete Manufacturing (PPI) (lags 2, 3, and 4)
- Construction Sand, Gravel, and Crushed Stone (PPI) (lags 2 and 3)
- Construction Equipment (PPI) (lag 3)
- Fabricated Structural Metal Manufacturing (PPI) (all lags)

4.4.3 COVID and High Inflation Impact

Among the sixteen factors listed, the following are most likely related to or influenced by **COVID-19** and **high inflation**:

Oil Prices ($/Barrel): The COVID-19 pandemic had a dramatic impact on global oil prices, initially causing a sharp decline in demand due to lockdowns and travel restrictions. However, as economies started to recover, oil prices rebounded sharply, contributing to inflation. Supply chain disruptions and geopolitical tensions, particularly in 2022, further drove up oil prices, significantly contributing to the broader inflationary environment.

Asphalt (PPI): Asphalt prices are directly affected by oil prices since asphalt is a petroleum by-product. The volatility in oil prices due to COVID-19, combined with supply chain constraints, impacted the cost of asphalt. This price rise was exacerbated by inflationary pressures in the construction industry as demand surged post-pandemic recovery.

Concrete (PPI) and **Ready-Mix Concrete Manufacturing (PPI)**: Both **Concrete PPI** and **Ready-Mix Concrete Manufacturing PPI** were impacted by rising costs of raw materials, labor shortages, and supply chain disruptions caused by COVID-19. Post-pandemic recovery efforts, coupled with rising demand for construction materials, brought significant inflationary pressure on concrete prices, reflecting the broader inflation trends during this period.

Hot Finished Steel Bars (PPI): The price of steel was significantly influenced by the COVID-19 pandemic due to supply chain disruptions, labor shortages, and increased demand. In 2021, as economies recovered and demand surged, steel prices spiked, contributing to inflation. These factors, combined with tariffs and global supply constraints, intensified the price volatility of steel products.

Number of Building Permits in Michigan: The issuance of building permits can **indirectly** reflect the impact of COVID-19 and inflation. During the pandemic, construction activity slowed due to lockdowns and material shortages, but post-pandemic recovery saw an increase in permits as demand for housing surged. However, rising material and labor costs, driven by inflation, affected new construction projects and housing affordability.

The factors most directly influenced by COVID-19 and high inflation are **Oil Prices**, **Asphalt PPI**, **Concrete PPI**, **Ready-Mix Concrete Manufacturing PPI**, and **Hot Finished Steel Bars PPI**. These materials saw significant price fluctuations due to supply chain disruptions, labor shortages, and increased demand during the pandemic recovery period.

4.5 Quarterly MHCCI Prediction

Upon the identification of potential explanatory variables, three models—**VECM**, **LSTM**, and **Seasonal ARIMA**—were developed and trained using the collected data. This section provides a detailed description of the development process for each model.

4.5.1 VECM

VECM is a time series model based on linear relationships between the variables. Multicollinearity in VECM (i.e., when independent variables are highly correlated with each other) can distort the estimates of coefficients, making it difficult to understand the true relationship between the variables. High multicollinearity can lead to unstable and unreliable coefficient estimates, which affects the accuracy of short-term dynamics in the model and can make the interpretation of individual coefficients more difficult.

Therefore, we calculated the **Variance Inflation Factor (VIF)** for each feature in the model. VIF quantifies how much the variance of a regression coefficient is inflated due to multicollinearity with other features. Features with a VIF greater than 10 were identified as having high multicollinearity and were excluded from the model. After this filtering step, the features with a VIF less than 10 were retained (see Table 12). Finally, the **'MHCCI'** variable was reintroduced to the list of selected features, ensuring that the dataset was optimized for further analysis while minimizing multicollinearity issues.

Table 12. Selected explanatory variables

Selected Features via Statistical Tests	**VIF**
Oil prices ($/Barrel)	1.63717
Asphalt (PPI)	2.69593
Concrete (PPI)	9.68414
Ready-Mix Concrete Manufacturing (PPI)	7.16775
Hot finished steel bars (PPI)	1.43207
Construction sand, gravel and crushed stone (PPI)	3.45389
Number of Building Permits in Michigan	1.52633

Table 12 presents **Selected Features** that were included in a model based on statistical tests, along with their corresponding **VIF** values. Asphalt is a key material in road construction, and fluctuations in its price affect project costs. This metric measures the number of building permits issued, which indicates construction activity in Michigan. Its low VIF reflects minimal multicollinearity, making it a stable predictor.

After conducting Granger Causality tests and VIF, the Cointegration Test was used in the time series analysis, to examine the **most appropriate time-series model** for the dataset. Cointegration analysis helps determine whether a long-term equilibrium relationship exists between two or more time series. Specifically, when two or more non-stationary time series are found to be cointegrated, it implies that these variables share a stable, long-term relationship, even if they may deviate or drift apart in the short term.

To assess the presence of cointegration in the multiple time series, such as MHCCI and the chosen explanatory variables, the Johansen Cointegration Test was employed. It is a robust statistical method to identify cointegrating relationships in a dataset containing several time series. The results of this test include both the Trace statistics and the Maximum Eigenvalue statistic, along with their corresponding p-values, which help us evaluate the significance of the cointegrating relationships.

The Johansen Cointegration Test specifically checks for the number of cointegrating relationships among the variables in the dataset. If the Trace statistic exceeds the critical value for a given significance level, such as 5%, it indicates the presence of one or more cointegrating relationships. For instance, a trace statistic (Table 13) that suggests up to **Six** cointegrating relationships means that the data contains up to five distinct long-term equilibrium relationships. The optimal cointegration rank was found to be 4, which implies the presence of long-run relationships between the series.

Table 13. Johansen Cointegration Test Results: Quarterly MHCCI

Null Hypothesis	**Trace_stat**	**Trace_crit_vals 95%**
r=0	434.60	197.38
r<=1	279.33	159.53
r<=2	193.22	125.62
r<=3	133.46	95.75
r<=4	89.15	69.82
r<=5	51.16	47.85
r<=6	21.15	29.80
r<=7	8.35	15.49
r<=8	1.94	3.84

Given the presence of cointegration, the VECM **(Multivariate time-series models**) can be applied to capture both the short-term dynamics and the long-term equilibrium relationships among the variables. The VECM approach is particularly useful because it accounts for the adjustments needed when the variables deviate from their long-term equilibrium, allowing for more accurate forecasting and analysis of the system's behavior over time. Based on the cointegration results, a VECM was developed using variables such as oil price, concrete price PPI, and steel bar PPI. The VECM model was fit for training data, and forecasts were generated for future quarters.

4.5.2 LSTM

The Long Short-Term Memory (LSTM) was selected as one of the key models for predicting the MHCCI. LSTM is well-suited for this task because it is designed to handle time-series data effectively, capturing both short- and long-term dependencies in the data. Given the sequential nature of economic and construction-related factors that influence the MHCCI, LSTM's ability to process and learn from time-dependent patterns makes it a robust choice for improving prediction accuracy. Figure 40 represents the LSTM neural network architecture being applied for the prediction of MHCCI, using a set of key economic and construction-related factors. These explanatory variables **(Left Side)** represent the various external factors that are used as inputs to predict the MHCCI. Each of these factors is a crucial indicator of economic and construction trends. The input variables (e.g., GDP, oil prices, employment rates) are fed into the LSTM network over sequential time steps. The MHCCI is the target variable being predicted and influenced by the input factors. After passing through multiple LSTM cells, the final output is the predicted MHCCI value for a given future time period.

The LSTM processes these variables through a series of hidden states, retaining relevant long-term information and discarding unnecessary details. The LSTM model is designed to predict future values of the MHCCI by learning from the relationships between these variables over time. The middle section illustrates the inner workings of the **LSTM cell**, which is designed to learn from sequential data. LSTM models are widely used for time-series predictions because they can remember long-term dependencies in data.

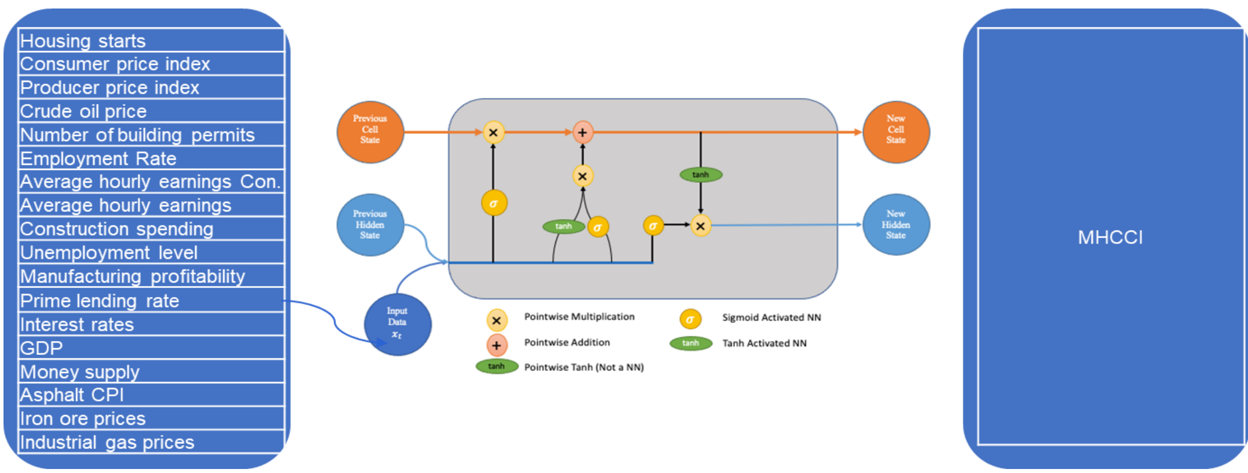

Figure 40. LSTM diagram for MHCCI Forecast

- **Previous Cell State**: This stores information from previous time steps. It passes through the network unmodified, except when adjusted by the forget and input gates.
- **Input Data (Xt)**: The current time-step input data (in this case, the economic factors for the given time).
- **Forget Gate**: This part of the LSTM decides which information from the previous cell state should be discarded. It uses a sigmoid activation function to produce a value between 0 and 1, representing how much of each piece of information should be kept.

- **Input Gate**: This updates the cell state with new information. A sigmoid function decides which values to update, while a tanh function creates new candidate values that can be added to the state.
- **Pointwise Multiplication and Addition**: These operations are used to adjust the cell state based on the forget gate's decision and the new input.
- **Output Gate**: This controls the new hidden state, which is passed to the next LSTM cell. A sigmoid function is used to decide what information to pass forward, and a tanh function generates the output.

The **New Cell State** and **New Hidden State** are then passed on to the next cell in the sequence, allowing the LSTM to retain long-term dependencies in the data, which is important for time-series predictions like MHCCI.

The hyperparameter settings for the LSTM model (see Table 14) were carefully chosen to balance performance and stability while ensuring that the model could effectively capture the patterns in the time series data. A **learning rate of 0.005** was selected as it provided a good balance between convergence speed and accuracy. The model used **32 hidden units per layer**, which were sufficient to capture the underlying relationships in the data without introducing unnecessary complexity. The **Adam optimizer** was chosen due to its efficiency and adaptive learning rate capabilities, which allow it to perform well in a variety of machine learning tasks, including time series forecasting. The model was trained for **50 epochs**, which was determined to be the optimal number of epochs based on early stopping criteria, ensuring that the model was not overfitting the data. **MinMax scaling** was applied to normalize the features and target variables, ensuring that all inputs were on the same scale and improving the performance of the LSTM model. A **dropout rate of 0.5** was used to prevent overfitting, and **three layers** (two LSTM layers and one dense output layer) were included to capture both short-term and long-term dependencies in the data. These settings were tuned based on cross-validation and ensured robust performance on the MHCCI forecasting task.

Table 14. Hyperparameter for LSTM

Hyperparameter	Value	Hyperparameter	Value	Hyperparameter	Value
Learning rate	0.005	Hidden units/layer	32	Number of layers	3
Optimization solver	Adam	Number of epochs	50	Dropout rate	0.5
Feature scaling	MinMax scaling				

4.5.3 Seasonal ARIMA

The Seasonal ARIMA model was designed to predict future values solely based on previously observed data (Hwang, 2011; Hamilton, 1994). Accordingly, historical MHCCI data, consisting of 56 quarterly index values, were utilized to train and test the models. Following the 80/20 rule, 80% of the historical MHCCI data was used for training the models, while the remaining 20% was reserved for testing. The results of the analysis showed that the Seasonal ARIMA (AR=0, I=0, MA=0)(Seasonal AR=1, Seasonal I =1, Seasonal MA=1) model outperformed the ARIMA model in forecasting quarterly MHCCI. The MHCCI forecasts produced by this model are explained in the following section. The model consists of two parts: the non-seasonal component and the seasonal component. Non-Seasonal Component: **1) AR (Autoregressive) = 0**: This means there is no autoregressive term, i.e., the model does not rely on past values to predict future values; 2) **I (Integrated) = 0**: This indicates that no differencing is required to make the data stationary, meaning the data is already stationary without transformation; 3) **MA (Moving Average) = 0**: There is no moving average component, meaning the model does not account for past forecast errors in the prediction process. Seasonal Component: 1) **Seasonal AR (Autoregressive) = 1**: This means that there is one seasonal autoregressive term, which accounts for the relationship between past values at the same season (e.g., previous quarters); 2) **Seasonal I (Integrated) = 1**: This indicates that the model applies one differencing operation to account for seasonal trends or patterns in the data; 3) **Seasonal MA (Moving Average) = 1**: This indicates that one seasonal moving average term is included, meaning the model accounts for forecast errors that repeat in a seasonal pattern.

4.5.4 Comparison of Predictive Models

To evaluate the effectiveness of the selected models, the out-of-sample forecasting was performed. Figure 41 represents the forecasting results of the MHCCI for six future quarters using the three models, based on historical and current values of selected features. The blue line denotes the actual MHCCI values from 2013 Q4 through to 2023 Q2, showcasing historical fluctuations in the construction cost index. The graph also compares the forecasting performance of three different models—VECM, LSTM, and Seasonal ARIMA—for the predicted MHCCI over the next six quarters, starting from 2022 Q1.

- **VECM (Orange Dashed Line)**: The Vector Error Correction Model (VECM) forecasts more volatility in future MHCCI values, with significant peaks at **2022 Q3** (around **2.1774**)). This model predicts higher cost volatility than the others.
- **LSTM (Purple Line)**: The Long Short-Term Memory (LSTM) model predicts a smoother, less volatile increase in MHCCI values.
- **Seasonal ARIMA (Green Line)**: The Seasonal ARIMA model's forecast falls between the LSTM and VECM predictions, but generally aligns more closely with LSTM in predicting gradual growth.

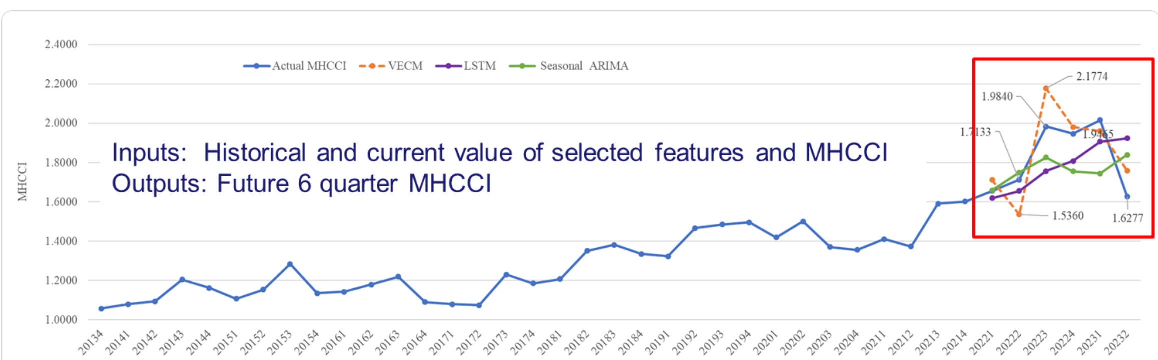

Figure 41. Future 6 quarter predictions of the selected models

Table 15 compares the **MSE** values for three different forecasting models. The MSE is a performance metric that measures the average squared difference between the actual and predicted values. A lower MSE indicates better model performance, as it reflects how close the predictions are to the actual values. The evaluation results showed that the VECM model provided robust predictions for MHCCI with reasonable error margins, particularly for short- to mid-term forecasts.

Table 15. Metric for the index forecast

	Seasonal ARIMA	LSTM	VECM
MSE	0.0303	0.0293	0.0156

4.5.4.1 Vector error correction method

Given the superior performance of the VECM model, a more in-depth evaluation was conducted to assess their predictive capabilities further. The model was initially tested for forecasts over various time horizons, e.g., 8, 10, and 12 quarters. However, the results showed that the highest accuracy was achieved with a 6-quarter forecast. Then, the testing was expanded by predicting the period from 2021 Q1 to 2022 Q2. For subsequent tests, one new quarter was incrementally added to the forecast, and one quarter was moved into the training dataset. For example, in the second test, the period from 2021 Q2 to 2022 Q3 was predicted, with 2021 Q1 being added to the training set. The outcomes of these tests are displayed in Figure 42. The first graph in this figure compares the historical MHCCI values with the forecasted values for the period from 2021 Q1 to 2022 Q2. The model's forecast for the MHCCI is shown with an orange line, while the historical MHCCI data is represented by a blue line. The predicted MHCCI values were evaluated using several performance metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE).

The seven graphs collectively present the forecast performance of the VECM model for **6-quarter predictions** over different periods, with a particular focus on how the model responds to the economic volatility caused by the COVID-19 pandemic. The key metrics highlight the accuracy and reliability of the model over different time periods, especially as the pandemic's effects on the construction sector become evident. All tests consistently showed the strongest accuracy across the testing periods. The **short-term predictions**—especially those starting around 2021—indicate the VECM model's reliability for shorter forecast windows even amidst the uncertainty caused by COVID-related disruptions.

The **earlier periods (2021 Q1 – 2022 Q2)** represent the immediate aftermath of the pandemic's most disruptive phases. Despite the economic turbulence, the VECM model performs well in these 6-quarter forecasts, maintaining relatively low error metrics. For example, **Graphs 1 through 4** in Figure 42 show **MAE** values between **0.056** and **0.142**, and **MAPE** values range between **3.10% and 8.87%**, suggesting that the model was able to handle some of the volatility introduced by the pandemic. In the **2021 Q2 to 2022 Q3** and **2021 Q3 to 2022 Q4** periods, **MAPE** values remained below **4%**, reflecting strong predictive performance. During these times, construction materials faced supply shortages and inflationary pressures, but the model was able to capture these trends accurately. The **2021 Q4 – 2023 Q1** period produced the lowest error values, with a **MAPE of 3.10%**. This demonstrates that the VECM model could accurately predict MHCCI trends during a recovery period when the economy was stabilizing post-pandemic. As the model moves into forecasting periods beyond early 2023, the **economic effects of inflation and supply chain disruptions** become more pronounced, causing a noticeable increase in forecasting errors. For example, the **2022 Q2 to 2023 Q3** period reflects a significant rise in error metrics, with **MAPE jumping to 11.03%**. This indicates that the VECM model struggled to predict the heightened volatility in MHCCI caused by post-pandemic economic shocks, such as increased material costs and labor shortages. Similarly, the **2022 Q3 to 2023 Q4** period (Figure 4) saw an improvement from the previous test but still presented higher errors compared to pre-2022 periods. This suggests that while the model can capture short-term trends, it becomes less effective when attempting to account for long-term pandemic-induced economic variability.

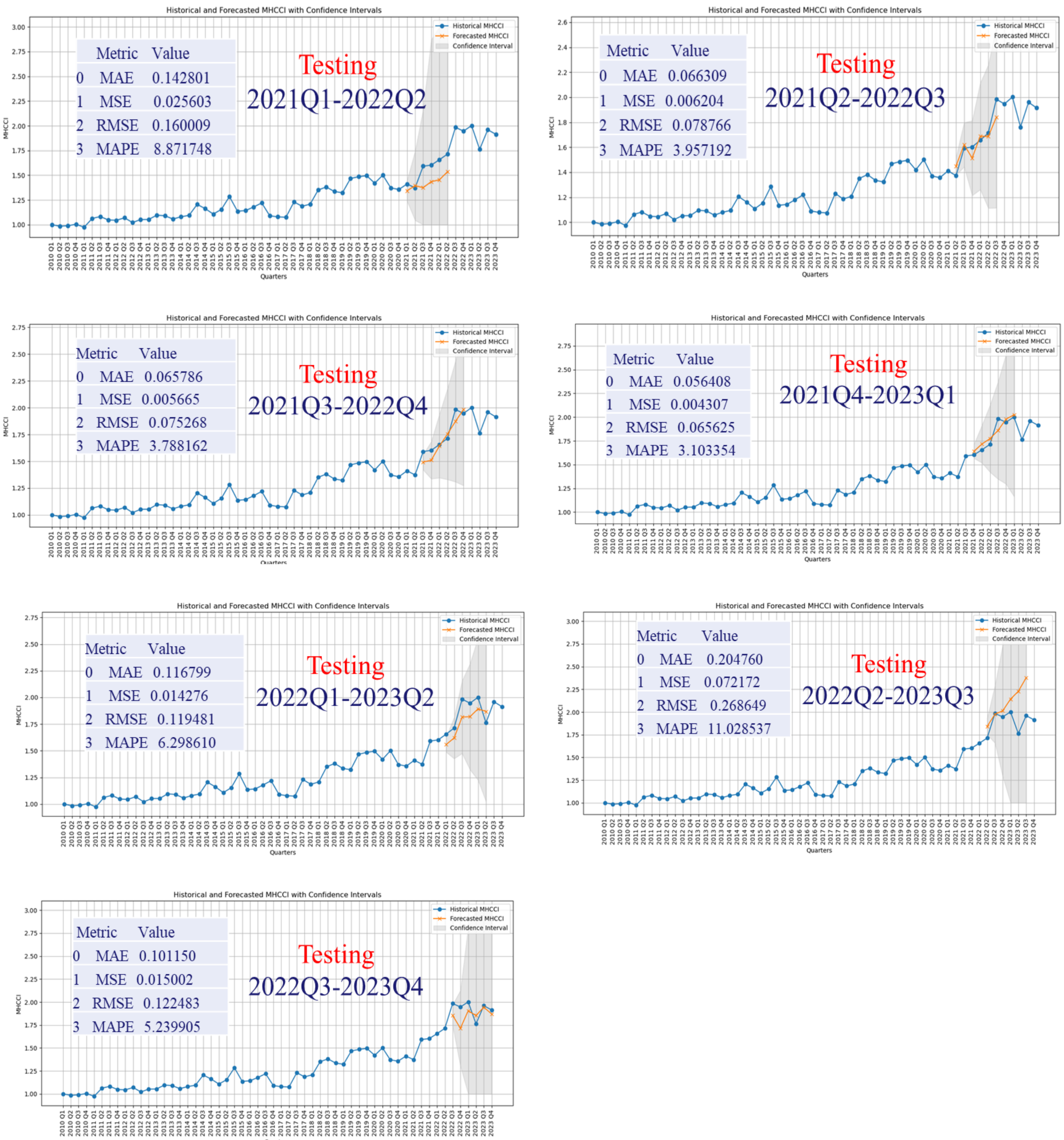

Figure 42. Six quarter predictions of VECM

4.6 Other MHCCI Predictions

4.6.1 Annual MHCCI Prediction

The annual MHCCI predictions followed a similar procedure (shown in Figure 38) to the quarterly MHCCI forecasts, with a few key distinctions. One major difference lies in the data preparation phase. Instead of quarterly data, the raw data collected from various sources was aggregated into annual data before any statistical analysis or predictive modeling was conducted. This aggregation ensured that the data aligned with the annual prediction time frame.

After data preparation, a series of statistical tests and analyses were performed. The **Granger Causality Test** was first applied to identify the directional relationships between the variables. This was followed by **VIF** analysis for time series analysis, which was used to assess multicollinearity among the predictor variables. Finally, the **Johansen Cointegration Test** was conducted to determine the number of long-term equilibrium relationships among the variables. The Cointegration test indicates that VECM is an appropriate time series model for forecasting the annual MHCCI. These steps were crucial in ensuring that the most relevant variables were incorporated into the predictive model, resulting in more accurate annual MHCCI forecasts. The results of these tests are summarized in Table 16, Table 17, and Table 18

Table 16. Granger causality tests results for Annual MHCCI and explanatory variables

Factors		Lag	
		1	2
GDP (Billions)	p_values	**0.0118**	0.2599
	f_statistics	**12.7558**	2.1832
Money supply (M2) (Billion)	p_values	0.0569	0.1098
	f_statistics	5.5325	5.0421
Total construction spending on highway and streets in US (Millions)	p_values	0.6183	0.4110
	f_statistics	0.2758	1.2136
Number of Building Permits In Michigan	p_values	0.8540	0.9086
	f_statistics	0.0369	0.0990
Housing units starts	p_values	0.0658	0.4317
	f_statistics	5.0429	1.1262
Intrest rate (FFR)	p_values	0.6027	0.1836
	f_statistics	0.3016	3.1439
Inflation rate (CPI)	p_values	**0.0385**	0.3753
	f_statistics	**6.9720**	1.3829
Oil prices ($/Barrel)	p_values	0.5563	0.2941
	f_statistics	0.3879	1.8920
Unemployment %	p_values	0.3915	0.1514
	f_statistics	0.8522	3.7800
Asphalt (PPI)	p_values	0.8199	0.7815
	f_statistics	0.0566	0.2680

Factors		Lag 1	Lag 2
Concrete (PPI)	p_values	0.0608	0.3462
	f_statistics	5.3074	1.5422
Ready-Mix Concrete Manufacturing (PPI)	p_values	0.7394	0.3363
	f_statistics	0.1214	1.6015
Cold finished steel bars (PPI)	p_values	**0.0030**	0.0430
	f_statistics	**23.1485**	10.7143
Fabricated Structural Metal Manufacturing (PPI)	p_values	**0.0003**	0.0376
	f_statistics	**54.2794**	11.8573
Hot finished steel bars (PPI)	p_values	**0.0061**	0.1370
	f_statistics	**17.0617**	4.1434
Construction equipment (PPI)	p_values	0.1271	0.5454
	f_statistics	3.1329	0.7472
Construction Machinery Manufacturing (PPI)	p_values	0.2453	0.1404
	f_statistics	1.6583	4.0541
Avg hourly earnings of all emp (Construction)	p_values	0.0773	0.4381
	f_statistics	4.5343	1.1005
Construction sand, gravel and crushed stone (PPI)	p_values	0.1675	0.6222
	f_statistics	2.4645	0.5581
Construction Machinery Manufacturing: Power Cranes, Draglines, and Shovels (PPI)	p_values	0.3362	0.2059
	f_statistics	1.0922	2.8021
Unemployment in Construction %	p_values	0.7739	0.1233
	f_statistics	0.0903	4.5555
Avg Weekly Hours of Construction Emp	p_values	0.4209	0.2588
	f_statistics	0.7461	2.1938
Bank Prime Loan Rate %	p_values	0.4462	0.2931
	f_statistics	0.6642	1.8993

Table 17. Selected explanatory variables: Annual MHCCI

Selected Features via Statistical Tests	VIF
GDP (Billions)	2.9994
Inflation rate (CPI)	1.5462
Cold finished steel bars (PPI)	29.7973
Fabricated Structural Metal Manufacturing (PPI)	12.0913
Hot finished steel bars (PPI)	26.0337

Table 18. Johansen Cointegration Test Results: Annual MHCCI

Null Hypothesis	Maximum Eigenvalue Statistics	Critical Values for Max Eigenvalue Statistic (90%)	Critical Values for Max Eigenvalue Statistic (95%)	Critical Values for Max Eigenvalue Statistic (99%)
r=0	16.67211951	12.2971	14.2639	18.52
r<=1	2.32683738	2.7055	3.8415	6.6349

The Johansen Cointegration results demonstrated that at least one long-term equilibrium relationship exists among GDP, CPI, and Annual MHCCI. Based on this finding, the **VECM model** was established for forecasting the annual MHCCI, taking advantage of its ability to model both short-term dynamics and long-term relationships between these variables.

In addition to VECM, **Linear Regression** was applied to the annual MHCCI predictions. This decision was informed by a strong linear relationship observed between GDP and Annual MHCCI, as indicated by the scatter plot (see Figure 43). This linear trend suggested that a simple linear model could offer reasonable predictive capability for the index. A regression model was established based on the data, which further supported the assumption of a linear relationship. The resulting linear regression equation is as follows:

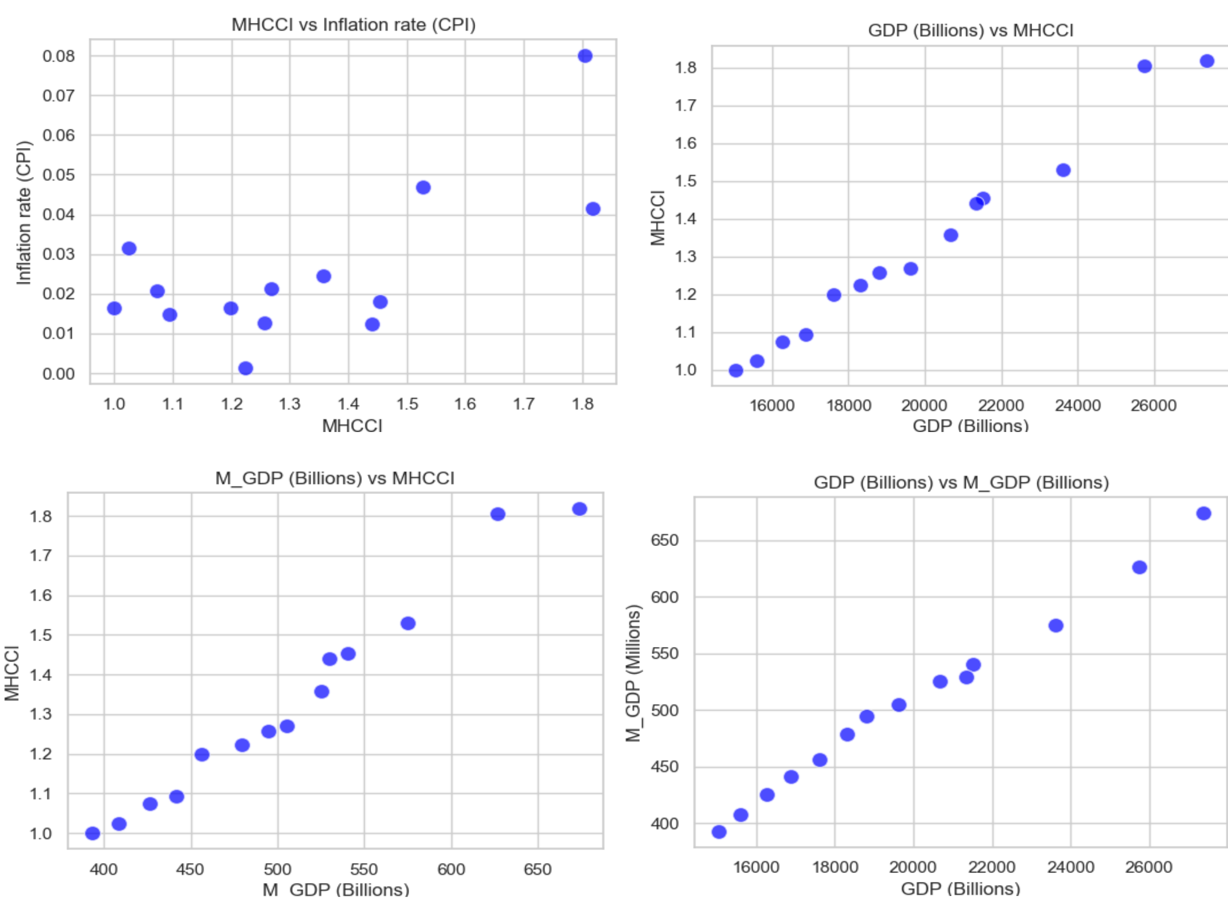

Figure 43. Scatter plot: GDP, Michigan GDP, and Inflation Rate vs Annual MHCCI

$$\text{Annual MHCCI} = (6.944\times10{-}5) \times \text{GDP}{-}0.0558$$

It is important to note that another test was conducted using Michigan's GDP. Michigan's GDP represents approximately 2.5% of the state's total GDP over the period from 2010 to 2023, as illustrated in Figure 43. This percentage fluctuates slightly over time. In this research, however, national GDP was used, as the linear regression models rely on GDP forecasts. National GDP data provides more reliable predictions and is easier to obtain.

Furthermore, the **ARIMA (2, 0, 2) model** was also used for comparison alongside VECM and linear regression. Previous research has shown ARIMA (Liu et al., 2020) to effectively predict annual MHCCI with high accuracy. Therefore, comparing the ARIMA model with VECM and Linear Regression allowed for a comprehensive evaluation of which model could deliver the best prediction results for the Annual MHCCI. The forecast results are shown in Figure 44.

As shown in Figure 44, VECM may have factored in additional variables (e.g., inflation rates) that help explain the trends in MHCCI, which is why the projection is smooth yet conservative, reflecting the model's emphasis on **long-term stability** while accounting for short-term fluctuations. ARIMA, due to its nature, captures **short-term fluctuations** very well, which is why noticeable variability between 2020 and 2023 existed. The model's reliance on **autoregressive and moving averages** of previous MHCCI values makes it responsive to short-term trends, but it might be less effective in capturing structural breaks or sudden shifts unless they are reflected in the data history. Linear regression assumes that the **past trends will continue at the same rate**, which may not always be realistic in an environment with significant economic or market disruptions. While this approach is simple and easy to interpret, it doesn't account for the possibility of nonlinear changes or sudden shifts in the factors affecting MHCCI.

The performance compassion for these three models is shown in **Error! Reference source not found.**. **VECM** performs the best across all metrics, with the lowest errors (MAE: 0.080226, MSE: 0.007112, RMSE: 0.084331, MAPE: 4.976953). This indicates that VECM is more accurate at capturing the relationships between the variables and making better predictions. **GDP-based Linear Regression** performs moderately, with slightly higher error values than VECM but still lower than ARIMA in some metrics (e.g., MAE: 0.092200, MSE: 0.011055). **ARIMA (2, 0, 2)** shows the highest error rates across all metrics (e.g., MAE: 0.102371, MSE: 0.014026), suggesting that while it is a reliable statistical method, it may not capture all the complexities in the data as effectively as VECM or even the GDP-based linear model.

Table 19. Annual MHCCI Predictive Models: Performance Comparison

Metric	ARIMA (2, 0, 2) model	VECM	GDP-based Linear Regression
MAE	0.102371	0.080226	0.0922
MSE	0.014026	0.007112	0.011055
RMSE	0.118432	0.084331	0.105144
MAPE	5.95079	4.976953	5.450376

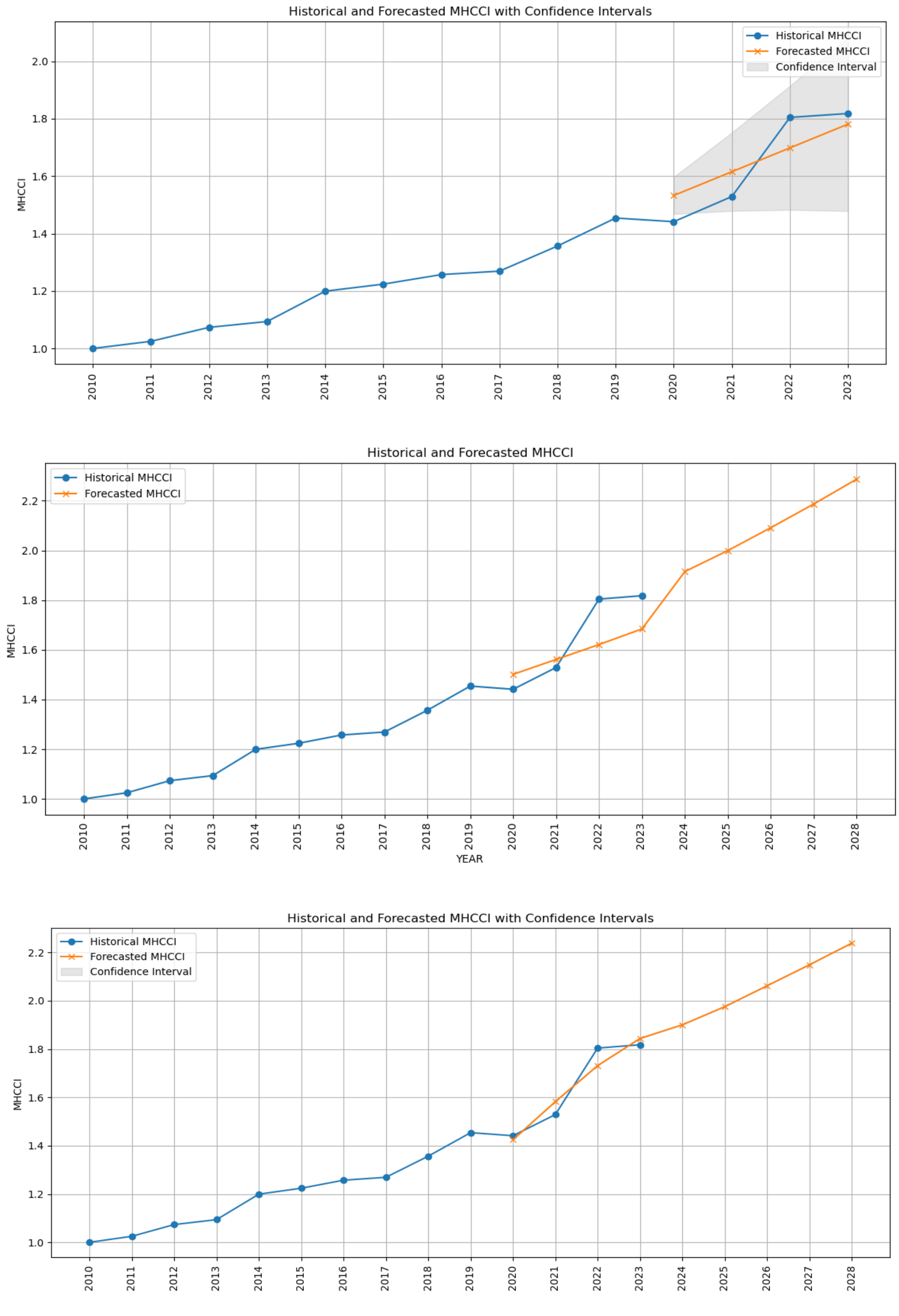

Figure 44. Annual MHCCI Forecasts: VECM, ARIMA, Linear Regression

4.6.2 Quarterly MHCCI Prediction: Contract-Level

Another quarterly prediction was conducted for contract-level MHCCI. The predictive modelling was conducted in the same procedure as the one shown in Figure 38. In this procedure, the state-level quarterly MHCCI was replaced with the contract-level MHCCI. The results also revealed that VECM is the best model among the three models. Figure 45 shows the predicted contract MHCCI over a series of quarters from **2022 Q3 to 2023 Q4**. The error metrics show that the model has a moderate degree of accuracy, with an MAPE of around 6.7%.

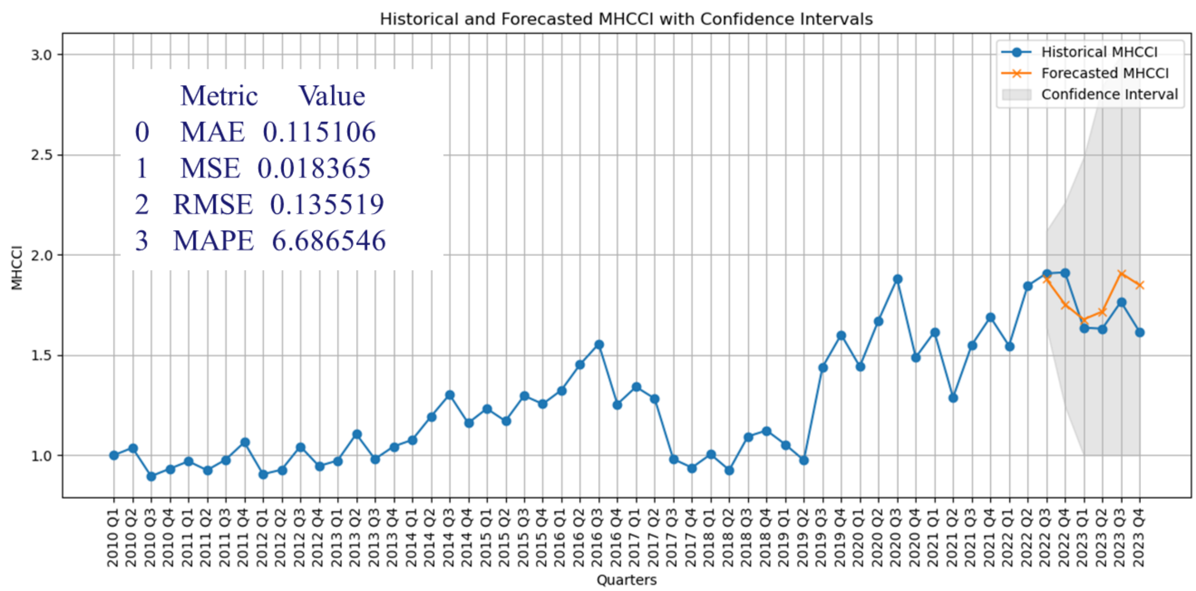

Figure 45. Contract-Level Quarterly MHCCI Forecast using VECM

4.7 Discussion

This research explored the integration of various external factors to improve the accuracy of MHCCI predictions, by employing advanced time-series and machine-learning models. The study began with an extensive literature review, guided by the PRISMA method, to identify relevant external factors such as economic indicators, construction activities, labor market conditions, and material costs. Factors like GDP, inflation rates, and steel price index were identified as strong predictors of MHCCI trends based on their frequent occurrence in the literature.

Three forecasting models—VECM, LSTM, and Seasonal ARIMA—were selected for their respective strengths in time-series analysis. VECM emerged as the best-performing model, particularly for both quarterly and annual MHCCI predictions. Its ability to capture long-term equilibrium relationships between variables gave it a distinct advantage, as reflected in the lower error metrics such as MAPE and RMSE, across different time horizons.

LSTM, while effective in modeling complex, non-linear relationships, was slightly less accurate than VECM in certain scenarios, particularly for short-term predictions. The complexity of LSTM, combined with its high sensitivity to hyperparameters and data size, made it less consistent, though it still provided strong results in cases involving intricate time-dependent patterns. Despite its capability to model long-term dependencies, LSTM's performance was hindered by the limited dataset size and the challenge of tuning parameters optimally.

Seasonal ARIMA, on the other hand, was useful for capturing seasonal trends but did not perform well when external factors were integrated. This model, being simpler and more traditional, lacked the ability to model dynamic economic relationships, which made it less effective in complex prediction scenarios.

The study also evaluated the impact of the COVID-19 pandemic and subsequent inflationary pressures on the MHCCI. Key materials such as steel, asphalt, and oil experienced significant price volatility during the pandemic, adding complexity to the forecasting process. Among the models, VECM was particularly effective in accounting for these fluctuations, showcasing its strength in handling real-world economic disruptions.

4.8 CONCLUSION

This research demonstrated the importance of incorporating external economic factors into predictive models to improve the accuracy of MHCCI forecasts, a critical tool for cost estimation and budget planning in highway construction. Among the models tested, VECM provided the most reliable predictions due to its ability to capture both short-term dynamics and long-term relationships. This made it especially useful for navigating price volatility in construction materials and broader economic conditions, such as those experienced during the COVID-19 pandemic.

LSTM, while promising for its ability to model non-linear dependencies, showed some limitations in consistency, particularly in scenarios where the dataset size and complexity were not fully aligned with its requirements. Further improvements, such as fine-tuning hyperparameters and expanding the dataset, could enhance LSTM’s performance in future studies.

Looking ahead, future research could focus on refining these models, particularly by incorporating more granular data and global economic indicators. This would enhance the models' ability to predict construction cost indices under a wider variety of conditions. For LSTM, larger datasets and more advanced hyperparameter tuning methods like Bayesian optimization could further improve its accuracy. Additionally, integrating hybrid models that combine the strengths of VECM and LSTM could offer a more comprehensive approach to forecasting construction cost indices, providing highway agencies with better tools for managing estimates and budgeting for future projects.

5. INDEX-BASED ESTIMATION AND BUDGET PLANNING

Contract-level MHCCI calculations and index predictions have been successfully conducted in this research. If future HCCI values could be accurately forecasted based on economic conditions and market trends, could MDOT leverage this information to make more informed decisions about cost estimates and future budget management? How can these predicted index trends and impact factors on construction pricing be integrated into cost estimation and budget planning processes? These questions highlight the need for further exploration into the potential use of the predictive HCCI in proactive cost management strategies.

Leveraging the newly calculated contract-level MHCCI and predictions, this chapter provides details on how to utilize the new index, index prediction, and pricing factors for cost estimation and budget planning in project development. It outlines the detailed steps involved in applying new index data to estimate project costs accurately, ensuring alignment with financial constraints and strategic goals. In particular, this chapter discusses the revisions made to the project scoping manual and Engineer's Estimate method to incorporate index-based methodologies to facilitate streamlined financial planning and resource allocation for upcoming projects.

5.1 CONTRACT-LEVEL INDEX-BASED PROJECT SCOPING

Incorporating cost escalation adjustments into project cost estimates is critical to ensure the financial viability and accuracy of long-term project planning. The following procedures (in Figure 46) outline the steps to effectively account for cost escalation (e.g., inflation) during the project scoping and estimation process, and the MHCCI and other tools can be used to maintain accurate cost projections. This procedure could be applied within **Step 13 Project Selection** in the Project Scoping Process and is described in the following subsections.

5.1.1 Determine Letting Date and Construction Mid-Point

The first step in the index-based estimating and budget planning is to determine the Letting Date, when the project will be advertised for bidding, and the Mid-Point of Construction, which reflects the time frame during which the majority of project expenditures will occur. These two dates help define when **cost escalation pressures** (including inflationary effects) are likely to impact the project. The midpoint of construction serves as a reference to adjust cost estimates, accounting for potential escalation risks. The cost adjustments are made in current dollars, ensuring consistency for comparison. The index is used to capture both **cost escalation pressures** (such as rising material and labor costs) and **inflationary pressures**.

5.1.2 Apply Historical Quarterly MHCCI Growth Rates

Once the letting date and mid-point of construction are identified, historical quarterly **cost escalation rates** should be calculated by dividing the contract cost index value of the most recent quarter by the index value of the quarters corresponding to the available unit bid prices). The rates can be used to adjust cost estimates prepared based on the historical unit bid prices of pay items. These rates reflect trends in material prices, labor costs, and other construction-related expenses over recent quarters. By incorporating historical escalation, the project team can build a contingency that accounts for **current cost pressures**, including inflationary impacts, while keeping the adjusted costs in current dollars. Again, this adjustment doesn't project costs into the future but provides a buffer for anticipated **escalation trends** that may affect the project in the near term.

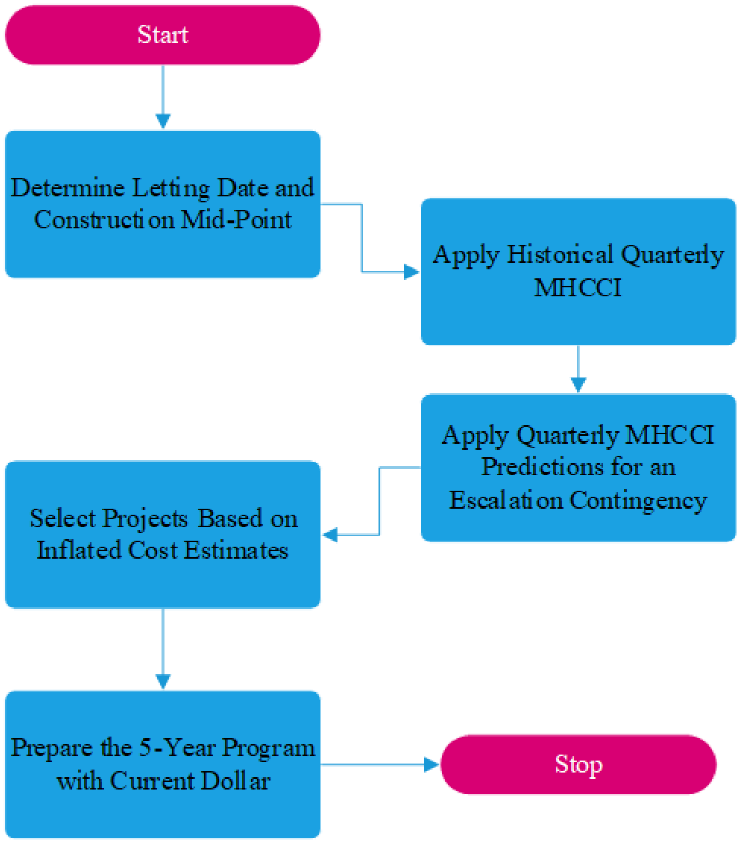

Figure 46. Inflation Consideration Procedure for Project Scoping Estimation

5.1.3 Apply Quarterly MHCCI Predictions for a Cost Escalation Contingency

Using MHCCI, the project team applies quarterly **cost escalation predictions** to the adjusted cost estimates in the last step (Section 5.1.2). The predicted MHCCI accounts for factors such as commodity prices, supply chain disruptions, labor costs, and regional market dynamics. This step helps create a contingency that reflects future **escalation pressures**, including inflationary trends. The adjustments maintain costs in current dollars, ensuring that the escalation buffer is integrated into the cost contingency without projecting future dollar amounts.

5.1.4 Select Projects Based on Inflated Cost Estimates

Once the cost estimates have been adjusted for **cost escalation** using historical rates and MHCCI predictions, projects should be selected based on their escalation-adjusted costs. These adjustments account for **escalation risks**, such as inflation, in current dollar terms, ensuring that projects with higher exposure to cost pressures receive appropriate funding consideration.

Projects should be evaluated based on how well they align with available funding, program goals, and escalation-contingent budgets.

5.1.5 Prepare the 5-Year Program

The final step is to prepare the 5-Year Program using **escalation-adjusted** costs that remain in current dollars. By applying state-level MHCCI data, projected quarterly **cost escalation trends**, including inflation, are factored in to create a buffer against cost pressures over the course of the program. This ensures that the program remains financially viable while accounting for escalation risks. Maintaining all costs in current dollars could ensure consistency across projects, facilitating effective resource allocation and financial planning.

By following these procedures, MDOT ensures that project cost estimates reflect current dollars while incorporating contingencies for **cost escalation** and inflation. The application of historical and MHCCI-based **escalation predictions** serves as a risk buffer, and the adjusted costs remain in today's dollar values. This approach enables consistent budget planning, reduces the risk of cost overruns due to inflation, and supports informed decision-making within MDOT's 5-Year Program

5.1.6 Rational for This Procedure

The rationale for using **cost escalation adjustments** as a contingency in budget planning is to manage rising cost risks, ensuring consistency and budget control. By applying historical escalation rates and MHCCI predictions, project estimates remain in current dollars with a built-in contingency that buffers against rising costs in materials, labor, and supply chain disruptions. This approach allows for consistent project comparisons, as all projects are evaluated on the same financial baseline, regardless of timing. It reduces the risk of budget overruns by proactively adjusting for **escalation risks**, ensuring that unforeseen economic changes do not disrupt funding. Additionally, it supports more effective long-term planning, enabling MDOT to manage resources across a multi-year program with stable, reliable cost projections. Ultimately, this method prevents overestimation and inefficient fund allocation by keeping escalation-adjusted costs in current dollars, promoting financial sustainability while ensuring projects are prioritized and executed efficiently.

5.1.7 Tools Used in the Process

Several tools can be employed to support accurate cost and budget estimation. The key tools include:

- **MHCCI Calculation Tool**: The MHCCI tool can be used to calculate the historical and projected values of contract-level and state-level MHCCI.
- **Historical Data**: Historical data from previous quarters is utilized to prepare current estimates and account for past price fluctuations.
- **AASHTOWare Project Estimation Tool**: This tool provides support for estimating current costs based on historical bid data.

5.2 INDEX-BASED PROCEDURE FOR ENGINEER'S ESTIMATE

Figure 47 illustrates the steps for preparing Engineer's Estimates for construction projects using **MHCCI**. The estimation process relies on timely economic and market data and project-specific conditions to ensure that estimates reflect economic trends and project complexities. The following presents a detailed description of the new estimation procedures.

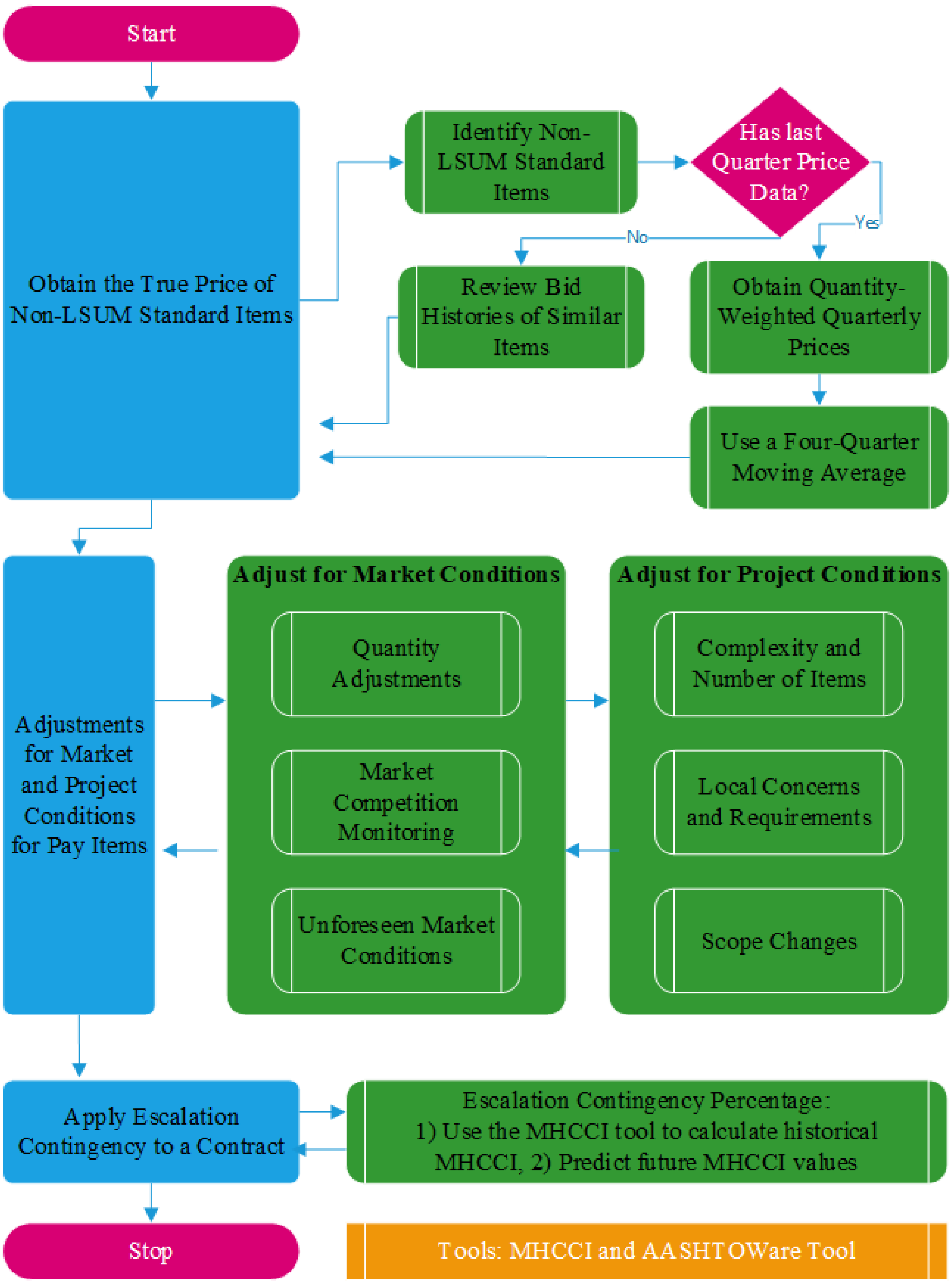

Figure 47. Bid-based Estimating Procedures with Cost Escalation and Inflation Adjustments

5.2.1 Obtain the True Price of Non-LSUM Standard Items in Current Contract

The first step in estimating is to obtain accurate prices (e.g., the last four quarters' moving average) for the non-LSUM standard items involved in the project/contract. This is accomplished by using historical bid data, monitoring economic factors, and checking the item index for variations.

- **Non-LSUM Standard Item Identification**:
    - Get non-lump sum (LSUM) standard items.
    - Flagging these items that exhibit high variability or susceptibility to price fluctuations.
- **Obtain Quantity-Weighted Quarterly Prices in the Last Quarter**.
    - **Frequency of Data Collection**: For items with unstable prices, especially during market volatility, update the quarterly unit bid price of each item more frequently (e.g., quarterly) instead of relying on averages from the past two years or similar projects.
    - When calculating quarterly prices, **exclude extreme outliers** that fall beyond a statistically acceptable range (e.g., more than 1.5 times the interquartile range or 3 standard deviations from the mean).
- **Use a Four-Quarter Moving Average**: Smooth out short-term fluctuations by averaging prices over the last four quarters to provide a balanced view of cost trends for pay items.
- **When There Is No Recent Data**:
    - **Adjust Older Data Using the Contract Index**: If there is no relevant historical data for the past quarter, use the historical **Contract Index values** to adjust older or incomplete information. This method updates outdated data to reflect current market conditions, ensuring a more accurate estimate for pay items.
    - **Review Bid Histories**: Analyze historical unit bid prices for similar items to establish a reliable baseline.
    - **Economic Factors Monitoring**: Continuously monitor major commodities such as **steel, asphalt, diesel, concrete, aggregates**, and labor rates (e.g., **Davis-Bacon prevailing wage rates**) to account for recent market changes and factor analysis results
    - **Leverage Expert Judgment**: When relevant data is scarce, rely on industry experience and expertise to develop pricing estimates, supplemented by analysis of bid patterns and market conditions.

5.2.2 Price Adjustments to Certain Pay Items Based on Market and Project Conditions

After obtaining the base prices in the last quarter for non-LSUM standard items, adjust the unit bid prices for specific market and project-related conditions. Various factors can influence the final estimate, and it is critical to account for them, such as the ones discussed in *Chapter 2, Identification of Factors in Construction Pricing*. These factors and their corresponding data can be compiled into a **dashboard** to facilitate cost estimation.

- **Adjust for Market Conditions**:

    - **Market Competition Monitoring**: Assess current market competition levels, such as the number of bidders (plan holders). Projects attracting more bidders typically result in lower unit bid prices due to increased competition.
    - **Unforeseen Market Conditions**: Be aware of unforeseen conditions like shifts in supply and demand that could impact pricing. These conditions can arise due to a variety of factors: **Supply Chain Disruptions**: Shortages in materials, delays in production, or transportation bottlenecks can cause spikes in prices. For example, unexpected interruptions in global supply chains (e.g., shortages of steel or concrete) can result in higher costs and project delays. **Labor Market Volatility**: Labor availability and wages can fluctuate due to economic conditions, regulatory changes (such as wage adjustments driven by prevailing wage laws like Davis-Bacon), or industry competition for skilled workers. In high-demand regions or times of labor shortages, these costs can increase sharply. **Logistics Challenges**: The cost of transporting materials to project sites can fluctuate due to fuel prices, availability of transportation resources, or shifts in global logistics systems. Projects that are geographically isolated or in regions with poor infrastructure may be particularly susceptible to logistics-driven price escalations.
- **Adjust for Project/Contract Conditions**:
    - **Quantity Adjustments**: Large quantities can reduce unit costs due to economies of scale, while smaller quantities may result in higher prices per unit.
    - **Complexity and Number of Items**: Projects with a high number of items or complex requirements often have higher unit bid price due to specialized work.
    - **Local Concerns and Requirements**: Account for local regulations, environmental considerations, and community impacts that may affect project costs.
    - **Scope Changes**: Be prepared to adjust estimates if project scope changes (e.g., number of pay items) occur during the planning phase.

5.2.3 Apply Cost Escalation Contingency to Current Contract

To ensure that project costs account for future **cost escalation**, a contingency is applied. This contingency acts as a buffer to manage **escalation risks**, including inflationary pressures, during the project's timeline, particularly up to the mid-point of construction.

- **Escalation Contingency Application**:
    - **Mid-Point of Construction**: Adjust estimates to account for **cost escalation** up to the mid-point of construction. Rather than projecting the current costs into future dollars, this adjustment is applied as a contingency to provide budget flexibility in managing **escalation pressures**, including inflation.
    - **Use of Contract Index**: Apply the **Contract Index's growth rate** (between last quarter and mid-point construction) to account for expected escalation, but treat the adjustment as a contingency, keeping the total estimate in **current dollars**.
- **Economic Factors and Unforeseen Events**:
    - Continuously monitor economic shifts, such as **commodity price fluctuations**, logistics challenges, and **supply chain disruptions** to further inform the contingency amount.

5.2.4 Additional Considerations

- **High Inflation Items (e.g., Steel, Asphalt, Diesel-Earthwork)**

Certain items, such as **steel**, **asphalt**, and **diesel for earthwork**, are particularly susceptible to high inflation rates due to fluctuations in commodity markets. These items require special consideration and more frequent updates to their unit bid price. **Frequent Updates**: When dealing with high-inflation items, regularly review and revise estimates based on real-time market changes to mitigate the risks associated with volatile material costs. For materials prone to inflation, it is suggested that commodity prices be continuously tracked and the estimate updated every **three months**. This helps to ensure that the most recent price data is reflected in the project estimate and avoids significant deviations in cost during construction.

- **Dashboard Monitoring**

Insights from dashboard monitoring could be used to refine estimates and ensure that the inflation contingency is sufficient. Market competition, economic disruptions, local concerns, and scope changes need to be considered when updating the contingency.

- **Tool Usage**

In this estimation process, the following tools could be used to facilitate the estimation**:**

MHCCI Tool: The **MHCCI tool** is a key resource for projecting contract-level and state-level inflation based on economic factors. This tool provides accurate quarterly and annual projections, helping to keep estimates up-to-date with the market and economic conditions.

AASHTOWare Project Estimation Tool: This tool supports item-based cost estimation by using historical bid data. AASHTOWare enables engineers to create estimates based on both historical trends, ensuring comprehensive and accurate projections. It can be used to retrieve the unit bid prices of pay items.

This estimation procedure combines historical bid-based estimating techniques with timely cost escalation considerations to develop accurate and reliable cost projections for construction projects. By applying adjustments for project-specific factors and accounting for inflation at both the item and contract level, It could ensure that projects are scoped with a clear understanding of potential cost fluctuations, improving budget planning and resource allocation.

5.2.5 Implementation Examples

Using the proposed estimation procedures, two contract examples were selected to demonstrate the new process. These contracts represent typical cases, with one large and one small project/contract based on contract values and the number of pay items.

Contract: 13051-207826

The project 13051-207826 involves **1.79 miles of hot mix asphalt (HMA) cold milling, resurfacing, and pavement markings** on M-66, located between north of Wanadoga Creek and Baseline Road in **Calhoun County, Michigan**. The letting date for this contract was **November 1, 2019**. The project duration was between May 21, 2020, and June 05, 2020. The scope includes various tasks such as **cold milling of HMA surface, HMA resurfacing, and detailed pavement markings**.

There is a total of **37 items**, with **4 items** being lump sum (LSUM) and the remaining items being unit-priced. Here's a breakdown of pay items:

LSUM Items:

1. **Mobilization, Max**: Covers contractor setup costs, including moving equipment and personnel to the site.
2. **Minor Traffic Devices**: Includes small traffic control devices such as cones and barriers used during the construction period.
3. **Traffic Regulator Control**: Involves controlling and regulating traffic safely around the work zone using flaggers or temporary signals.
4. **Contractor Staking, Road Only**: This task involves the contractor staking and laying out the project's road work according to design specifications.

Other Unit-Based Items (Examples):

- **Cold Milling HMA Surface** (29,880 square yards)
- **HMA, LVSP** (2,545 tons)
- **Hand Patching and HMA Approaches**
- **Pavement Markings**, including 4-inch and 6-inch waterborne markings in both white and yellow, applied in two layers for visibility and durability.
- **Channelizing Devices** and **Traffic Control** measures, such as lighted arrows and temporary signs.

The **HCCI for this contract** depicted in Figure 48 and Table 20 shows changes in MHCCI over time, starting from **2019 Q3** to **2021 Q1**. The cost index shows how prices of pay items **in this contract** have fluctuated. The upward trend observed in the graph highlights a consistent increase in construction costs over this period, with some fluctuations due to market conditions, supply chain issues, or economic events. The predicted index peaked at 1.4647, indicating significant cost pressures before a temporary dip (e.g., an 12.8% drop) in 2020 Q4, compared with the index in 2019 Q3.

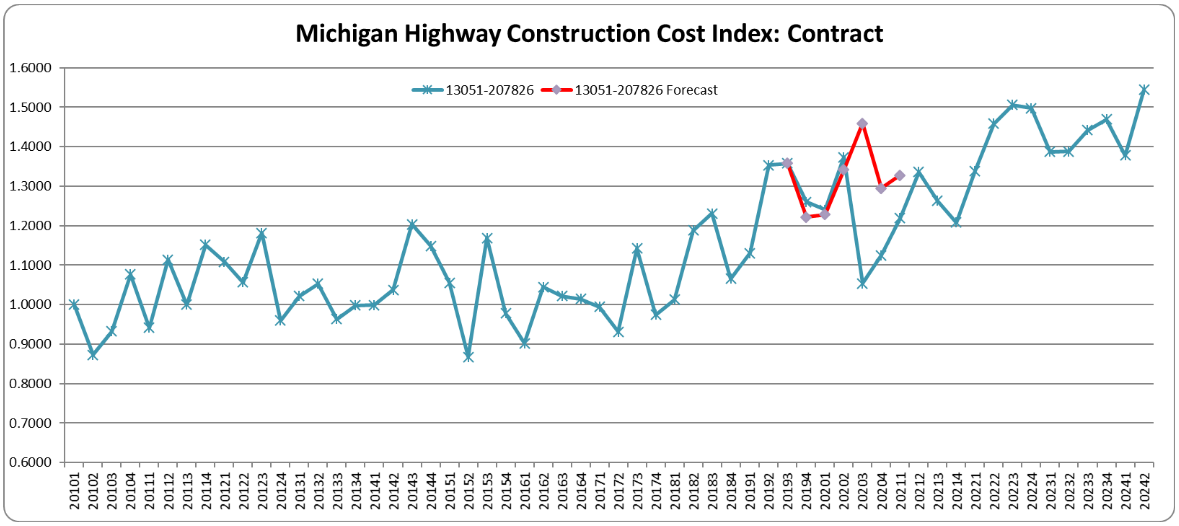

Figure 48. Actual and Forecasted HCCIs for Contract: 13051-207826

Table 20. Actual and Forecasted HCCIs for Contract: 13051-207826

Quarter	Actual Index	Forecasted Index	Growth Compared with Current Quarter
20193	1.3610	**1.3610**	
20194	1.2596	1.2220	
20201	1.2363	1.2312	
20202	1.4221	**1.3481**	
20203	1.0688	1.4647	
20204	1.1324	1.2982	1.3481/1.3610
20211	1.2215	1.3325	-1= -0.94%

Table 21 presents key metrics used to evaluate the accuracy of an index forecast for the contract 13051-207826. It shows a reasonable level of accuracy but has room for improvement. The MAE of 0.1316 and the RMSE of 0.1841 suggest that, on average, the forecast errors are relatively small. However, the MAPE of 11.56% indicates that the forecast deviates by nearly 11% from actual values, which may be acceptable but could be optimized for more precision. The MSE of 0.0339 suggests that larger errors are not common.

Table 21. Metric for the index forecast: 13051-207826

Metric	MAE	MSE	RMSE	MAPE
Value	0.1316	0.0339	0.1841	11.56%

For all non-lump sum standard items, the winner's total amount is $198,053.54, compared to the engineer's estimate of $295,429.79. The proposed new method results in an estimate of $270, 923.44, as shown in Table 22. Detailed descriptions are presented as follows:

Table 22. Cost Estimation Comparison 13051-207826: EE, index-based, and Winner's Bid

Method	Total Amount for Non-LSUM Standard Items
1st low Bid	$198,053.54
Index-based Method	$273,505.88 × (1-0.94%) = $270, 923.44
EE	$295,429.79

1. 1st Low Bid: $198,053.54

- This is the **actual bid** submitted by the lowest bidder for the project, excluding lump sum items. It represents the cost that the contractor has committed to completing the non-LSUM items of the project. This is the figure accepted for the contract.

2. Index-Based Method: $270, 923.44

- This is a calculated estimate based on an **index-based method**. The original estimate was **$273,505.88 using a Four-Quarter Moving Average of quarterly prices and item quantities in this contract**, but it was adjusted by a factor of **(1 – 0.94%)**. This adjustment likely reflects a **cost index reduction** accounting for recent market fluctuations (possibly based on quarterly adjustments in pricing indices), resulting in a revised total of **$270, 923.44**. The index-based method is used to adjust historical data to current market conditions.

3. EE (Engineer's Estimate): $295,429.79

- The **Engineer's Estimate (EE)** is an internal estimate prepared using the traditional bid-based estimation method. It represents what the project engineers believe the actual cost should be for completing the non-LSUM items. The EE is often used to evaluate bids for fairness, but in this case, it is higher than both the 1st low bid and the index-based method.

Based on the results, the **index-based method** offers a different estimate than the **engineer's estimate (EE)**. The index-based method, which adjusts historical data for recent market fluctuations, produced an estimate of $270, 923.44, closer to the actual low bid than the engineer's estimate. The adjustment of **0.94%** based on cost indices reflects responsiveness to current market trends, making this method more reliable than the unadjusted amount.

Contract: 07023-126827

The second example is the contract 07023-126827. This contract focuses on 2.17 miles of hot mix asphalt (HMA) reconstruction and bridge rehabilitation, including critical tasks such as full-depth deck patching, hot mix asphalt removal, and overlay. The project also involves improvements to drainage, guardrail installation, signing, and pavement markings to enhance the safety and longevity of the roadway and bridge. The letting date for this contract was **December 06, 2019**. The project duration was between April 28, 2020, and October 08, 2020. This project is typical of large-scale road and bridge reconstruction efforts aimed at extending the lifespan of critical infrastructure while improving safety for drivers.

There is a total of **176 items**, with **11 items** being LSUM and six non-standard items.

Key Tasks:

- **HMA Reconstruction**: Involves the removal of existing asphalt pavement and the application of new HMA layers to improve the road surface.
- **Bridge Rehabilitation**: Includes full-depth patching to repair and restore structural integrity, as well as resurfacing to improve the durability of the bridge deck.
- **Additional Infrastructure Work**: This includes drainage improvements, guardrails, and pavement markings, which are essential for roadway safety and functionality.

This contract also experienced fluctuations in the construction cost index over time, as represented by the HCCI for the quarters from **2019 Q3 to 2021 Q1 (see** Figure 49**)**. The predicted index values initially peaked in 2020 Q4 at 1.8217. The largest quarterly drop occurred in 2019 Q4, with the index decreasing by 9.4%, reflecting a period of easing cost pressures. The index then reached its lowest value in 2020 Q1 at 1.52, a decrease of 5.1% from the previous quarter, likely influenced by market disruptions, material supply constraints, or labor availability during the early stages of the pandemic. A recovery followed, with the index rebounding to a peak of 1.8217 in 2020 Q4 **(shown in** Table 23**)**.

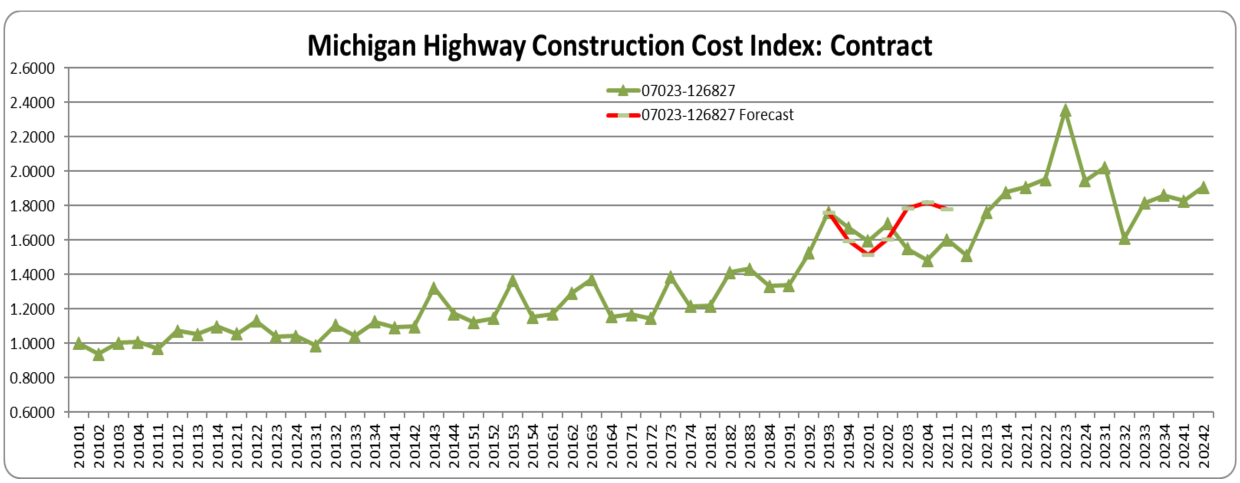

Figure 49. Actual and Forecasted HCCIs for Contract: 07023-126827

Table 23. Actual and Forecasted HCCIs for Contract: 07023-126827

Quarter	Actual Index	Forecasted Index	
20193	1.7639	1.7639	
20194	1.6746	1.5989	
20201	1.5957	1.5165	
20202	1.6963	**1.6075**	
20203	1.5520	**1.7853**	1.6964/ 1.7639-1= - 3.83%
20204	1.4834	1.8217	
20211	1.6027	1.7810	

The index prediction model demonstrates moderate performance, with an MAPE of 10.61% in Table 24, which indicates a medium level of precision in predicting index values. The MAE and RMSE values show that most predictions are close to the actual cost index, with several large errors. Overall, the model provides reasonable forecasts of the cost index, making it suitable for use in cost planning and financial projections, where accurate cost index estimates are crucial.

Table 24. Metric for the index forecast: 07023-126827

Metric	MAE	MSE	RMSE	MAPE
Value	0.1656	0.0368	0.1917	10.61

Table 25 compares three different methods for estimating project costs. Overall, the EE of $5,143,630.40 is the closest to the 1st low bid ($5,046,093.68), with a difference of only $97,536.72 (1.93%), demonstrating its strong alignment with real-world bidding outcomes. The index-based method, after applying a 3.83% reduction, estimates the cost at $5,411,693.21, which is further from the 1st low bid, with a difference of $365,599.53 (7.25%).

Table 25. Cost Estimation Comparison 07023-126827: EE, index-based, and Winner's Bid

Method	Total Amount for Non-LSUM Standard Items
1st low Bid	$ 5,046,093.68
Index-based Method	$5,626,935.19 × (1-3.83%) = $5,411,693.21
EE	$ 5,143,630.40

1. **1st Low Bid: $5,046,093.68**
    - This represents the lowest bid submitted for the project, excluding lump sum items. This is the winning bid that has been accepted for the project.
2. **Index-Based Method: $5,411,693.21**
    - The index-based method starts with an original estimate of **$5,626,935.19**. This was adjusted using the cost index, reducing the total by **3.83%** to account for market changes, yielding a final estimate of **$5,411,693.21**.
3. **Engineer's Estimate (EE): $5,143,630.40**
    - The engineer's estimate reflects a detailed calculation of expected costs based on material, labor, and project complexity. In this case, the EE is higher than both the 1st low bid and the index-based method, suggesting a more conservative cost projection by the project engineers.

This difference may be explained by the fact that this project involves **large quantities for certain pay items**, which tend to receive **quantity discounts** in real-world bidding, as demonstrated in Chapter 2 and Appendix A. Examples of the pay items are shown in Table 26. For instance, pay item 3020022 had a quantity of 24,801 Syd, with the EE unit price at $10.02 and the 1st low bid at $7.01. In comparison, the four-quarter average unit price, which does not account for quantity discounts, was approximately $13.65. In this example, such discounts were not applied, however, suggesting that **additional adjustments** to the unit bid prices for large quantities are necessary to improve its accuracy. While the index-based method remains valuable for accounting for **market fluctuations**, the EE's closer alignment with the 1st low bid underscores its effectiveness in reflecting actual bidding outcomes for projects where large quantities and corresponding discounts are significant factors.

Table 26. Unit Bid Prices for Certain Items in 07023-126827

Item	Description	Item Quantity	Unit	Bid Price (HCCI)	Engineer Estimated Unit Price	Bid Price from 1st Low Bidder
3020022	Aggregate Base, 9 inch	24801	Syd	$13.65	$10.02	$7.10
2040050	Pavt, Rem	32187	Syd	$10.42	$8.00	$5.40
3020016	Aggregate Base, 6 inch	33771	Syd	$8.96	$8.00	$4.90
3010002	Subbase, CIP	34990	Cyd	$14.94	$11.00	$12.10
8160100	Slope Restoration, Type A	36076	Syd	$3.27	$2.37	$1.10
5010045	HMA, 3E3	5292	Ton	$79.10	$76.00	$68.15
5010057	HMA, 5E3	6758	Ton	$84.35	$71.25	$76.30
5010005	HMA Surface, Rem	60555	Syd	$3.39	$2.50	$2.75
8160102	Slope Restoration, Type C	15718	Syd	$3.75	$3.05	$1.95
5010703	HMA, LVSP	6448	Ton	$69.59	$66.00	$66.25

5.3 Conclusion

This research demonstrated the application of the MHCCI and index-based methods in refining project cost estimates, showcasing their effectiveness through two contract examples. Key conclusions are as follows:

1. **Contract-Level MHCCI and Index Predictions**:
    - The index-based method effectively adjusts historical data to reflect market conditions, resulting in accurate cost projections. By applying quarterly historical cost trends and predictions, the method could integrate factors such as commodity prices, offering a reliable tool for adjusting estimates to account for cost escalation.
    - One of the contract examples highlighted that the index-based method could estimate closer to the actual low bids compared to the EE, with adjustments reflecting real-time market fluctuations. This demonstrates the potential for the index-based method to improve MDOT’s cost estimation processes.
    -

2. **Accuracy of Index Predictions**:
    - The metrics for index prediction models showed strong performance with low error rates across both contracts. For example, the MAPE of 10.61% for contract 07023-126827 and 11.56% for contract 13051-207826 indicate a moderate level of accuracy in forecasting cost index trends. These models can be valuable for long-term budget forecasting and financial planning but need to be further improved.
3. **Cost Escalation and Inflation Adjustments**:
    - Incorporating cost escalation adjustments through the MHCCI ensures that project estimates remain in current dollars, with built-in contingencies that buffer against inflation risks. This approach enhances budget flexibility, allowing MDOT to manage inflationary pressures without inflating costs into future dollars.
    - By utilizing these escalation-adjusted estimates in project selection, MDOT can prioritize projects with higher exposure to cost pressures and ensure that appropriate funding considerations are made.
4. **Practical Application in Project Development**:
    - Tools like the MHCCI and AASHTOWare offer significant benefits in project estimates for real-world conditions, ensuring that estimates reflect current market trends and mitigating the risks associated with volatile material and labor costs.

In summary, the research findings indicate that index-based methods, particularly those leveraging the MHCCI, provide a reliable framework for MDOT's cost estimation and budget planning processes.

Despite the success of using the MHCCI and index-based methods in refining cost estimates, there are several limitations and areas for future research that should be addressed:

1. **Data Availability and Quality**

    - **Limitation**: The accuracy of the MHCCI and index-based predictions heavily relies on the availability and quality of historical data on economic factors. If sufficient, high-quality data on economic factors are not available or incomplete, it may compromise the accuracy of the index prediction. Additionally, unforeseen market conditions such as supply chain disruptions or sudden economic shifts may not be fully reflected in the economic data.
    - **Future Research**: Further research could explore methods for enhancing the data collection process, such as incorporating real-time data streams or integrating external data sources (e.g., global commodity prices or regional economic indicators). This could improve the responsiveness of the index-based method to rapidly changing market conditions.

2. **Lump-Sum (LSUM) and Non-Standard Items Exclusion**

- **Limitation**: The research primarily focused on non-lump sum (non-LSUM) items for cost estimation, potentially overlooking a significant portion of project costs. Lump-sum and non-standard items, which often involve complex or unique aspects of a project, may not be as easily estimated through the index-based method.
- **Future Research**: Further research could develop methodologies for accurately estimating lump-sum items. Incorporating LSUM items into the model would provide a more comprehensive cost estimate, especially for complex or large-scale projects.

3. Long-Term Predictive Capabilities

- **Limitation**: While the MHCCI provides a reliable short-term estimate for cost escalation, its ability to predict long-term cost trends remains limited, particularly for projects spanning several years or beyond typical economic cycles.
- **Future Research**: Research could focus on improving the **long-term** forecasting capabilities of the MHCCI by incorporating macroeconomic models and inflation forecasting. A hybrid approach combining historical data with future-oriented models could enhance the index's prediction for long-term project planning.

6 STATE AND REGIONAL COST INDEX COMPARISON

Comparing the MHCCI across different regions and the state is crucial for understanding the variations in MHCCIs driven by local factors. These regional differences can be influenced by factors such as labor costs, material availability, transportation logistics, and market demand. Examining these variations can provide insight into the trends, anomalies, or inflationary pressures specific to each region. This comparison helps ensure more accurate cost projections, supports regionally tailored budget planning, and highlights areas where cost management strategies may need adjustment. Additionally, analyzing regional and state-level index variations can help forecast future cost trends, enabling proactive management of projects and resources across different areas. Ultimately, this approach improves the accuracy of cost estimates, enhances financial planning, and ensures that regional differences in construction cost trends are properly accounted for in project planning and execution. This chapter thus presents the comparison of regional annual MHCCI for the period of 2010-2023.

6.1 HCCI COMPARISON RESULTS

The analysis began by visualizing the index data and its statistics across different regions. This step provided an overview of how the MHCCI varies regionally, highlighting distinct patterns and fluctuations in the construction index over time. By employing data visualization techniques, such as trend plots and box plots, significant regional differences in the cost index were identified, which may result from factors such as market conditions. The statistical analysis was then conducted to complement the visual insights as it can quantify the extent of these variations, allowing us to pinpoint regions with higher or lower cost indices. This approach set the foundation for deeper comparative analyses and helped to ensure that the understanding of regional cost dynamics was both data-driven and statistically sound.

6.1.1 HCCI Trends Visualization

Figure 50 shows the trend of the annual MHCCIs across different regions over the years. It provides a clear comparison, highlighting how each region's cost index has evolved. Most regions show an upward trend in cost indices, indicating an overall increase in construction cost index over the years. However, different regions exhibit varying rates of increase. For instance, the Metro and University regions display a sharper rise compared to others, potentially reflecting urbanization, regional economic conditions, or specific construction market dynamics. The spikes in the trends might correspond to economic events, policy changes, or market disruptions. For example, the steep rise around 2021-2022 could be influenced by post-pandemic economic recovery and supply chain issues.

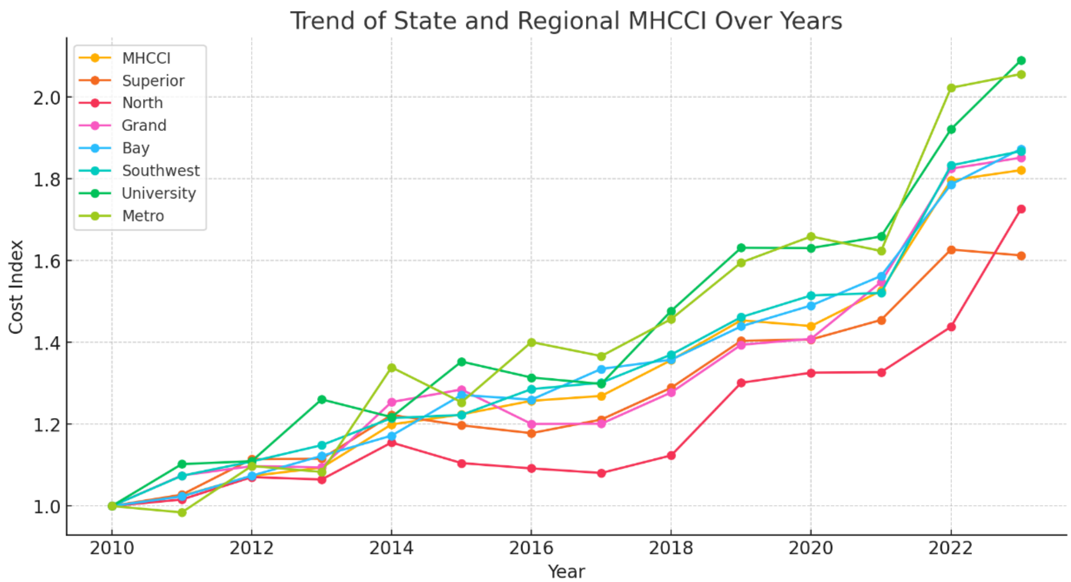

Figure 50. State and Regional MHCCIs over Years: Trend Lines

A distribution and statitisics of regional cost indices are shown in Figure 51 and Table 27, including the state-level MHCCI for comparison. The boxplot visually confirms the statistical findings. While most regions follow a similar cost index pattern as MHCCI, the **North** and **University** regions stand out with significant differences. These insights can guide further investigations into the unique factors affecting MHCCIs in these regions, enabling targeted strategies to address regional disparities. Some key statistical observations are as follows:

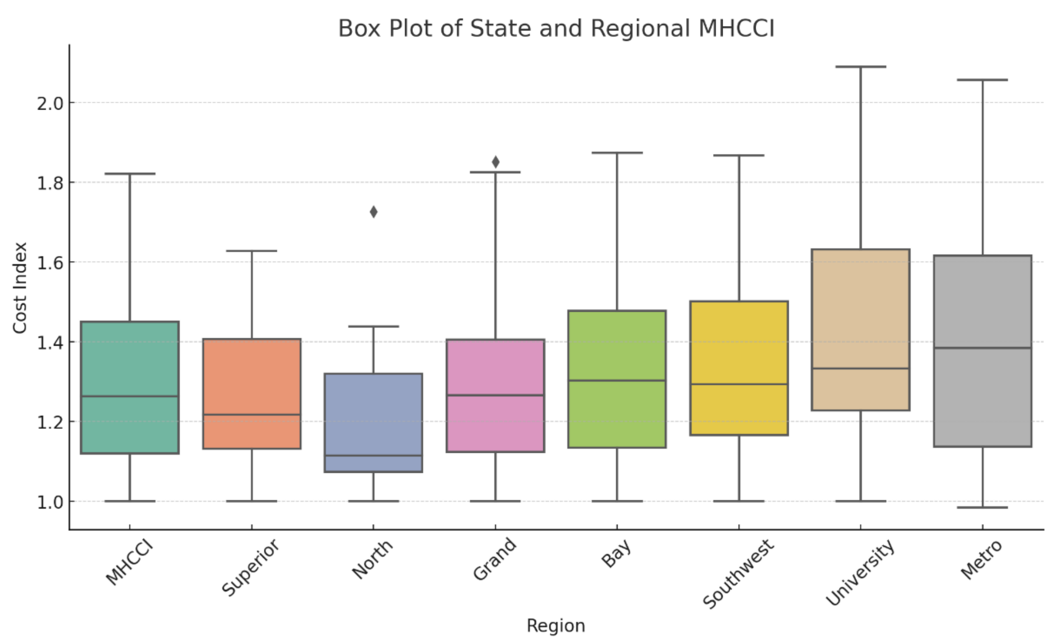

Figure 51. State and Regional MHCCIs: Box Plot

Table 27. Regional MHCCIs Statistics

	Superior	North	Grand	Bay	Southwest	University	Metro
Mean	1.2759	1.2019	1.3223	1.3405	1.3517	1.4331	1.4242
Standard Deviation	0.1990	0.2014	0.2632	0.2686	0.2643	0.3182	0.3417
Minimum	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9844
25th Percentile (Q1)	1.1312	1.0733	1.1233	1.1350	1.1653	1.2282	1.1368
Median (Q2	1.2170	1.1144	1.2659	1.3033	1.2936	1.3336	1.3837
75th Percentile (Q3)	1.4063	1.3198	1.4051	1.4775	1.5015	1.6311	1.6164
Maximum	1.6270	1.7259	1.8514	1.8730	1.8674	2.0893	2.0559

1. **Median Comparisons**: The medians of MHCCI, Superior, Grand, Bay, Southwest, University, and Metro are relatively close, indicating similar central tendencies. The North region has a lower median compared to the others, which aligns with the statistical results indicating significant differences from MHCCI and other regions.
2. **IQR and Variability**: The North region has a narrower IQR, suggesting less variability in its cost indices compared to other regions. University and Metro have wider IQRs, indicating greater variability in their cost indices.
3. **Range**: Most regions have a similar range, except for University, which shows a slightly wider range.
4. **Outliers and Extremes:** The North region has one outlier, which might indicate an unusual cost index value for a particular year.
5. **Consistency with MHCCI**: Superior, Grand, Bay, Southwest, and Metro have similar medians and IQRs compared to MHCCI, indicating that their cost indices are generally in line with the state-wide average.

The following sections provide a detailed analysis of the statistics for specific regions, including the Metro, University, and North regions. These three were chosen because the Metro and University regions have experienced sharper cost increases compared to other areas. In contrast, the North region saw a slower rate of increase, making it a useful point of comparison.

6.1.1.1 Metro Region

The Metro region stands out with the highest median and significant variability in construction cost indices. These observations highlight the need for targeted cost management strategies and further investigation to understand the underlying factors contributing to the higher and more variable construction costs in this region. By addressing these factors, stakeholders can work towards more consistent and manageable construction costs in the Metro region. Below are the key observations for the Metro Region:

1. **High Median Cost Index**: The median cost index for the Metro region is 1.3837, which is the highest among all the regions. This indicates that the central tendency of construction costs in the Metro region is higher compared to other regions.
2. **High Variability**: The standard deviation of 0.3417 is relatively high, indicating significant variability in the cost indices within the Metro region. This suggests that there is a wide range of MHCCI in this region.

3. **Wide Range**: The cost indices in the Metro region range from a minimum of 0.9844 to a maximum of 2.0559. This wide range shows that its MHCCI can vary greatly from year to year in the Metro region.
4. **Interquartile Range (IQR)**: The IQR for the Metro region spans from 1.1368 (Q1) to 1.6164 (Q3). This wide IQR indicates that the middle 50% of the cost indices are spread out, reflecting variability in the typical construction costs.
5. **Outliers and Extremes**: The minimum value of 0.9844 is slightly below 1, and the maximum value of 2.0559 is the second-highest value among all regions (after University), indicating that the Metro region experiences some extreme values in cost indices.

These statistical observations have several important implications:

1. **Higher Construction Costs**: The higher median and mean values suggest that, on average, MHCCI in the Metro region are higher than those in other regions. This might be due to factors such as **higher urbanization, increased demand for construction services**, **higher labor costs**, and **more expensive materials**.
2. **Significant Variability**: The high standard deviation and wide range indicate that MHCCI in the Metro region is not consistent and can vary significantly. This could be due to various project types, fluctuations in local economic conditions, and changes in market dynamics over the years.
3. **Further Investigation**: The significant variability and higher cost index in the Metro region warrant further investigation into specific factors driving these costs **(see Section 6.1.3)**. This might include analyzing local regulations, economic conditions, supply chain issues, labor market dynamics, and other relevant factors.

6.1.1.2 University Region

The University region stands out with one of the highest median values and significant variability in construction cost indices. Below are the key observations for the University Region:

1. **High Median Cost Index**: The median cost index for the University region is 1.4331, which is one of the highest among the regions. This indicates that the central tendency of construction costs in the University region is higher compared to many other regions.
2. **High Variability**: The standard deviation of 0.3182 is relatively high, indicating significant variability in the cost indices within the University region. This suggests that there is a wide range of construction cost index in this region.
3. **Wide Range**: The cost indices in the University region range from a minimum of 1.000000 to a maximum of 2.0893. This wide range shows that the construction cost index can vary greatly from year to year in the University region.
4. **Interquartile Range (IQR)**: The IQR for the University region spans from 1.2282 (Q1) to 1.6311 (Q3). This wide IQR indicates that the middle 50% of the cost indices are spread out, reflecting variability in the typical construction costs.
5. **Outliers and Extremes**: The maximum value of 2.0893 is the highest among all regions, indicating that the University region experiences some extreme values in cost indices.

These statistical observations have several important implications:

- **Higher Construction Costs**: The higher median and mean values suggest that, on average, MHCCI in the University region are higher than those in other regions. This might be due to factors such as specialized construction projects, and possibly higher quality or specialized materials and labor.
- **Significant Variability**: The high standard deviation and wide range indicate that construction cost index in the University region is not consistent and can vary significantly. This could be due to a variety of project types, fluctuations in local economic conditions, and changes in market dynamics over the years. The wider IQR and higher range suggest more variability and potentially higher cost indices, aligning with the significant difference from MHCCI found in the statistical tests (see the next section).
- **Further Investigation**: The significant variability and higher costs in the University region warrant further investigation into specific factors driving these costs. This might include analyzing local regulations, economic conditions, supply chain issues, labor market dynamics, and other relevant factors.

6.1.1.3 North Region

The lower median and narrower IQR for the North region indicate consistently lower cost indices, which is consistent with the significant differences found in the statistical tests (see the next section).

6.1.2 Regional HCCI: Significant Difference

With these visualizations, the index variations across regions can clearly be observed. To determine if these differences are statistically significant, further statistical tests were conducted. This approach allows us to quantify the extent of regional disparities and assess whether the observed variations are due to random fluctuations or represent meaningful differences in construction cost index.

6.1.2.1 Normality Check

Many statistical tests, such as t-tests, ANOVA, and regression analysis, assume that the data (or the residuals/errors in the case of regression) are normally distributed. If this assumption is violated, the results of these tests may not be valid. In this study, the Shapiro-Wilk test was first used to check the normality of these MHCCI results. The Shapiro-Wilk test is a widely used statistical test to determine whether a sample comes from a normally distributed population. Table 28 shows the normality test results of MHCCI for different regions based on the p-value. A p-value greater than 0.05 indicates that the data is normally distributed (fail to reject the null hypothesis $\mathbf{H_0}$), while a p-value less than 0.05 indicates the data is not normally distributed (reject $\mathbf{H_0}$). As shown in the table, The **MHCCI**, **Superior**, **Grand**, **Bay**, **Southwest**, **University**, and **Metro** regions all have p-values above 0.05, indicating their data is normally distributed. The **North** region has a p-value of 0.02, meaning its data is not normally distributed.

Table 28. Shapiro-Wilk test: Regional MHCCIs

Region	Statistics	p-value	Conclusion
MHCCI	0.92	0.21	Data is normally distributed (fail to reject H0)
Superior	0.94	0.39	Data is normally distributed (fail to reject H0)
North	0.85	0.02	Data is not normally distributed (reject H0)
Grand	0.91	0.13	Data is normally distributed (fail to reject H0)
Bay	0.92	0.24	Data is normally distributed (fail to reject H0)
Southwest	0.92	0.25	Data is normally distributed (fail to reject H0)
University	0.94	0.39	Data is normally distributed (fail to reject H0)
Metro	0.93	0.32	Data is normally distributed (fail to reject H0)

6.1.2.2 Friedman Test for Overall Comparison

The data for the North region is not normally distributed, so a **non-parametric test** should be used to assess significant differences. In this research, the Friedman Test is used for an overall comparison across all regions (or groups), and the Wilcoxon Signed-Rank Test with Bonferroni Correction is used for pairwise comparisons between these regions (or groups). These tests help to understand if there are significant differences in MHCCIs between the groups.

Table 29. Friedman Test: Regional MHCCIs

Region	Statistics	p-value	Conclusion
Friedman Test	45.231	0.000	Significant difference between regions (reject H_0)

The Friedman Test (see Table 29) indicates a statistically significant difference in cost indices across the regions. This means that the cost indices vary significantly between at least some of the regions.

6.1.2.3 Wilcoxon Signed-Rank Test for Pairwise comparison

Wilcoxon Signed-Rank Test results are summarized in Table 30. It represents pairwise comparisons between the MHCCI for various regions, including the North, University, Grand, Bay, and Southwest regions. Each comparison highlights the corrected p-value, indicating whether the cost index in a particular region differs significantly from either the statewide average (MHCCI) or another region. A corrected p-value of 0.041 across all comparisons signifies that the cost index in the North region is consistently distinct from the statewide average and the other regions analyzed.

Table 30. Wilcoxon Signed-Rank Test: **Significant Differences in** Regional MHCCIs

Comparison	Corrected p-value	Interpretation
MHCCI vs North	0.041	The cost index in the North region is significantly different from the statewide average (MHCCI).
MHCCI vs University	0.041	The cost index in the University region is significantly different from the statewide average (MHCCI).
North vs Grand	0.041	The cost index in the North region is significantly different from the Grand region.
North vs Bay	0.041	The cost index in the North region is significantly different from the Bay region.
North vs Southwest	0.041	The cost index in the North region is significantly different from the Southwest region.
North vs University	0.041	The cost index in the North region is significantly different from the University region.

These results provide a clear picture of how specific regions compare to the overall state-wide average cost index (MHCCI) and to each other. Here are some key findings:

1. **MHCCI vs North**: The North region has a cost index significantly different from the state-wide average, indicating unique factors affecting construction cost index in this region.
2. **MHCCI vs University**: The University region also differs significantly from the state-wide average, suggesting specific local conditions influencing construction costs.
3. **North vs Other Regions**: The North region shows significant differences with multiple other regions (Grand, Bay, Southwest, University), highlighting it as a region with distinct cost dynamics.
4. **Consistency with MHCCI**: Regions like Superior, Grand, Bay, Southwest, and Metro do not show significant differences from MHCCI, suggesting that their cost indices are in line with the statewide average.

The North and University regions stand out as having cost indices that significantly differ from the state-wide average (MHCCI). This could be due to various factors such as regional economic conditions, availability of resources, or market competition.

Wilcoxon Signed-Rank Test results also revealed some non-significant differences, as shown in Table 31. The regions Superior, Grand, Bay, Southwest, and Metro have cost indices that are statistically consistent with the state-wide average (MHCCI). This suggests that the factors influencing construction costs in these regions are similar to those affecting the overall state average.

Table 31. Wilcoxon Signed-Rank Test: Non-**Significant Differences in** Regional MHCCIs

Comparison	Corrected p-value	Comparison	Corrected p-value
MHCCI vs Superior	0.776	North vs Metro	0.083
MHCCI vs Grand	1	Grand vs Bay	1
MHCCI vs Bay	0.776	Grand vs Southwest	0.648
MHCCI vs Southwest	0.052	Grand vs University	0.083
MHCCI vs Metro	0.13	Grand vs Metro	0.445
Superior vs North	0.162	Bay vs Southwest	1
Superior vs Grand	1	Bay vs University	0.066
Superior vs Bay	0.367	Bay vs Metro	0.367
Superior vs Southwest	0.083	Southwest vs University	0.083
Superior vs University	0.083	Southwest vs Metro	0.538
Superior vs Metro	0.162	University vs Metro	1

From the visual trends, it's apparent that MHCCI and certain regions have similar patterns over time, but the statistical analysis provides more precise insights into whether these patterns translate into significant differences in cost indices. Here's a deeper analysis into why some regions do not show significant differences from MHCCI:

Similar Trends but Different Values

1. **Visual Similarity**: Even if the trends of MHCCI and some regions appear visually similar (following the same upward or downward patterns over time), the actual values of the cost indices might not be significantly different. This means the general movement of costs is similar, but the absolute levels of those costs might vary.
2. **Statistical Significance**: The Wilcoxon signed-rank test examines whether the differences between paired samples are consistently different from zero. If the differences between MHCCI and the cost indices of Superior, Grand, Bay, Southwest, and Metro are not large or consistent enough, they will not be statistically significant even if the trends are similar.

Lack of Significant Differences: Key Factors

1. **Magnitude of Differences**: The actual differences in cost indices between MHCCI and these regions might be small. For example, if the cost indices for Superior, Grand, Bay, Southwest, and Metro fluctuate around the MHCCI values with minor variations, these small differences might not reach statistical significance.
2. **Within-Group Variability**: High variability within each region's cost indices can make it harder to detect significant differences. If the cost indices for Superior, Grand, Bay, Southwest, and Metro vary widely within themselves, it can obscure differences when compared to MHCCI.
3. **Sample Size**: The number of observations (years) used in the analysis affects the power of the test. With a small sample size, even moderately large differences might not be

detected as significant. Only ten years of data might limit the ability to find significant differences.

The actual values of the cost indices are not significantly different from MHCCI for Superior, Grand, Bay, Southwest, and Metro. This lack of significant difference indicates that these regions follow the overall state-wide cost trends closely, both in pattern and in value. The analysis confirms that these regions are aligned with the state-wide average, suggesting homogeneity in the factors influencing construction costs in these regions. This insight helps to focus further investigation and resources on the regions that do show significant differences, such as **North** and **University (see** Figure 52**)**, to understand and address the unique factors affecting their cost indices.

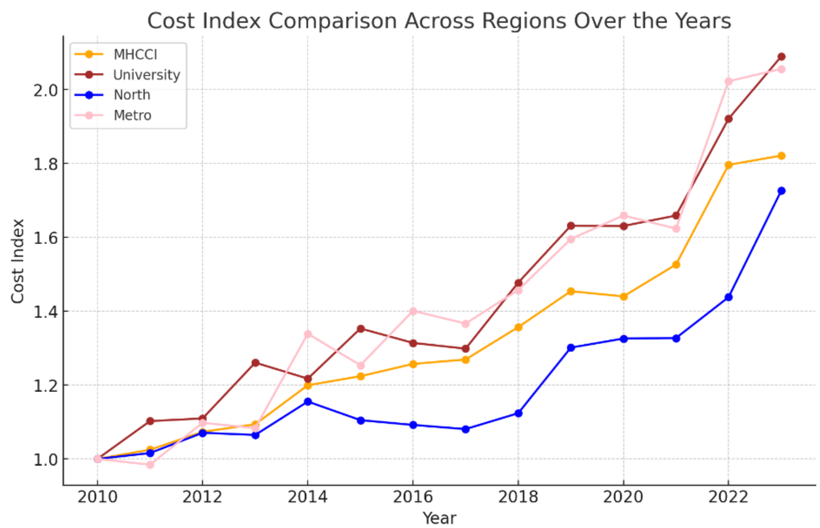

Figure 52. MHCCI Trend Lines: State, University, North, Metro

The Wilcoxon signed-rank test results show that Metro is not significantly different from MHCCI, while University is significantly different from MHCCI. Metro and MHCCI might share similar trends over time, meaning their cost indices move in parallel even if the absolute values differ. This parallel movement can result in a non-significant Wilcoxon test outcome because the paired differences over time may cancel out. The variability within the Metro and MHCCI indices might overlap, meaning that the differences in their distributions are not substantial enough to be statistically significant. The University trend line shows more pronounced deviations from MHCCI compared to Metro. University's cost index occasionally diverges significantly from MHCCI, especially in the later years, indicating different underlying factors affecting the cost index in University.

6.1.2.4 Cliff's Delta values

The heatmap with Cliff's Delta values provides a comprehensive view of the **differences** in cost indices across regions, including the state-wide average (MHCCI). Cliff's Delta values, which range from -1 to 1, are used to compare cost indices between regions. A positive value suggests that the cost index in the row region is generally higher than in the column region, while a negative value indicates the opposite. A value of zero signifies no difference between the regions. The strength of these differences can be inferred from the Delta values: values close to ±1 indicate a strong difference, while values near zero suggest little to no difference. The heatmap (Figure 53) represents the pairwise comparisons between regions using Cliff's Delta values, including MHCCI (the state-wide average index).

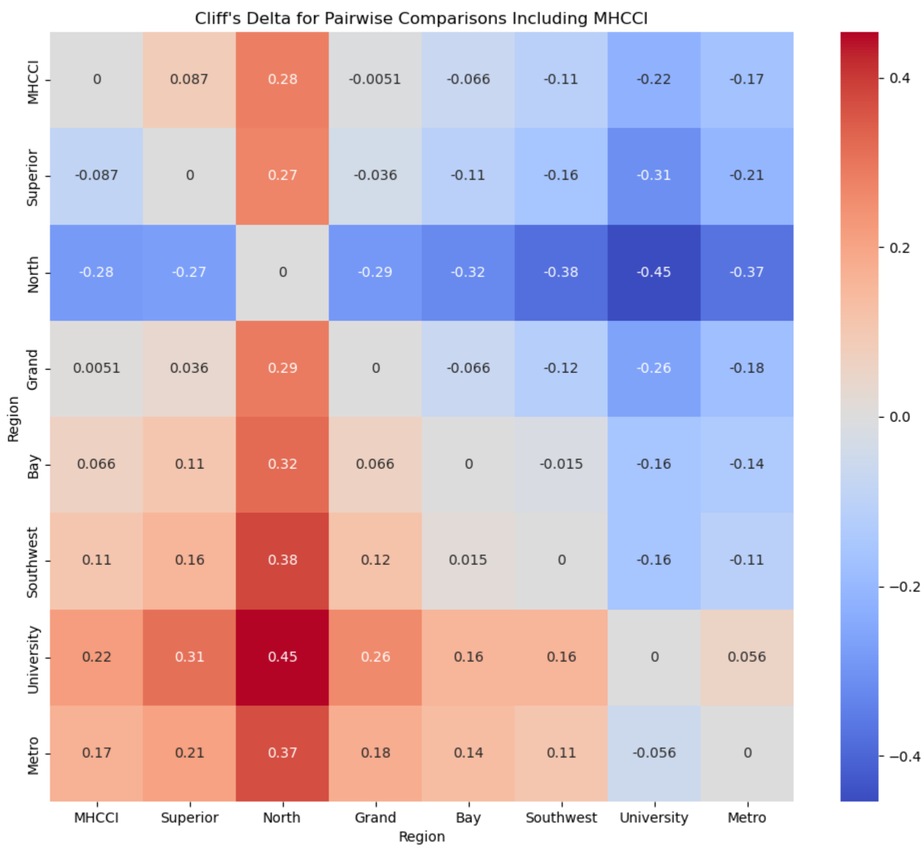

Figure 53. Heat Map of Cliff's Delta Values

The findings are summarized below:

1. **MHCCI Comparisons**:
    - **MHCCI vs. Superior**: Positive value (0.087), indicating that the state-wide average (MHCCI) tends to be slightly higher than Superior.
    - **MHCCI vs. North**: Positive value (0.28), indicating that MHCCI is generally higher than North.

- **MHCCI vs. University**: Negative value (-0.22), indicating that University tends to have a higher cost index than the state-wide average (MHCCI).
- **MHCCI vs. Metro**: Negative value (-0.17), indicating that Metro tends to have a higher cost index than MHCCI.

2. **Regional Comparisons**:
    - **North vs. Other Regions**: North generally shows negative values compared to other regions (Superior, Grand, Bay, Southwest, University, Metro), indicating it tends to have lower cost indices.
    - **University vs. Other Regions**: University has positive values compared to all other regions, with the highest positive value against North (0.45). This indicates that University has higher cost indices compared to other regions.
    - **Metro vs. Other Regions**: Metro shows positive values against North, Superior, and Grand, indicating it tends to have higher cost indices. However, it has lower values against University.
3. **Grand vs. Other Regions**:
    - Grand shows mostly positive values against Superior and North, indicating it tends to have higher cost indices. However, it shows negative values against Southwest, University, and Metro.

In short, the MHCCI, which represents the state-wide average, generally has higher construction cost indices than North and Superior, but lower indices than University and Metro. This suggests that the construction cost indices in University and Metro are higher than the state-wide average, while those in North and Superior are lower. North, in particular, tends to have the lowest cost indices compared to other regions and the state-wide average. On the other hand, University stands out with the highest cost indices among all regions and the state-wide average. Metro's cost indices are higher than those of North and Superior, but still lower compared to University.

The practical implications of these findings are as follows: 1) The regions with lower cost indices, such as North and Superior, may require fewer resources for construction compared to regions with higher indices like University and Metro; 2) Cost Management: Regions with higher construction cost indices, such as University and Metro, may necessitate more stringent cost management and budgeting strategies to ensure financial efficiency; 3) Benchmarking: The state-wide average, represented by MHCCI, serves as a benchmark for comparing the cost indices of each region. This can help in identifying which regions are above or below the average, providing valuable insights for strategic planning and decision-making; 4) Further Investigation: It would be beneficial to understand the factors contributing to the higher cost index in regions like University and Metro. This understanding could inform strategies to manage and potentially reduce construction costs in these regions, leading to more efficient resource utilization.

6.1.3 Underlying Factor Analysis

The statistics in the previous subsection confirm that the regions that do show significant differences, such as North and University. The other regions are aligned with the state-wide average, suggesting homogeneity in the **factors** influencing construction cost index in these regions. Further investigation into the regions such as North and University, is required to understand and address the unique factors affecting their cost indices.

6.1.3.1 Potential Factors Contributing to Regional MHCCI

There are numerous factors that can contribute to or affect regional MHCCI. In this research, several categories of these factors (see Table 32) are analyzed. By analyzing these features collectively, a comprehensive view of the factors influencing the MHCCI is obtained.

1. **Demographic and Labor Market Features:** This includes data related to population, workforce, and employment conditions in various regions. These factors are crucial for understanding the availability and cost of labor, which significantly impacts construction costs.
2. **Economic Features:** These provide insights into the broader economic context in which construction activities occur. They capture the overall economic health and performance of the regions, influencing construction costs and activities.
3. **Construction Activity Features:** This category includes data on the spending and volume of construction contracts. These features are essential for analyzing the financial aspects of construction activities and understanding spending patterns.
4. **Contract Characteristics:** These provide details about the specific characteristics of construction contracts, such as the number of bidders and contract values. They are crucial for understanding the nature and complexity of construction projects.

The data for these factors were collected from various Michigan-specific agencies and national sources focused on state-level statistics. For instance, **Population** and **Income** data are sourced from the **Michigan Department of Technology, Management, and Budget (DTMB)** and the **U.S. Census Bureau**, providing insights into demographic and economic conditions specific to Michigan. **Labor Force** and **Unemployment Rate** statistics come from the **Bureau of Labor Market Information and Strategic Initiatives (BLMISI)**, which tracks employment trends across the state. **GDP (Construction)** and **GDP (All Industries)** figures are reported by the **Regional Economic Analysis Project (REAP)**, offering insights into Michigan's economic performance across sectors, including construction. However, only five years of Regional **GDP** data in Michigan, covering the period from 2017 to 2022, was collected. Due to the limited availability of this data, it was excluded from the analysis. Data on the **Number of Contracts Per Region** and **Total Amount Per Region** are provided by the **MDOT**, which tracks infrastructure projects and associated funding at both regional and state levels.

Table 32. Underlying Factors for Regional MHCCIs Discrepancy

Category	Name	Note
Economic Indicators		
	GDP (All Industries)	The total gross domestic product of the region, representing the overall economic output
	GDP (Construction)	The gross domestic product, specifically from construction activities, indicating the value of construction work done within the region
Construction Market		
	NUM_CONTRACTS__PER_REGION	The number of construction contracts awarded per year in the region.
	TOTAL_AMOUNT_PER_REGION	The total monetary value of construction contracts awarded per year in the region
	NUM_CONTRACTS_PER_YEAR_STATE	The number of construction contracts awarded per year at the state level
	TOTAL_AMOUNT_PER_YEAR_STATE	The total monetary value of construction contracts awarded per year at the state level
Demographic and Labor Market		
	Population	The total number of people residing in the region.
	Labor Force	The total number of people available for work, including both the employed and the unemployed
	Unemployment Rate	The percentage of the labor force that is unemployed and actively seeking employment.

Category	Name	Note
	Income	The average income level of individuals within the region.
	Number Jobs	The total number of jobs available in the region
Contract Characteristics (Mean per year)		
	AWARDED AMOUNT	The average amount awarded for construction contracts
	Num of Items	The number of items or tasks included in construction contracts
	Number Bidders	The average number of bidders for construction contracts, indicating the level of competition
Temporal Factors		
	YEAR	The year in which the data was collected

Table 33 provides 2022 data as an example, highlighting key statistics across categories.

Table 33. Regional Economic Factors: 2022 Calendar Year

	Superior	North	Grand	Bay	Southwest	University	Metro
Population	8807.00	10417.00	121210.00	102821.00	152900.00	79748.00	874195.00
Labor Force	3228.00	3867.00	62102.00	48979.00	71953.00	40317.00	443204.00
Unemployment Rate	7.20	6.70	3.60	5.10	4.40	3.80	3.70
Income	362593.00	514811.00	6660219.00	5106814.00	9221598.00	4530790.00	47046713.00
Number Jobs	3714.00	3528.00	58179.00	47472.00	83837.00	29778.00	479319.00
GDP (Construction)	10615.00	8431.00	384421.00	145636.00	264385.00	198672.00	2434194.00
GDP (All Industries)	304246.00	280942.00	6056634.00	4591500.00	9029909.00	2856494.00	46794637.00
NUM_CONTRACTS_ PER_REGION	37.00	31.00	31.00	42.00	31.00	44.00	38.00
TOTAL_AMOUNT_ PER_REGION	95669300.70	102903790.53	89932467.96	154239186.78	257558991.92	557902384.02	509784423.23
NUM_CONTRACTS_ STATE	254.00						
TOTAL_AMOUNT_ _STATE	1767990545.14						
AWARDED AMOUNT (Mean)	3811901.38	1887520.78	2901047.35	3577068.49	8522246.05	10772258.28	22294860.03
Num of Items (Mean)	68.02	59.04	100.32	79.50	83.00	115.14	131.63
Number Bidders (Mean)	2.05	2.71	2.45	2.88	2.70	3.09	2.56
MHCCI	1.2759	1.2019	1.3223	1.3405	1.3517	1.4331	1.4242

6.1.3.2 Visualization of Potential Factors Contributing to Regional MHCCI

Figure 54 shows the trend lines for the average number of bidders per contract over time from 2010 to 2022 across different regions. Overall, there is a declining trend in the number of bidders across most regions from 2010 to 2022. This suggests a reduction in competition for construction projects over the years. The North region exhibits a fluctuating trend with a slight decline towards the end of the period. The Grand region initially starts high but shows a notable decline after 2011, stabilizing around 3 bidders from 2014 onwards. The University region experiences a steady decline in the number of bidders with significant variability. The Metro region starts with a higher number of bidders but shows a significant decline over time, especially from 2010 to 2012, and then fluctuates around 3 bidders.

In short, Superior and North Regions show a significant drop in the number of bidders, indicating lower competition. Despite some fluctuations, the Metro region consistently has more bidders compared to others, reflecting higher competition in this urban area. Grand and Bay Regions also show variability but generally have more stable trends compared to others. **In 2011,** most regions, except for Metro, show lower numbers of bidders around 2011.

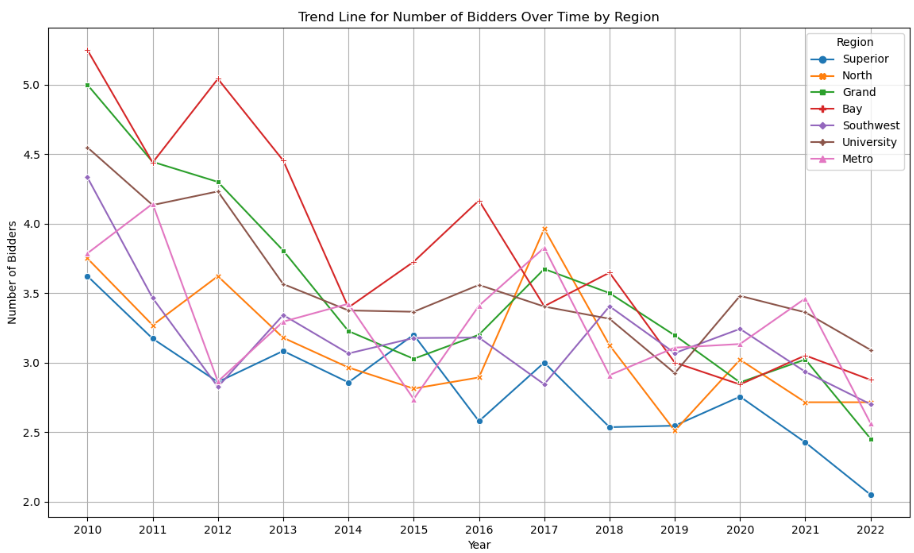

Figure 54. Number of Bidders per Contract Over Time by Region

In Michigan, there were 600 prequalified contractors in 2021 (Liu et al., 2021). For 2024, this number has slightly increased to 601, indicating minimal change over the period. Figure 55 illustrates the distribution of bidders across various regions in 2024, with the largest portion categorized as Unknown (40.3%). The **Metro** region follows, comprising **20.6%** of the total, while the **Bay** (10.0%) and **Grand** (9.0%) regions account for smaller portions

Figure 56 presents the bar chart of the top 50 cities by vendor count in 2024. Detroit has the highest number of vendors: With a count exceeding 20, Detroit leads all other cities in terms of vendor presence for construction projects. This suggests that Detroit is a major hub for vendors working on state transportation projects. Grand Rapids and Shelby Township also have significant vendor counts: Both cities show vendor counts close to 20, indicating they are key locations for contractors, likely due to the demand for infrastructure projects in these areas. It reflects the strong concentration of vendors in larger metropolitan areas, while smaller cities and townships also participate but with fewer vendors.

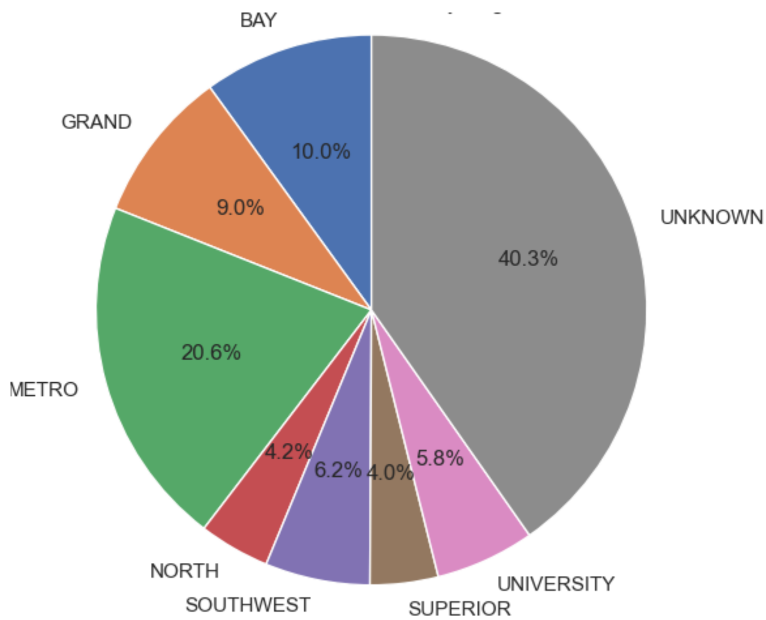

Figure 55. Number of Prequalified Bidders per Region

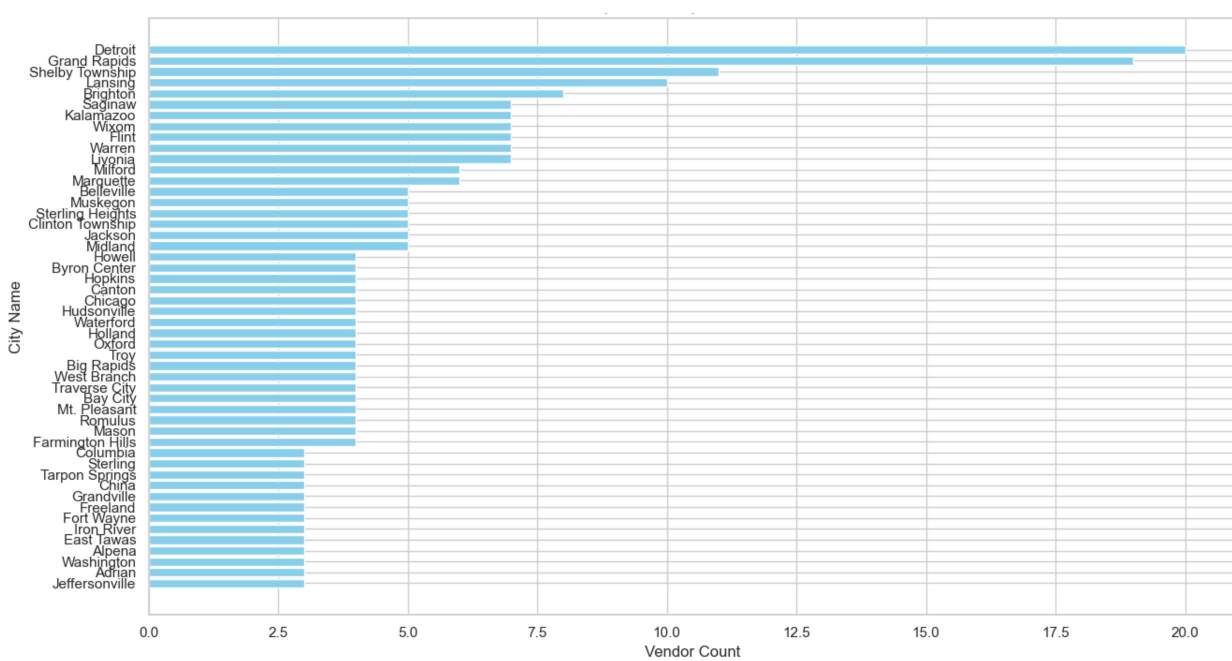

Figure 56. Number of Prequalified Bidders per City: Top 50 Cities

Figure 57 represents the number of bidders who have bid on MDOT construction contracts for each year from 2010 to 2023. There seems to be a general downward trend in the number of unique bidders during this period. In 2010, **233** unique vendors bid, while by 2023, this number had dropped to **114**. This indicates that fewer vendors have been bidding on contracts over time. While there is an overall decline, there are fluctuations. For instance, from 2011 to 2013, the number of bidders was relatively stable, hovering between **189** and **193**, but then it dropped significantly in 2014 to **154** and continued decreasing in the subsequent years, reaching a low of **114** in 2023. This decrease in the number of bidders might reflect a consolidation in the market, where fewer companies are competing for contracts, or it could indicate that there are barriers to entry for new bidders.

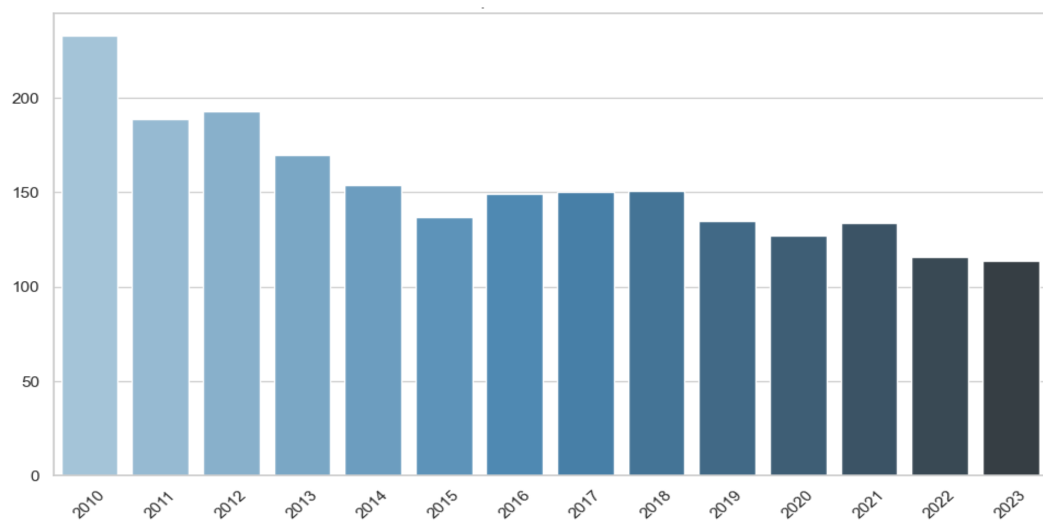

Figure 57. Total Number of Bidders over Years

Figure 58 shows the number of **bidders** by **year** and **region** who bid on the MDOT construction projects. Similar to the overall trend observed in the previous analysis, there is a noticeable general decline in the number of unique vendors bidding over the years, with a few regions demonstrating more significant drops than others. **2010** had a high number of bidders across all regions, ranging from 51 bidders in the North region to 103 in the Grand region. By 2023, vendor participation had decreased across most regions, with counts now ranging between 26 and 48, a stark contrast from the higher numbers observed at 2010.

- Most Affected (Decline):
    - The Superior region saw one of the sharpest declines in vendor participation. From 56 unique vendors in **2010**, this number dropped to just **26** in **2023**. The lowest point for this region occurred in **2022**, with only **19 bidders**, marking more than a **50% reduction** since 2010.
    - The Bay region experienced a decline from **102 bidders in 2010** to **43 bidders in 2023**. While still maintaining a relatively strong showing compared to other regions, the Bay region has nearly **halved its vendor count (i.e., bidders)** over this period.

- Southwest Region saw a drop from **76 bidders in 2010** to **34 bidders in 2023**, marking a significant decrease. The decline has been relatively steady over the years, with a low of **28 bidders in 2022**.

- Least Affected:

  - The University region has remained resilient, maintaining a steady vendor participation over the years. Starting with **87 bidders in 2010**, it only saw a minor decline, standing at **48 bidders in 2023**. In fact, it experienced a peak of **60 bidders in 2021**, indicating that this region continues to be attractive to vendors.
  - The Metro region, while not immune to the general downward trend, has experienced a more gradual decline. Starting with **72 bidders in 2010**, it fell to **34 bidders in 2023**. Despite a low point of **36 bidders in 2020**, the region has maintained a fairly stable number of participants in the past few years.
  - The Grand region also shows a more moderate decline in participation, starting with **103 bidders in 2010** and ending at **42 bidders in 2023**. Although this is a significant reduction, the region's vendor count has stayed relatively consistent since **2021**.

In short, a trend of declining vendor participation in MDOT construction projects across almost all regions from 2010 to 2023. Despite this, regions like **University** and **Metro** continue to attract a relatively stable number of bidders, while **Superior** and **Bay** regions have seen the most substantial reductions in vendor participation.

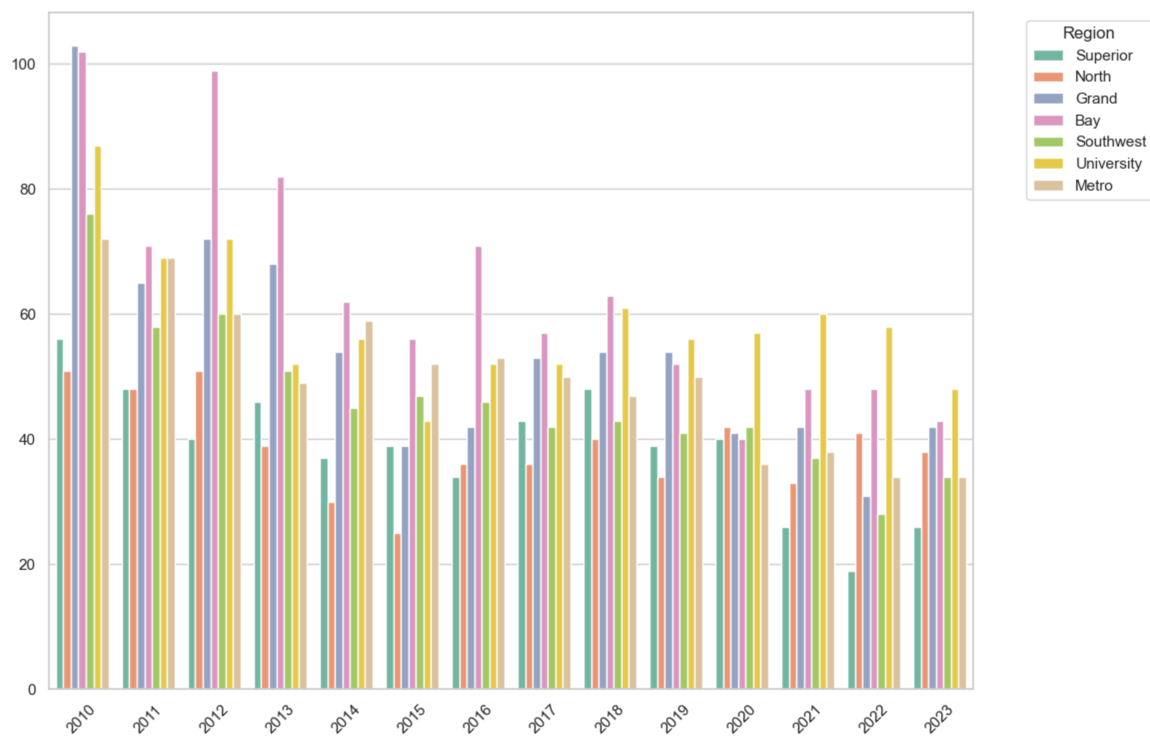

Figure 58. Total Number of Bidders over Years by Region

Figure 59 shows the trend of unemployment rates across Michigan's regions from 2010 to 2022. Overall, unemployment rates steadily declined across all regions, reflecting improved employment conditions. The **North** region consistently had the highest unemployment, while the **Metro** and **University** regions generally experienced lower rates. A sharp spike in 2020 across all regions corresponds to the economic effects of the COVID-19 pandemic, with the **Metro**, **University**, and **North** regions seeing the largest increases. Post-2020, unemployment rates quickly dropped, though some regions, like **North** and **University**, showed a slower recovery to pre-pandemic levels.

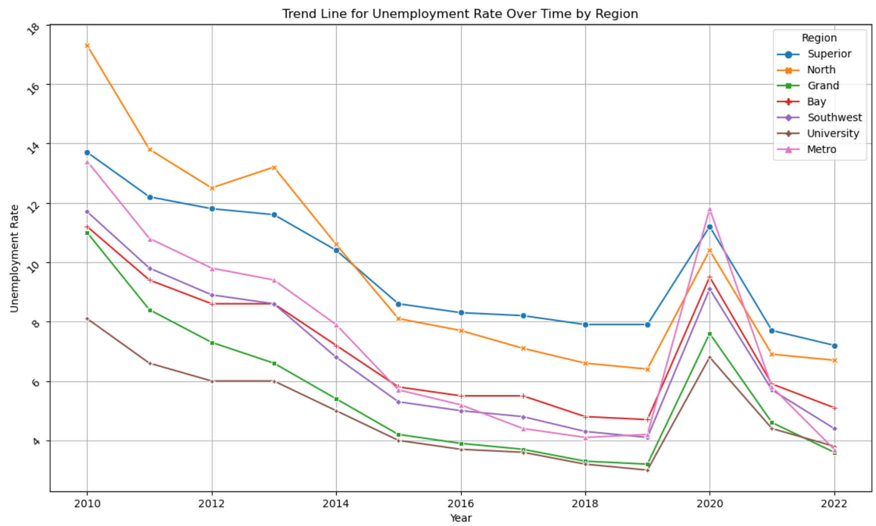

Figure 59. Unemployment Rate over Years by Region

The trend of the number of items in a contract from 2010 to 2022 for various regions is presented in Figure 60. The number of items remains relatively stable over the years with periodic spikes and drops. The Metro region has shown a significant increase in the number of items in recent years, peaking around 2021-2022. This region also exhibits an increasing trend, particularly noticeable from 2020 onwards. Other regions show more fluctuations and some decline, indicating variability in project scope. The rise in the number of items in regions like Metro and University could indicate increasing project complexity or larger project scopes in these areas. **The increased complexity and number of items in recent years might offset the higher competition**, requiring careful cost management.

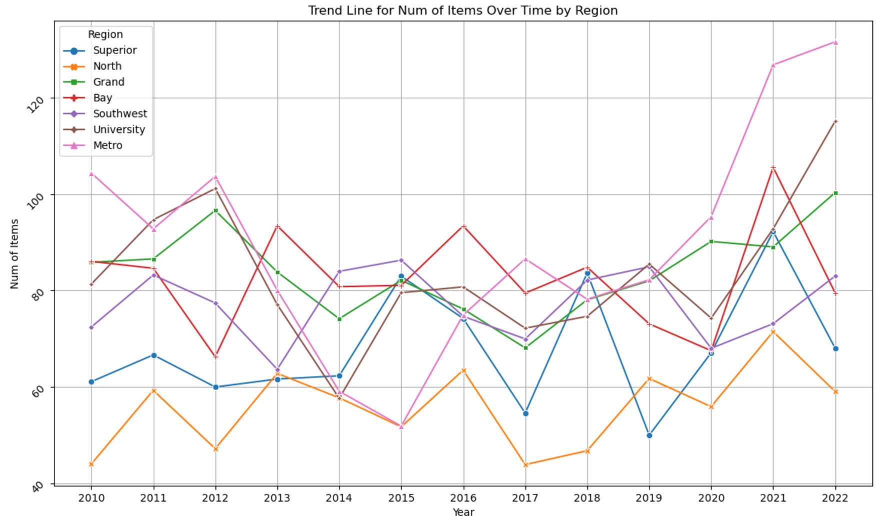

Figure 60. Number of Items over Years by Region

Figure 61 shows the trend of the awarded amount over time from 2010 to 2022 for different regions (Superior, North, Grand, Bay, Southwest, University, and Metro). There is a general increase in the awarded amounts over the years across most regions, indicating a rise in the size or value of contracts being awarded. Metro and University Regions show significant spikes in awarded amounts, particularly in recent years. The Metro region has the highest awarded amounts, especially noticeable around 2021-2022. Southwest and Bay Regions also show notable increases, with substantial fluctuations indicating variability in contract sizes. Regions like North, Superior, and Grand exhibit more stable trends with moderate increases, reflecting steady growth in contract sizes. The significant increases in regions like Metro and University indicate higher project investments, likely due to urbanization, increased demand for infrastructure, and higher construction activity.

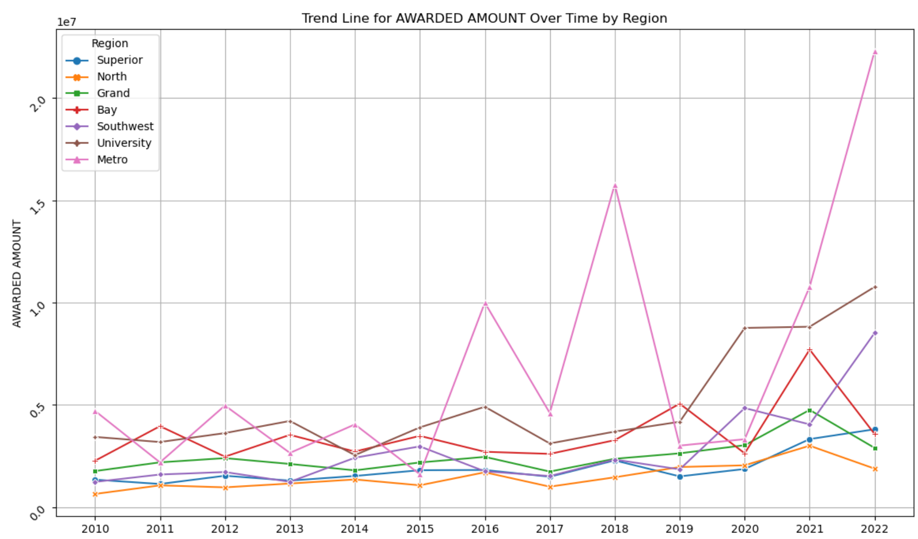

Figure 61. Awarded Amount over Years by Region

The increase in both awarded amounts and the number of items in Metro Region suggests that contracts are becoming larger and more complex. This aligns with higher urbanization and infrastructure demands in the Metro region, requiring more extensive projects. Similar to Metro, the University region shows significant increases in awarded amounts and the number of items, indicating larger, multifaceted projects. Despite a stable number of items, the awarded amount in North region shows moderate increases, suggesting that while the complexity (number of items) of projects remains consistent, the value or size of these projects is **increasing**.

Figure 62 shows the trend line for the number of contracts per year at the state level from 2010 to 2022. The line chart tracks the changes over time. The number of contracts at the state level exhibits fluctuations over the years, with notable peaks in 2010 and 2019. After peaking in 2019, the number of contracts has steadily declined, reaching its lowest point in 2022.

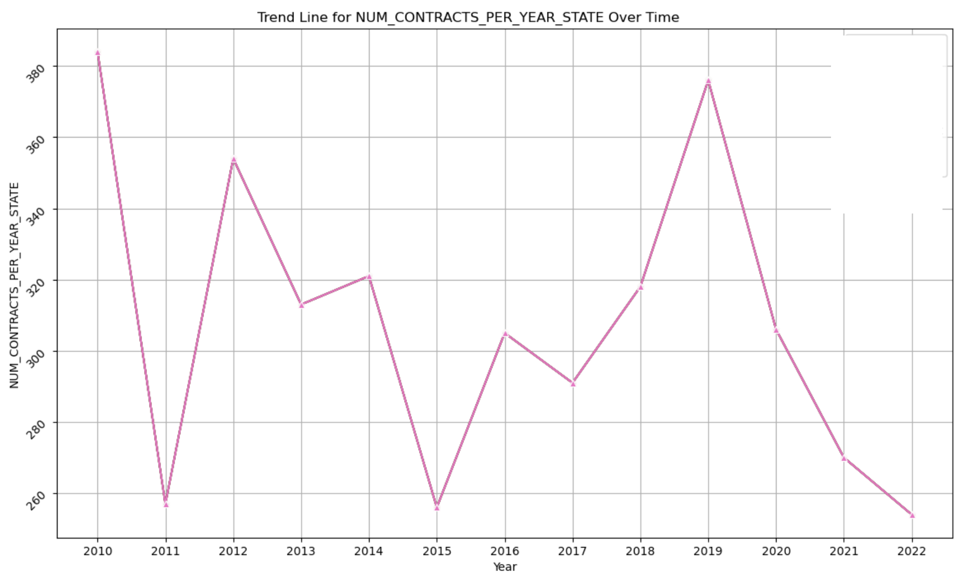

Figure 62. Number of Contract over Years in Michigan

Figure 63 presents the trend line for the **total amount per year** at the state level from 2010 to 2022. The chart tracks the annual total contract value in dollars. Unlike the fluctuating number of contracts observed in the previous figure, the total contract amount shows a clear upward trajectory, especially from 2017 onward. Figure 64 presents Number of Contract over Years by Region. Metro and University regions have a higher number of contracts, while North and Superior regions have fewer contracts.

While the **number of contracts** has declined significantly after 2019, the **total amount** awarded for contracts has increased sharply. This suggests a trend toward fewer but larger contracts in recent years. This could imply that fewer projects are being initiated, but they involve more extensive work or higher costs, possibly due to inflation, increased complexity, or a focus on larger-scale infrastructure improvements. It may also reflect economic factors like rising material costs or labor rates, which drive up the value of individual contracts despite a lower volume of contracts overall.

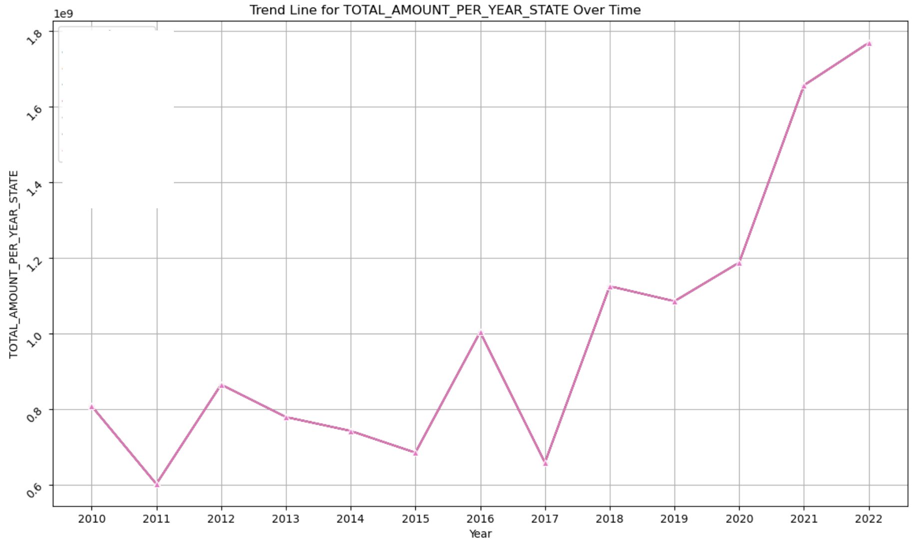

Figure 63. Total Awarded Value over Years in Michigan

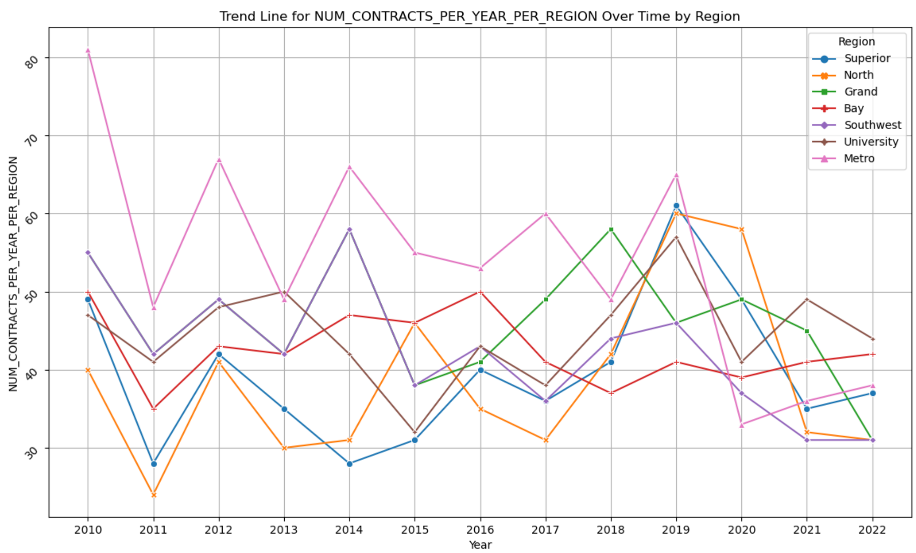

Figure 64. Number of Contract over Years by Region

The total amount spent per year per region (as shown in Figure 65) reflects the overall construction spending trends for each region. Metro and University Regions show the highest spending with considerable variability, reflecting the large and complex nature of projects. North Region exhibits more stable spending trends, indicating consistent but smaller-scale projects.

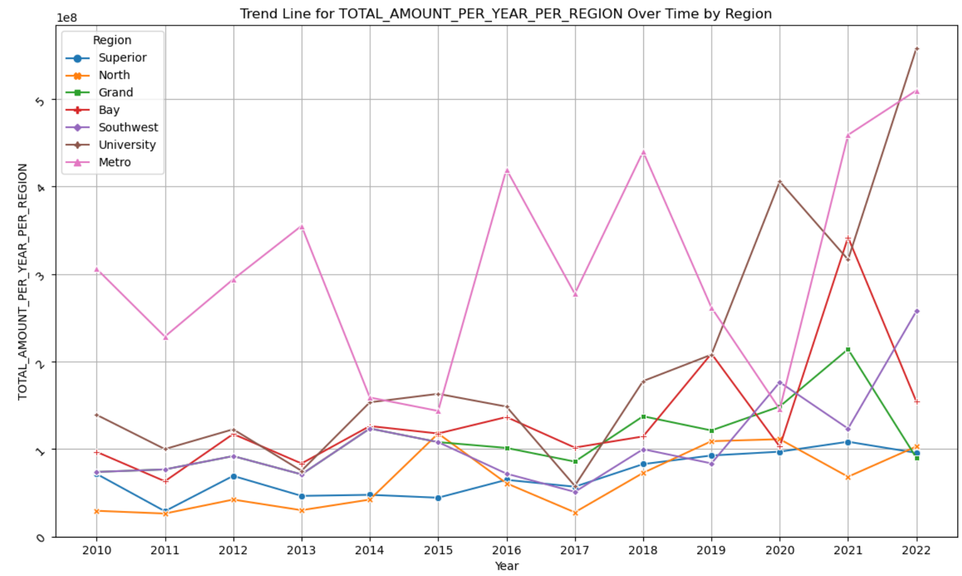

Figure 65. Total Awarded Value over Years by Region

Figure 66 displays the trend line for income over time by region from 2010 to 2022. The Metro region (in pink) has a much higher income compared to all other regions. It shows consistent growth from 2010 to 2022, increasing from around 25 billion to nearly 40 billion dollars. All other regions show far lower income levels, with marginal growth over the years. Southwest (in purple) stands out slightly above the rest but is still significantly below Metro. The lines for regions like Bay (orange), Grand (green), and North (yellow) remain quite flat, indicating that income levels in these regions have not changed substantially over time.

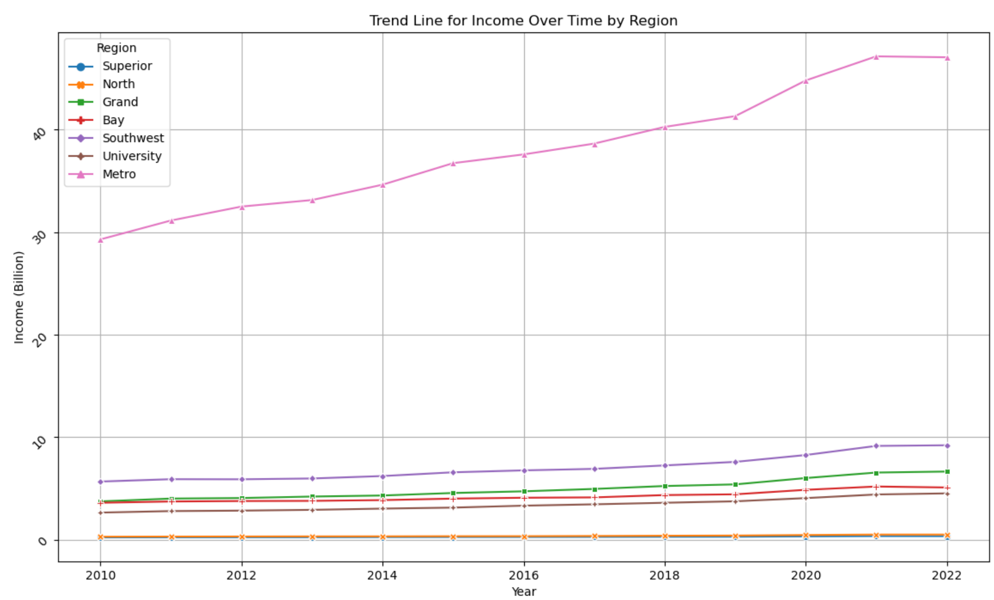

Figure 66. Income over Years by Region

6.1.3.3 Statistical Test: Granger Causality and Correlation

This section focuses on the use of **Granger causality tests** and **correlation analysis** to identify significant predictors of the regional MHCCI. The Granger causality test is a statistical hypothesis test that helps determine whether one time series can predict another. In the context of this analysis, it is used to examine whether certain economic or construction-related variables have predictive power over regional MHCCI fluctuations. By assessing the **p-values** from these tests, the significance of various factors and their potential to cause or influence changes in regional MHCCI can be evaluated. These findings are critical for identifying the underlying factors driving regional variations in MHCCI and understanding how specific predictors contribute to cost index shifts across different regions.

The p-values from the Granger causality tests are summarized in Table 34, which indicates the significance of various predictors for the MHCCI across different regions.

Table 34. Granger Causality for Regional Comparison

Factor	**Region(s) with Significant Causality**	**P-Value**
YEAR	None	All p-values > 0.05
Labor Force	None	All p-values > 0.05
Population	None	All p-values > 0.05
NUM_CONTRACTS_PER_YEAR_PER_REGION	None	All p-values > 0.05
TOTAL_AMOUNT_PER_YEAR_STATE	None	All p-values > 0.05
AWARDED AMOUNT	Bay	0.0402
TOTAL_AMOUNT_PER_YEAR_PER_REGION	Bay, Grand	0.0121, 0.0422
Unemployment Rate	Metro	0.02
Income	Metro (Close to significance)	0.05
Number_Jobs	Southwest, Superior	0.03
NUM_CONTRACTS_PER_YEAR_STATE	North	0.0356
Num of Items	Superior	0.10
Number_Bidders	North	0.01

The following sections provide a detailed explanation of the factors influencing the regional MHCCI under analysis.

Influencing Factors in Metro Region

Both Granger causality results and the correlation matrix (see Figure 67) can provide a clearer picture of how different factors influence the MHCCI in the Metro region.

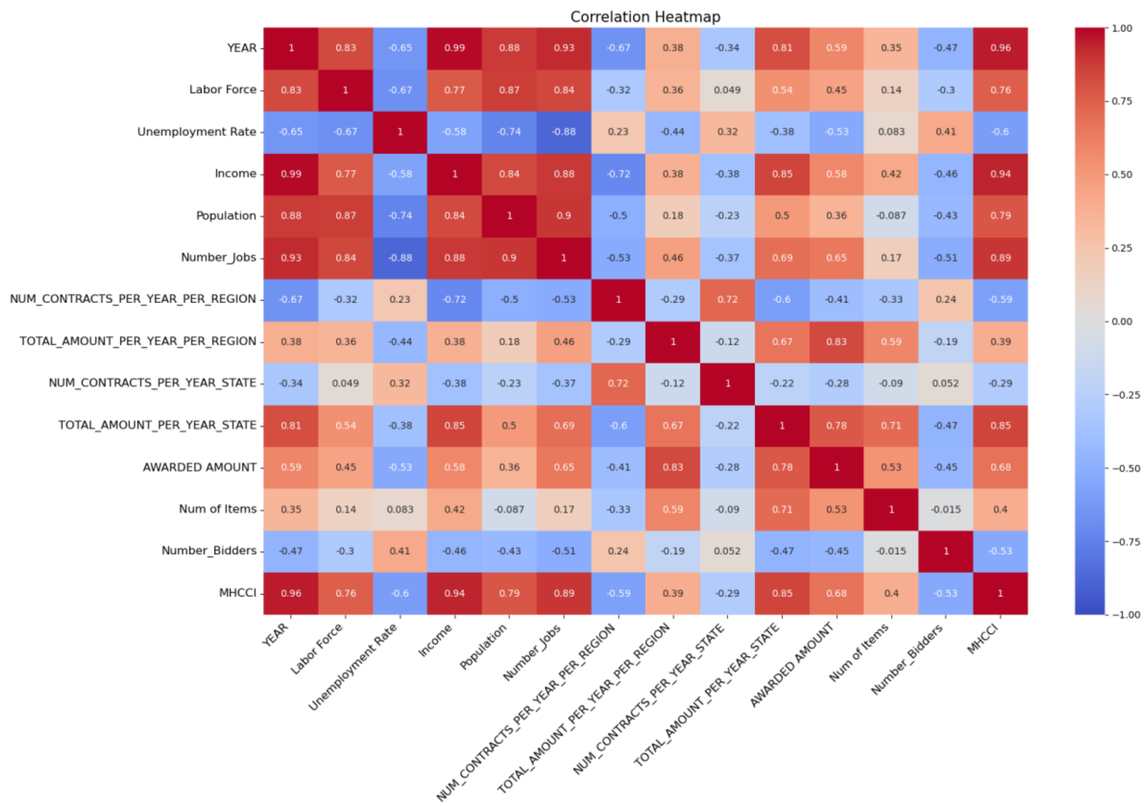

Figure 67. Correlation Heatmap: Metro Region

Key Influencing Factors:

1. **Unemployment Rate**:
    - **Causality**: The Unemployment Rate significantly predicts MHCCI ($p = 0.0188$).
    - **Correlation**: There is a negative correlation (-0.60) between the Unemployment Rate and MHCCI.

There is a significant causal relationship between the Unemployment Rate and the Metro-MHCCI. Changes in the Unemployment Rate can predict changes in the MHCCI. As the Unemployment Rate decreases, indicating more employment, the Metro-MHCCI tends to increase. This suggests that when more people are employed, there is higher demand for construction services and labor, driving up costs. Conversely, higher unemployment can lead to lower construction costs due to reduced demand.

2. **Income**:
    - **Causality**: Income is a near-significant predictor of Metro-MHCCI ($p = 0.0528$).
    - **Correlation**: There is a strong positive correlation (0.94) between Income and MHCCI.

Economic growth and wage changes may have an indirect effect on construction costs. Higher income levels are associated with higher construction costs. As income increases, people have more spending power, which can lead to higher demand for construction services, thus pushing up costs and MHCCI. Additionally, higher incomes could mean higher wages for construction workers, adding to the overall cost of projects.

3. **Total Amount Per Year Per Region**:
    - **Causality**: This factor is near the threshold of significance ($p = 0.0622$), indicating potential causality.
    - **Correlation**: There is a positive correlation (0.85) with MHCCI.

Increased construction spending in the region correlates with higher construction costs. This indicates that when more funds are allocated to construction projects, it can drive up prices and MHCCI due to heightened demand for materials, labor, and other resources.

The following will provide a comprehensive summary of the factors contributing to regional variations in the MHCCI in the Metro Region.

1. **Higher MHCCI:**

The Metro region shows higher median and mean MHCCI values compared to other regions. This can be attributed to factors **like urbanization, which increases demand for construction services and materials, leading to higher MHCCI**. The correlation data supports this by showing strong positive correlations between income levels and construction spending (i.e., Total Amount Per Year Per Region) with MHCCI.

2. **Significant Variability:**

The Metro region experiences significant variability in construction cost index, as indicated by the high standard deviation and wide range of MHCCI values. This variability is influenced by multiple factors, including **employment rates, income levels, and construction spending**. Different project types and fluctuations in local economic conditions also contribute to this inconsistency. This variability is often due to the nature of the projects being undertaken. For instance, **large infrastructure projects like highways and bridges typically have higher costs compared to smaller projects like local road repairs**. Larger and more complex projects tend to have more variability in costs due to unforeseen challenges, changes in project scope, and variations in material and labor requirements. This complexity is likely reflected in the high standard deviation observed in the Metro region's MHCCI values and contract size (i.e., **Awarded Amount and Number of Items in contracts**). These correlations between MHCCIs, income, and unemployment suggest that as the local economy strengthens, construction costs tend to increase, and vice versa.

In short, the analysis reveals that **unemployment rates, income levels, and regional construction spending** are key factors influencing the MHCCI in the Metro region. Their trend lines and scatter plots are shown in Figure 68, Figure 69, and Figure 70. The interplay between these factors and their impact on construction costs underscores the complexity of the construction market. Given the high variability and elevated construction costs in the Metro region, stakeholders and policymakers need to carefully plan and budget for construction projects. Effective strategies to manage and control costs could include monitoring employment rates, income changes, and spending patterns. These strategies can help anticipate cost fluctuations and ensure that resources are allocated efficiently.

Figure 68. Trend Lines: Unemployment Rate, Income, and MHCCI in Metro

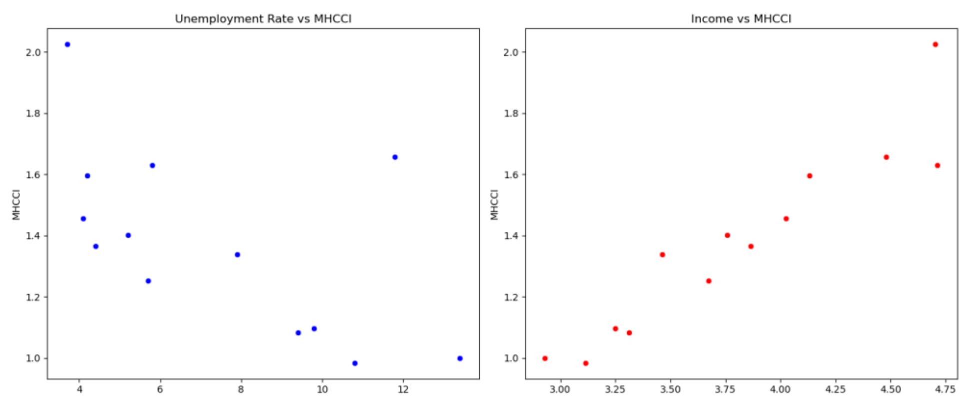

Figure 69. Scatter Plot: Unemployment Rate, Income, and MHCCI in Metro

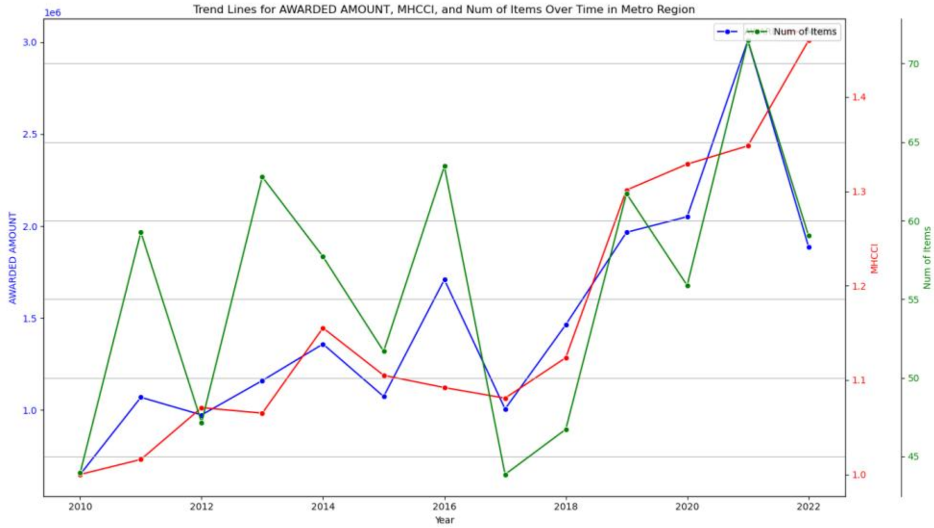

Figure 70. Metro Region: Awarded Amount, Number of Items, and MHCCI

The observed significant and near-significant factors highlight the need for further investigation into specific drivers of construction costs and indexes in the Metro region. Understanding the impact of local regulations, economic conditions, supply chain dynamics, and labor market trends (e.g., a shortage of skilled labor, rising wages, or high demand for construction workers) can provide deeper insights into managing and potentially mitigating rising construction costs.

Influencing Factors in University Region

No significant predictors were found in the University region based on the given p-values. Awarded amount with a p-value of 0.1312 in Granger Causality test with a maximum lag of 1 year shows a strong association but is still not statistically significant in affecting the cost index in the University region.

Number of jobs with a p-value of 0.09510 in the Granger causality test with a maximum lag of 3 years indicates weak evidence of Granger causality at a 10% significance level but not at a 5% significance level. This suggests that the past three years of one time series have some predictive power over the current values of another, but the evidence is not robust.

Data Characteristics: The data for the University region might not exhibit strong temporal relationships between the potential predictors and the University-MHCCI. The absence of significant p-values indicates that the lagged values of the predictors do not provide useful information for predicting the MHCCI in this region.

Regional Differences: The University region might have **unique characteristics or factors** influencing its construction cost index that are not captured by the variables included in the analysis. This region could be influenced by different economic, demographic, or project-specific factors that were not considered.

Variability and Noise: High variability or noise in the data could obscure potential causal relationships. If the construction costs in the University region fluctuate due to random factors or unaccounted influences, it becomes difficult for the Granger causality test to detect significant predictors.

Insufficient Lag Structure: The chosen lag structure for the Granger causality test might not be suitable for the University region. The relevant relationships might occur over different time lags than those considered in the analysis.

Model Specification: The model used for the Granger causality test might not be adequately specified for the University region. There could be omitted variables or interactions that are important for this region but were not included in the model.

Influencing Factors in North Region

Key Influencing Factors:

1. **NUM_CONTRACTS_PER_YEAR_STATE**:
    - **p-value**: 0.0356
    - **f-statistic**: 7.283103, it measures the overall significance of the regression model. A higher F-statistic indicates that the model explains a significant portion of the variability in the dependent variable (MHCCI) due to the predictor variable (number of contracts). An F-statistic of 7.283103 indicates a strong relationship.

The number of contracts in Michigan is a significant predictor of the MHCCI in the North region. This suggests that changes in the number of contracts issued at the state level can help forecast future changes in construction costs. It implies that an increase in the number of contracts tends to be followed by changes in MHCCI in the North Region. Policymakers and planners should consider this relationship when issuing contracts, as it could help in anticipating and managing construction costs.

2. **Number of Bidders**:
    - **p-value**: 0.0072
    - **f-statistic**: 15.931727: It indicates a very strong relationship between the number of bidders and MHCCI. This high value suggests that the number of bidders significantly explains the variability in the MHCCI.

The number of bidders is a significant predictor of the MHCCI in the North region. This implies that the level of competition among bidders for contracts can help forecast changes in the construction cost index. A higher number of bidders in the North Region is typically associated with more competitive pricing, leading to lower construction costs. Encouraging more competition among bidders could be an effective strategy for managing and reducing construction costs in the region.

Both the number of contracts per year and the number of bidders are significant predictors of MHCCI, as indicated by their p-values being below the 0.05 threshold. The correlation coefficients for these predictors are negative (as shown in Figure 71), with the number of bidders showing a stronger inverse relationship (-0.67) compared to the number of contracts per year (-0.26).

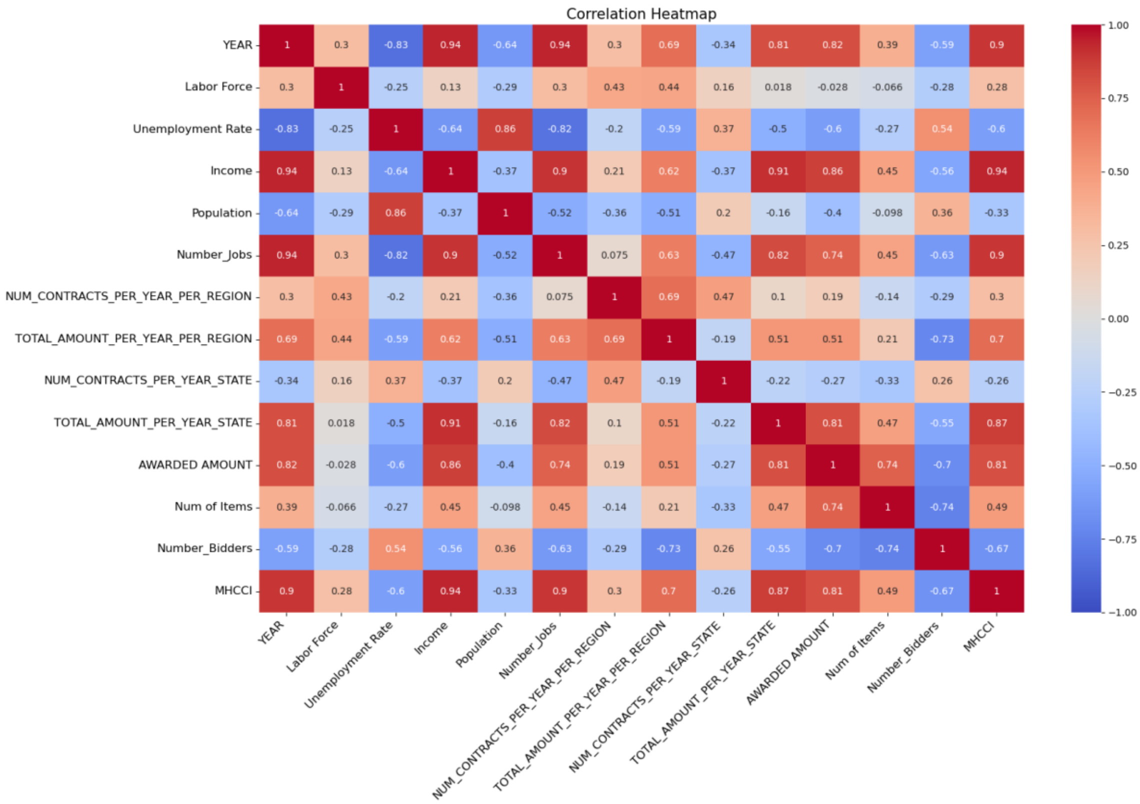

Figure 71. Correlation Heatmap: North Region

The following will outline the practical implications of identifying regional cost drivers for the MHCCI in the North Region.

1. **Influence of Number of Contracts Per Year in Michigan:**

Inverse Relationship: The negative correlation coefficient suggests that increasing the number of contracts in Michigan can lead to lower construction cost index. This could be due to **economies of scale**, **increased efficiency**, or **more competitive bids** received when more contracts are issued.

Removing 2020-2022 data from the analysis significantly alters the relationship between the **Number of Contracts Per Year** and the **MHCCI** in the North region. Initially, with the 2020-2022 data included, the coefficient is **-0.26**, suggesting a **negative correlation**—as the number of contracts increases, the MHCCI decreases. However, when the 2020-2022 data is removed, the coefficient shifts to **0.29**, indicating a **positive correlation**—as the number of contracts increases, the MHCCI also increases. The removed years might have contained outliers or anomalies that disproportionately affected the overall trend. If these years had unusually high or low values that created a negative correlation, removing them could shift the correlation to positive. **Anomalous Events**: Specific events during those years (e.g., economic downturns) could have caused abnormal spikes or drops in the number of contracts or cost indices, affecting the overall correlation. **Structural Breaks**: There might have been structural breaks or changes in trends during the removed years. Removing these years could align the remaining data better with an underlying positive trend.

2. **Influence of Number of Bidders:**

Strong Inverse Relationship: The strong negative correlation (-0.67) indicates that higher competition among bidders significantly reduces construction costs and MHCCI. This highlights the importance of promoting competitive bidding processes. **Policy Implication:** Encouraging more bidders through transparent and accessible bidding processes can help reduce construction costs. Measures such as simplifying the bidding process, reducing barriers to entry, and ensuring fair competition are crucial.

The analysis reveals that both the number of contracts in Michigan and the number of bidders significantly influence the MHCCI in the North region. The inverse relationships indicated by the correlation coefficients and Figure 72 suggest that increasing competition and managing the volume of contracts can effectively control the construction cost index in the North region. These findings provide valuable insights for policymakers and stakeholders in the construction industry, guiding them toward strategies that promote cost efficiency and competitive pricing.

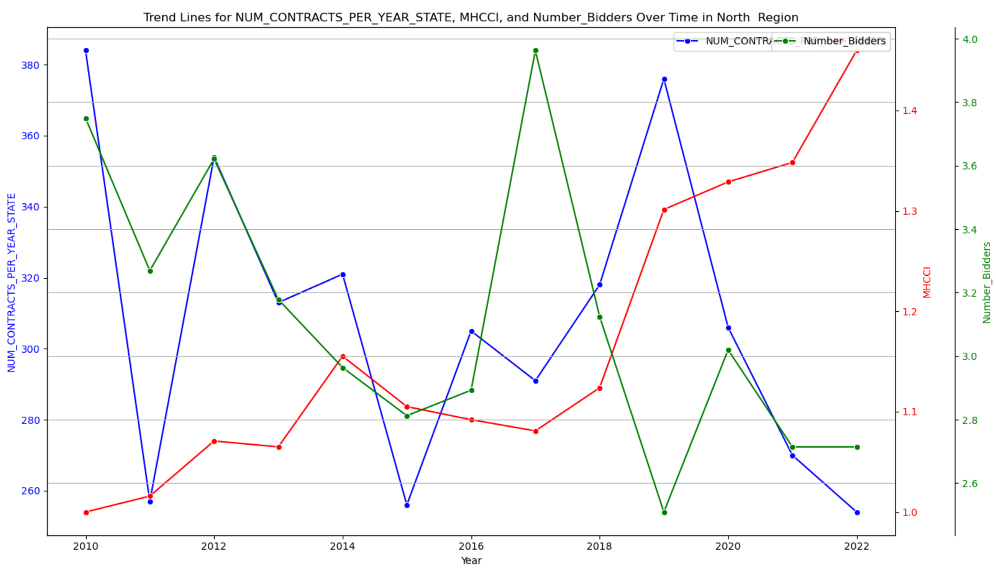

Figure 72. North Region: Number of Contracts Per Year, Number of Bidders, and MHCCI

On average, as the number of contracts per year at the state level increases, the MHCCI tends to decrease in this region. This might seem counterintuitive given the Granger causality result indicating NUM_CONTRACTS_PER_YEAR_STATE as a significant predictor of MHCCI. Here's how to interpret these seemingly conflicting pieces of information:

- **Increased Competition and Economies of Scale:**
  - **Competition Effect:** An increase in the number of contracts per year might lead to increased competition among contractors. As competition rises, contractors may lower their bids to secure contracts, resulting in lower construction costs and a lower MHCCI.
  - **Economies of Scale:** A higher volume of contracts could also lead to economies of scale. Contractors handling multiple projects may achieve cost efficiencies, reducing overall construction costs.
- **Resource Availability and Utilization:**
  - **Resource Allocation:** With more contracts awarded, resources (such as labor and materials) might be utilized more efficiently, leading to lower per-unit costs.
  - **Price Negotiation:** Contractors might be able to negotiate better prices for materials and labor when they have a higher volume of work, further driving down costs.
- **Time Lag Effects:**
  - **Short-term vs. Long-term Effects:** The Granger causality test might capture short-term predictive relationships that do not necessarily reflect long-term trends. While increased contracts predict MHCCI changes in the short term, the immediate effect of increased contracts might be cost reduction due to the factors mentioned above.

Influencing Factors in Other Regions

Southwest

- Number of Jobs (p = 0.0258):
  - **Interpretation:** Number of jobs is a significant predictor.
  - **Implication:** Employment in construction might directly influence construction costs.
- Income (p = 0.067):
  - **Interpretation:** Close to significance.
  - **Implication:** Economic conditions may indirectly affect construction costs.

Bay

- **TOTAL_AMOUNT_PER_YEAR_PER_REGION**:
  - **p-value**: 0.0121
  - **f-statistic**: 12.586621
  - Interpretation: The Total Amount Per Year Per Region is a significant predictor of the MHCCI in the Bay region. Spending in construction significantly impacts cost trends
- **AWARDED AMOUNT**:
  - **p-value**: 0.0402
  - **f-statistic**: 6.808357
  - Interpretation: The Awarded Amount is a significant predictor of the MHCCI in the Bay region.

- Number of Items (p = 0.0758):
  - Interpretation: Near significant.
  - Implication: Complexity or variety in projects may impact construction costs.

Grand

- **TOTAL_AMOUNT_PER_YEAR_PER_REGION**:
  - **p-value**: 0.0422
  - **f-statistic**: 8.67239243
  - Interpretation: The Total Amount Per Year Per Region is a significant predictor of the MHCCI in the Grand region. Spending in construction significantly impacts cost trends

Superior

- **Number_Jobs**:
  - **p-value**: 0.0345
  - **f-statistic**: 8.310067
  - Interpretation: The Number of Jobs is a significant predictor of the MHCCI in the Superior region.

These results indicate that different factors drive changes in the highway construction cost index (MHCCI) in different regions, highlighting regional variations in economic dynamics.

6.1.4 Conclusion

The observation that causing factors are different across regions rather than being universally applicable across all regions can be explained by several factors related to regional variations. These variations are driven by local economic conditions, market dynamics, and project characteristics. Here's a more detailed exploration of **why factors of regional MHCCI differ across regions**:

1. Local Economic Conditions:

- **Economic Diversity:** Different regions have diverse economic bases. For example, a region with a strong industrial base may experience different economic dynamics compared to a region reliant on agriculture or services. These economic bases affect the labor market, income levels, and demand for construction differently.
- **Cost of Living:** Variations in the cost of living across regions impact wages, construction costs, and overall economic activity. Higher cost of living areas may see higher wages and material costs, affecting the MHCCI differently than in lower cost areas.

2. Market Dynamics:

- **Labor Market Conditions:** The availability of skilled labor can vary significantly between regions. Regions with a higher concentration of skilled labor may have lower labor costs and more competitive bidding environments, affecting the number of bidders and contract costs.

- **Material Availability and Costs:** Proximity to resources and suppliers can impact material costs. Regions further from major supply centers might face higher transportation costs, affecting overall construction costs.
- **Historical Development Patterns:** Regions with mature infrastructure might see different cost dynamics compared to rapidly developing areas. Mature regions might focus on maintenance and upgrades, while developing regions might focus on new constructions, leading to different causative factors for MHCCI.

3. Regulatory and Policy Differences:

- **Local Regulations:** Building codes, environmental regulations, and zoning laws can vary significantly between regions. These regulations can affect construction timelines, costs, and the types of projects that are feasible, influencing the MHCCI differently in each region.
- **Government Policies:** Local government policies on infrastructure investment, incentives, and subsidies can drive differences in construction activity and costs. Regions with more supportive policies for construction may experience different causative factors than regions with more restrictive policies.

4. Project Characteristics:

- **Project Types and Sizes:** The types and sizes of construction projects prevalent in each region can influence cost dynamics. Regions focusing on large-scale infrastructure projects may face different cost pressures compared to those focusing on small-scale maintenance projects.

5. Competitive Environment:

- **Bidding Competition:** The number of bidders and the competitiveness of the bidding process can vary by region. More competitive regions may see lower costs due to competition, while less competitive regions may see higher costs due to lack of competition.
- **Contractor Availability:** The availability and capacity of local contractors can influence project costs. Regions with more contractors might experience more competitive pricing, impacting the MHCCI differently than regions with fewer contractors.

The differences in causing factors across regions reflect the complex interplay of local economic conditions, market dynamics, regulatory environments, project characteristics, and competitive landscapes. These factors create unique cost structures and dynamics in each region, making it essential to analyze regional data to understand the specific drivers of construction costs.

The reason why the Metro region has a higher cost index compared with other regions can be attributed to several factors, including both the value of influencing factors and the type of factors. The combination of the influencing factors, e.g., **higher wages and construction**

spending can have a synergistic effect, compounding to result in a higher cost index in the Metro region. The trend lines for awarded amounts, number of items, and total construction spending indicate higher values in the Metro region, supporting the conclusion of higher costs and index.

The data available for Granger causality tests might not capture all relevant variables influencing construction cost index. Even if certain factors were not identified through Granger causality, their correlation with the MHCCI can still be significant. For example, a high correlation between labor force characteristics and the MHCCI suggests a relationship even if it's not causal in the strict Granger sense.

6.2 REGIONAL BID PRICE

In addition to comparing regional indices, this study also analyzed unit bid prices across different regions. Figure 73 illustrates the trend of unit bid prices for the item "5010002" across various regions over time. From 2010 to 2022, the unit bid prices have shown a general increase in all regions, although the magnitude and timing of the increase vary between them. **Metro region** (in pink) consistently shows the highest unit bid prices, especially after 2016, with a sharp increase post-2020, reaching its peak in 2022. **University region** (in brown) also experienced significant fluctuations, particularly a rapid rise between 2020 and 2022, aligning with the Metro region's peak. Other regions, such as **Bay**, **Grand**, and **Southwest**, show smaller and more gradual price increases, indicating more stable pricing trends.

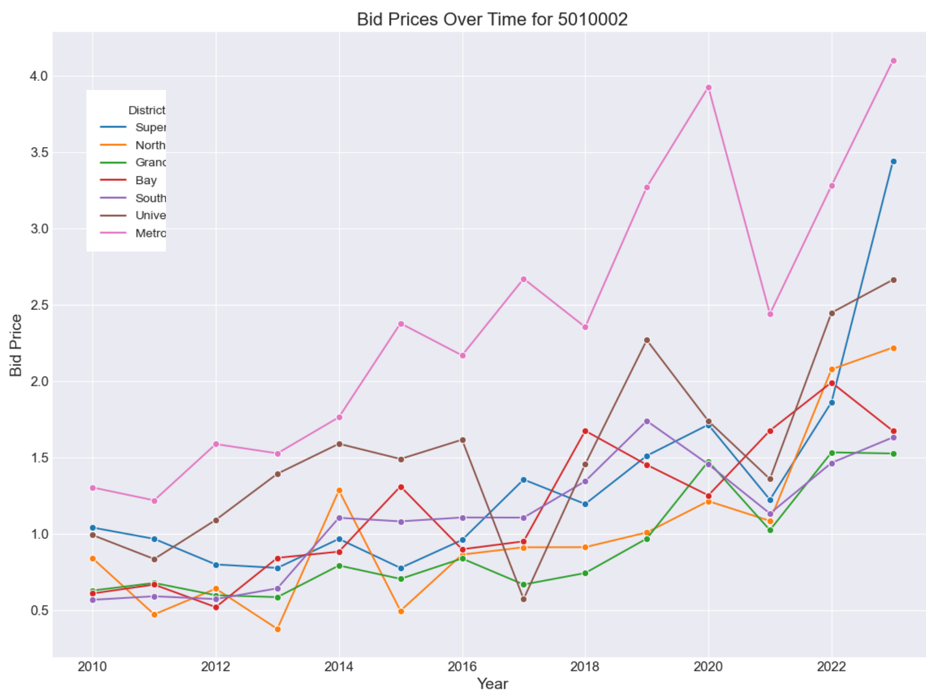

Figure 73. Annual Price Trends across Regions

Figure 74 illustrates the distribution of unit bid prices for the item "5010002" across different regions. **Metro region** (in pink) has the highest bid price range and the greatest variability. The median bid price is higher than any other region, with a significant spread. This suggests that Metro experiences the most substantial fluctuations in unit bid prices compared to other regions. **University** (in brown) and **Bay Region** (in red) also show relatively higher median unit bid prices, but their spread is narrower than Metro’s, indicating more stability. **Superior** (in blue) has a wider distribution, with several outliers indicating occasional higher bids, though the median price remains moderate. **North** (in orange), **Grand** (in green), and **Southwest** (in purple) show lower and more consistent unit bid prices. Grand has several outliers, but its median remains the lowest among all regions.

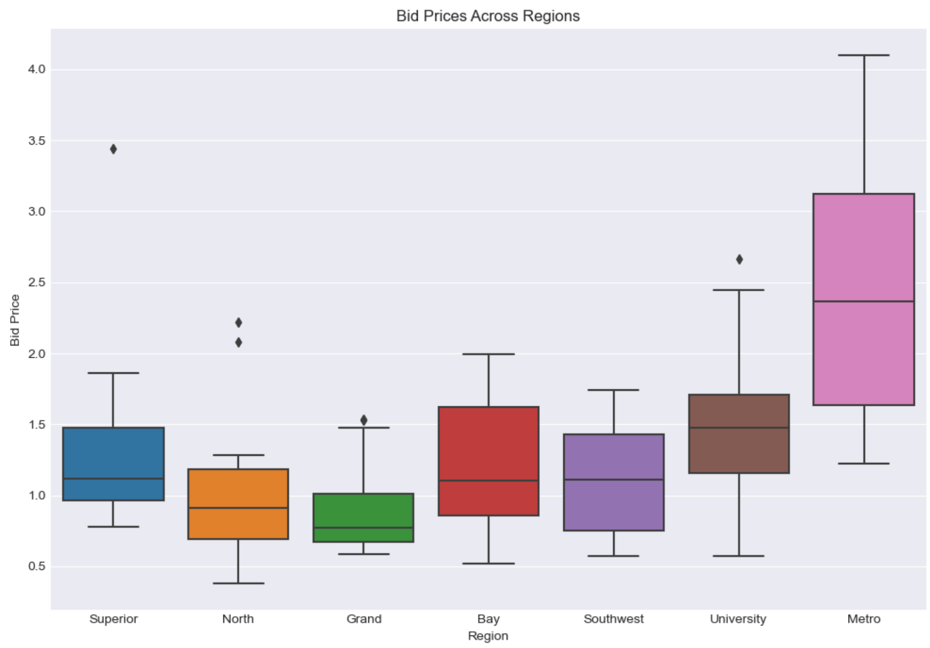

Figure 74. Annual Price across Regions: Box Plot

Given the significant variations in unit bid prices across regions as observed in the box plot, it is necessary to perform statistical tests to determine whether these differences are statistically significant. The **Friedman Test** would be appropriate for an overall comparison across all regions. This non-parametric test evaluates whether the bid price distributions across the regions differ in a statistically significant way.

6.2.1 Friedman Test Results

- **Test Statistic (52.990)**: This value indicates the calculated test statistic for the Friedman Test. A higher value suggests a greater difference between the groups being compared.
- **p-value (0.000)**: The p-value indicates the probability that the observed differences between the groups are due to chance. A p-value of 0.000 (typically reported as <0.001) is extremely low, meaning the observed differences are very unlikely to be due to random variation.

Reject H0 (Null Hypothesis): The null hypothesis (H0) of the Friedman Test states that there are no differences between the groups (regions) in terms of their unit bid prices. Since the p-value is less than the conventional threshold of 0.05, the null hypothesis is rejected. **Conclusion**: There is a statistically significant difference in unit bid prices across the different regions. This means that at least one region's unit bid prices are significantly different from the others.

6.2.2 Post-Hoc Analysis

Since the Friedman Test indicates a significant difference, the next step is to determine which specific regions differ from each other. This can be done using pairwise comparisons with the Wilcoxon signed-rank test and applying a Bonferroni correction to adjust for multiple comparisons. It should be noted that the Wilcoxon signed-rank is non-parametric test used to compare two related samples (in this case, the unit bid prices between two regions). It ranks the differences between paired samples and assesses whether their distribution differs significantly from zero. Bonferroni Correction is applied to adjust the p-values obtained from multiple pairwise comparisons. It controls the family-wise error rate to reduce the likelihood of Type I errors (false positives).

Each pairwise comparison includes:

- **Wilcoxon Test Statistic**: The test statistic from the Wilcoxon signed-rank test.
- **p-value**: The raw p-value from the Wilcoxon signed-rank test.
- **Corrected p-value**: The p-value after applying the Bonferroni correction to account for multiple comparisons.
- **Reject H0**: Indicates whether the null hypothesis of no difference between the two regions is rejected (True) or not (False).

Based on the corrected p-values (Bonferroni correction), significant differences (Reject H0: True) are found in the following pairs in Table 36.

Table 35. Wilcoxon signed-rank test with a Bonferroni correction

	Statistics	p-value	Corrected p-value	Reject H0
Superior vs North	13	0.01	0.23	FALSE
Superior vs Grand	0	0.00	0.00	TRUE
Superior vs Bay	43	0.58	1.00	FALSE
Superior vs Southwest	29	0.15	1.00	FALSE
Superior vs University	32	0.22	1.00	FALSE
Superior vs Metro	0	0.00	0.00	TRUE
North vs Grand	32	0.22	1.00	FALSE
North vs Bay	35	0.30	1.00	FALSE
North vs Southwest	40	0.46	1.00	FALSE
North vs University	4	0.00	0.02	TRUE
North vs Metro	0	0.00	0.00	TRUE
Grand vs Bay	14	0.01	0.28	FALSE
Grand vs Southwest	18	0.03	0.62	FALSE
Grand vs University	1	0.00	0.01	TRUE
Grand vs Metro	0	0.00	0.00	TRUE
Bay vs Southwest	43	0.58	1.00	FALSE
Bay vs University	12	0.01	0.18	FALSE
Bay vs Metro	0	0.00	0.00	TRUE
Southwest vs University	11	0.01	0.14	FALSE
Southwest vs Metro	0	0.00	0.00	TRUE
University vs Metro	0	0.00	0.00	TRUE

Table 36. Regional Unit Bid Price: Significant Difference Pairs

Comparison Pairs	**Corrected p-value**
Superior vs Grand	0.003
Superior vs Metro	0.003
North vs University	0.018
North vs Metro	0.003
Grand vs University	0.005
Grand vs Metro	0.003
Bay vs Metro	0.003
Southwest vs Metro	0.003
University vs Metro	0.003

In summary, the **Metro** region is significantly different from all other regions, including **Superior**, **North**, **Grand**, **Bay**, **Southwest**, and **University**. The **Superior** region differs significantly from **Grand** and **Metro**, while **North** shows significant differences from **University** and **Metro**. **Grand** is significantly different from **Superior**, **University**, and **Metro**, and both **Bay** and **Southwest** are only significantly different from **Metro**. Lastly, **University** differs significantly from **North**, **Grand**, and **Metro**.

No significant differences (Reject H0: False) are found in the remaining pairs, meaning the differences in unit bid prices between these regions are not statistically significant after correcting for multiple comparisons.

6.2.3 Conclusion

The analysis of unit bid prices for the item "5010002" across different regions from 2010 to 2023 reveals significant variations in pricing trends and bid price distributions. The Metro region consistently exhibits the highest unit bid prices, particularly after 2016, with a sharp increase post-2020, culminating in a peak in 2023. Other regions, such as University and Superior, show notable fluctuations, while regions like Bay, Grand, and Southwest exhibit more gradual and stable price trends.

The results of the Friedman Test, followed by pairwise comparisons using the Wilcoxon signed-rank test with Bonferroni correction, confirm that the differences in unit bid prices across regions are statistically significant. Specifically, Metro region's unit bid prices are significantly different from all other regions, reinforcing its position as the region with the highest and most variable prices. Other regions also exhibit significant differences in unit bid prices, such as Superior vs. Grand, North vs. University, and Grand vs. University.

These findings underscore the importance of considering regional factors when estimating project costs. The Metro region, with its consistently higher unit bid prices and substantial variability, may reflect unique economic conditions, labor market dynamics, material costs, and competitive pressures that are not as pronounced in other regions.

7. RECOMMENDATIONS AND CONCLUSIONS

7.1 CONCLUSIONS

This report has demonstrated the need for advanced methods in construction cost estimation and budget planning, particularly for transportation projects managed by agencies like MDOT. Traditional cost estimation methods that rely solely on historical data and broad indices fall short in capturing the dynamic nature of construction costs, which fluctuate due to a variety of economic, market, and project-specific factors.

The development of **contract- and item-level cost indices** provides a more granular and accurate approach to cost estimation, allowing MDOT to track price trends specific to individual contracts and items. These indices, when integrated with **economic factor-based predictive models**, offer MDOT a powerful tool for cost estimation based on forecasted MHCCI, accounting for inflation and market trends in a way that static historical data cannot.

The integration of these advanced methodologies into **budget planning** ensures that project costs remain aligned with financial resources and strategic goals. This index-based approach provides MDOT with the flexibility to **adjust estimates dynamically** as economic conditions change, reducing the risk of cost overruns and improving financial management.

In conclusion, the adoption of **index-based estimation techniques** and **predictive models** could significantly enhance MDOT's ability to manage construction costs effectively. By incorporating these advanced tools into project development and financial planning, MDOT can ensure accurate cost forecasts, better resource allocation, and improved decision-making, ultimately leading to more successful project delivery.

7.2 RECOMMENDATIONS

Based on the findings of this report, several recommendations are proposed to improve the accuracy and reliability of cost estimation and budget planning in highway construction projects. These recommendations leverage advanced index-based methodologies and predictive models to provide MDOT with more robust tools for construction cost management.

1. **Adoption of Contract- and Item-Level Cost Indices**

MDOT should implement **contract- and item-level cost indices** to improve bid-based estimation accuracy. These indices provide a more granular view of price trends, offering insights into specific contracts and pay items. By using these indices, MDOT can better account for the unique characteristics of each contract and project type, resulting in more precise cost adjustments and forecasts.

In order to enhance the accuracy of MDOT's bid-based cost estimation process, the adoption of a new index-based estimating method (described in Chapter 5) is recommended. This method would integrate both **contract-level** and **item-level cost indices**, which are tailored to the specific characteristics of individual contracts and projects. This approach is superior to the generalized HCCI method, which does not account for the unique mix of pay items and contract-specific factors that influence contract costs.

2. **Integration of Index Predictive Models in Cost Estimation**

The report recommends adopting **economic factor-based predictive models** to forecast the MHCCI. These models, which incorporate timely economic indicators such as inflation, labor costs, and material prices, will enhance MDOT's ability to predict future MHCCI fluctuations. Integrating these models into the cost estimation process can help mitigate the risks of under- or overestimation.

3. **Implementation of the developed MHCCI Tool**

MDOT should use and continuously monitor the developed **MHCCI tool** that integrates contract- and item-level cost indices, predictive models, and historical price data. Regular monitoring will ensure the tool remains reliable and effective in reflecting market conditions, economic trends, and specific project requirements. This tool will allow MDOT to dynamically adjust cost estimates based on market conditions, economic trends, and specific project requirements, ensuring more accurate cost forecasting and budget planning.

4. **Refinement of Budget Planning and Scoping Procedures**

MDOT could revise its **budget planning and project scoping procedures** to integrate index-based methodologies. By including predicted cost index trends in budget planning, MDOT can more accurately align project costs with financial constraints, improving resource allocation and financial planning. This approach will enhance long-term project management and reduce the likelihood of budget overruns.

5. **Continual Monitoring and Comparison of Regional Cost Indices**

It is recommended that MDOT continue ongoing **comparisons of state and regional cost indices** to account for geographic variations in construction price rising. This will allow MDOT to adjust cost estimates for projects in different regions, ensuring that estimates reflect local economic conditions and cost drivers.

7.3 FUTURE RESEARCH

While this report introduces advanced methodologies for improving construction cost estimation and budget planning, there are several areas that warrant further research to continue refining these approaches and expanding their applicability.

1. **Development of Index and Pricing Factor Dashboards for Decision-Making**

One potential area for future research is the development of a visual dashboard to retrieve and display key cost indices and economic factor trends in real-time. Such a tool would allow project managers, estimators, and stakeholders to easily track cost fluctuations across regions and projects, providing a more dynamic view of the pricing landscape.

2. **Development of Real-Time Data Integration Systems**:

Future research should explore the development of **real-time data integration systems** that can continuously update construction cost index predictions using live data feeds from market sources, the Department of Labor Statistics, and other economic data providers. This would allow for more dynamic and timely adjustments in cost estimation, providing agencies like MDOT with the ability to respond to real-time economic fluctuations.

3. **Incorporating Advanced Machine Learning Techniques**:

While this report incorporates several predictive modeling, such as VECM, further exploration into **additional advanced machine learning techniques**—such as deep learning, reinforcement learning, and other neural networks—could enhance the accuracy of cost index prediction models. These techniques could offer more detailed insights into how complex factors like supply chain disruptions, contractor performance, and regional economic shifts affect cost indices.

4. **Monitoring of Index-Based Project Scoping and Engineer's Estimate**:

Future studies could also focus on applying the newly developed index-based estimation methods to a broader range of construction contracts. This would allow for continuous monitoring and validation of the new approach to ensure its reliability and effectiveness. Furthermore, the revised project scoping procedures should be tested and validated in real-world contracts to assess their impact on improving cost estimation accuracy and budget planning.

5. **Expansion of Contract-Level Index Applications**:

Research could further examine the potential applications of **contract-level indices** in other areas of project management, such as risk mitigation, performance measurement, and contractor evaluation (e.g., bid rejection justifications). Understanding how these indices could be integrated with other management tools would provide a more holistic approach to cost control and project delivery.

By addressing these areas in future research, transportation agencies will be better equipped to deal with the complexities of modern construction, ensuring that cost estimation techniques continue to evolve and adapt to emerging challenges in the industry.

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APPENDIX A: Construction Pricing Factors for Major Pay Items

Item Number	Top Five Important Factors				
2010001	ITEM QUANTITY	ENR_Labor_Index	Number_Bidders	TOTAL_AMOUNT_PER_QUARTER_PER_COUNT	Num of Items
2020004	ITEM QUANTITY	HighwaySpend_Mil	CONTRACT DESCRIPTION	Num of Items	NewRes_Building_Permits
2030015	ITEM QUANTITY	TranspWare_AvgEarn	REFVENDOR_NM	CONTRACT DESCRIPTION	DISTRICT
2040020	Num of Items	ITEM QUANTITY	CONTRACT DESCRIPTION	Number_Bidders	AWARDED AMOUNT
2040050	ITEM QUANTITY	Num of Items	Number_Bidders	CONTRACT DESCRIPTION	TotalPrivate_AvgEarn
2040055	Num of Items	ITEM QUANTITY	CPI_Northeast	CONTRACT DESCRIPTION	AWARDED AMOUNT
2040080	ITEM QUANTITY	TOTAL_AMOUNT_PER_MONTH_PER_COUNTY	TOTAL_AMOUNT_PER_MONTH_PER_REGION	REFVENDOR_NM	AWARDED AMOUNT
2050010	ITEM QUANTITY	AWARDED AMOUNT	Num of Items	Const_Unemployment_Pct	REFVENDOR_NM
2050011	ITEM QUANTITY	Const_Avg_HrlyEarn	CPI_Gasoline_12MChg	TOTAL_AMOUNT_PER_QUARTER_PER_COUNTY	REFVENDOR_NM
2050016	ITEM QUANTITY	TotalConst_Spend	Number_Bidders	Num of Items	Const_Mach_PPI
2050041	DISTRICT	ITEM QUANTITY	CPI_Northeast	SP500_Index	TOTAL_AMOUNT_PER_YEAR_PER_COUNTY
2060002	ITEM QUANTITY	CPI_Northeast	Num of Items	PRIMARY COUNTY	Number_Bidders
2060010	ITEM QUANTITY	CPI_Northeast	Number_Bidders	NUM_CONTRACTS_PER_QUARTER_PER_REGION	Num of Items
2080020	NonResConst_Spend	ITEM QUANTITY	REFVENDOR_NM	CONTRACT DESCRIPTION	PRIMARY COUNTY
2080036	ITEM QUANTITY	Const_Mach_PPI	Num of Items	CONTRACT DESCRIPTION	REFVENDOR_NM

Item Number	Top Five Important Factors				
3010002	ITEM QUANTITY	CPI_Northeast	DISTRICT	CONTRACT DESCRIPTION	TOTAL_AMOUNT_PER_QUARTER_PER_COUNTY
3020001	ITEM QUANTITY	ReadyMix_Concrete_PPI	TOTAL_AMOUNT_PER_QUARTER_PER_REGION	Num of Items	TOTAL_AMOUNT_PER_MONTH_PER_REGION
3020010	ITEM QUANTITY	NewRes_Building_Permits	CPI_Northeast	DISTRICT	Num of Items
3020016	ITEM QUANTITY	SP500_Index	CPI_Northeast	Num of Items	TranspWare_AvgEarn
3020020	DowJones_Avg	ITEM QUANTITY	ColdSteel_Bar_PPI	CONTRACT DESCRIPTION	Concrete_PPI
3050002	Household_Est_Thou	CPI_Inflation	US_Consumer_Conf	MONTH_NUM	ITEM QUANTITY
3070001	ITEM QUANTITY	NewRes_Building_Permits	REFVENDOR_NM	Const_Unemployment_Pct	Num of Items
3070008	Const_Unemployment_Pct	ITEM QUANTITY	TOTAL_AMOUNT_PER_YEAR_PER_REGION	MONTH_NUM	MI_Building_Permits
3070021	Const_Unemployment_Pct	ITEM QUANTITY	Num of Items	CONTRACT DESCRIPTION	HighwaySpend_Mil
3070121	ITEM QUANTITY	REFVENDOR_NM	DowJones_Avg	NewRes_Building_Permits	Num of Items
3070200	ITEM QUANTITY	CONTRACT DESCRIPTION	Const_Unemployment_Pct	DISTRICT	Num of Items
3080005	ITEM QUANTITY	HighwaySpend_Mil	PRIMARY COUNTY	Num of Items	TOTAL_AMOUNT_PER_YEAR_PER_COUNTY
4020033	TranspWare_AvgEarn	ITEM QUANTITY	SP500_Index	Number_Bidders	HighwaySpend_Mil
4020035	DowJones_Avg	ITEM QUANTITY	CONTRACT DESCRIPTION	Const_Unemployment_Pct	Const_Materials_PPI
4020036	PowerCrane_PPI	Const_Mach_PPI	ITEM QUANTITY	TOTAL_AMOUNT_PER_YEAR_PER_REGION	NUM_CONTRACTS_PER_QUARTER_PER_COUNTY

Item Number	Top Five Important Factors				
4020600	Const_Materials_PPI	ITEM QUANTITY	NonResConst_Spend	Num of Items	ABI_Index
4030004	AWARDED AMOUNT	TOTAL_AMOUNT_PER_MONTH_PER_REGION	TOTAL_AMOUNT_PER_QUARTER_PER_REGION	Num of Items	CONTRACT DESCRIPTION
4030051	ITEM QUANTITY	DISTRICT	REFVENDOR_NM	TOTAL_AMOUNT_PER_YEAR_PER_REGION	PRIMARY COUNTY
4030200	NewRes_Building_Permits	DowJones_Avg	TranspWare_AvgEarn	CONTRACT DESCRIPTION	NUM_CONTRACTS_PER_YEAR_PER_COUNTY
4030210	SP500_Index	DowJones_Avg	DISTRICT	NonResConst_Spend	TOTAL_AMOUNT_PER_QUARTER_PER_REGION
4030220	HighwaySpend_Mil	DISTRICT	NonResConst_Spend	REFVENDOR_NM	TOTAL_AMOUNT_PER_YEAR_PER_REGION
4040043	Const_Mach_PPI	ITEM QUANTITY	AWARDED AMOUNT	FabMetal_PPI	DISTRICT
4040063	ITEM QUANTITY	REFVENDOR_NM	DISTRICT	DowJones_Avg	TOTAL_AMOUNT_PER_YEAR_PER_REGION
4040093	ResConst_Spend	ITEM QUANTITY	NonResConst_Spend	TranspWare_AvgEarn	SP500_Index
5010002	ITEM QUANTITY	TOTAL_AMOUNT_PER_YEAR_PER_REGION	REFVENDOR_NM	CONTRACT DESCRIPTION	TOTAL_AMOUNT_PER_MONTH_PER_REGION
5010005	ITEM QUANTITY	Num of Items	PRIMARY COUNTY	MI_Building_Permits	TOTAL_AMOUNT_PER_YEAR_PER_REGION
5010008	ITEM QUANTITY	CONTRACT DESCRIPTION	REFVENDOR_NM	Const_Unemployment_Pct	TOTAL_AMOUNT_PER_MONTH_PER_COUNTY
5010020	ITEM QUANTITY	Asphalt_PPI	Concrete_PPI	Household_Est_Thou	TOTAL_AMOUNT_PER_YEAR_PER_COUNTY

Item Number	Top Five Important Factors				
5010021	DISTRICT	ITEM QUANTITY	HighwaySpend_Mil	TOTAL_AMOUNT_PER_YEAR_PER_COUNTY	REFVENDOR_NM
5010025	ITEM QUANTITY	Num of Items	Number_Bidders	REFVENDOR_NM	CONTRACT DESCRIPTION
5010044	ITEM QUANTITY	CPI_Inflation	FFR_Rate	PRIMARY COUNTY	TOTAL_AMOUNT_PER_QUARTER_PER_REGION
5010045	ITEM QUANTITY	Const_Avg_HrlyEarn	Asphalt_PPI	MI_Const_Emp_Earnings_Thou	TOTAL_AMOUNT_PER_YEAR_PER_REGION
5010046	NUM_CONTRACTS_PER_QUARTER_PER_REGION	Household_Est_Thou	TOTAL_AMOUNT_PER_QUARTER_PER_REGION	DISTRICT	ITEM QUANTITY
5010050	ITEM QUANTITY	Const_Avg_Hrs	TOTAL_AMOUNT_PER_MONTH_PER_REGION	Asphalt_PPI	DISTRICT
5010051	ITEM QUANTITY	TOTAL_AMOUNT_PER_YEAR_PER_REGION	CONTRACT DESCRIPTION	TOTAL_AMOUNT_PER_YEAR_PER_COUNTY	Const_Avg_Earn
5010052	ITEM QUANTITY	TotalConst_Spend	REFVENDOR_NM	SP500_Index	ColdSteel_Bar_PPI
5010055	NaturalGas_PPI	ITEM QUANTITY	NUM_CONTRACTS_PER_QUARTER_PER_COUNTY	NUM_CONTRACTS_PER_QUARTER_PER_REGION	PowerCrane_PPI
5010056	ITEM QUANTITY	Asphalt_PPI	Const_Mach_PPI	TOTAL_AMOUNT_PER_QUARTER_STATE	REFVENDOR_NM
5010057	ITEM QUANTITY	FabMetal_PPI	ENR_Labor_Index	Asphalt_PPI	CONTRACT DESCRIPTION
5010058	ITEM QUANTITY	ColdSteel_Bar_PPI	Asphalt_PPI	TOTAL_AMOUNT_PER_QUARTER_PER_COUNTY	NaturalGas_PPI
5010059	Asphalt_PPI	CPI_Northeast	REFVENDOR_NM	NonResConst_Spend	Const_Unemployment_Pct

Item Number	Top Five Important Factors				
5010061	ITEM QUANTITY	DISTRICT	TOTAL_AMOUNT_PER_YEAR_PER_REGION	MortgageRate_30Yr	TOTAL_AMOUNT_PER_YEAR_PER_COUNTY
5010509	Asphalt_PPI	CONTRACT DESCRIPTION	ITEM QUANTITY	PRIMARY COUNTY	NUM_CONTRACTS_PER_MONTH_PER_COUNTY
5010514	HighwaySpend_Mil	Asphalt_PPI	ITEM QUANTITY	Number_Bidders	FFR_Rate
5010515	Const_Avg_HrlyEarn	ITEM QUANTITY	Asphalt_PPI	PRIMARY COUNTY	REFVENDOR_NM
5010516	MI_Const_Emp_Earnings_Thou	Asphalt_PPI	HotSteel_Bar_PPI	MI_Const_Emp_Thou	ITEM QUANTITY
5010520	CPI_Northeast	ITEM QUANTITY	Asphalt_PPI	HighwaySpend_Mil	CONTRACT DESCRIPTION
5010703	ITEM QUANTITY	TOTAL_AMOUNT_PER_YEAR_PER_REGION	Asphalt_PPI	Concrete_PPI	Num of Items
5010805	ITEM QUANTITY	Asphalt_PPI	MI_Building_Permits	TOTAL_AMOUNT_PER_QUARTER_STATE	FabMetal_PPI
5012013	PRIMARY COUNTY	REFVENDOR_NM	NUM_CONTRACTS_PER_MONTH_PER_REGION	NUM_CONTRACTS_PER_YEAR_PER_COUNTY	NUM_CONTRACTS_PER_QUARTER_PER_REGION
5012025	ITEM QUANTITY	CONTRACT DESCRIPTION	Number_Bidders	TOTAL_AMOUNT_PER_YEAR_PER_COUNTY	REFVENDOR_NM
5012036	Num of Items	TOTAL_AMOUNT_PER_QUARTER_PER_COUNTY	PRIMARY COUNTY	ITEM QUANTITY	AWARDED AMOUNT
5012037	TOTAL_AMOUNT_PER_YEAR_PER_COUNTY	ITEM QUANTITY	Num of Items	NUM_CONTRACTS_PER_YEAR_PER_COUNTY	ReadyMix_Concrete_PPI
5012085	ITEM QUANTITY	TOTAL_AMOUNT_PER_QUARTER_PER_COUNTY	PRIMARY COUNTY	REFVENDOR_NM	Number_Bidders

Item Number	Top Five Important Factors				
5020001	ITEM QUANTITY	NUM_CONTRACTS_PER_YEAR_PER_COUNTY	TOTAL_AMOUNT_PER_YEAR_PER_COUNTY	NUM_CONTRACTS_PER_MONTH_STATE	Num of Items
5020008	DISTRICT	AWARDED AMOUNT	TOTAL_AMOUNT_PER_QUARTER_PER_REGION	NUM_CONTRACTS_PER_QUARTER_PER_REGION	TOTAL_AMOUNT_PER_MONTH_PER_COUNTY
5020807	Const_Unemployment_Pct	ITEM QUANTITY	TOTAL_AMOUNT_PER_MONTH_PER_REGION	MortgageRate_30Yr	CONTRACT DESCRIPTION
5040020	NUM_CONTRACTS_PER_QUARTER_PER_REGION	ITEM QUANTITY	TOTAL_AMOUNT_PER_YEAR_PER_COUNTY	MortgageRate_30Yr	TOTAL_AMOUNT_PER_QUARTER_STATE
5040030	TOTAL_AMOUNT_PER_YEAR_PER_COUNTY	ITEM QUANTITY	US_Diesel_Price	NUM_CONTRACTS_PER_YEAR_PER_REGION	SteelMill_PPI
5050001	TOTAL_AMOUNT_PER_YEAR_PER_REGION	ITEM QUANTITY	MortgageRate_30Yr	TOTAL_AMOUNT_PER_MONTH_PER_COUNTY	TOTAL_AMOUNT_PER_YEAR_STATE
5050020	Asphalt_PPI	Number_Bidders	TOTAL_AMOUNT_PER_QUARTER_PER_REGION	US_Consumer_Conf	Const_Unemployment_Pct
5050040	PowerCrane_PPI	FabMetal_PPI	ColdSteel_Bar_PPI	REFVENDOR_NM	ITEM QUANTITY
6020019	MortgageRate_30Yr	TOTAL_AMOUNT_PER_QUARTER_PER_COUNTY	MI_Building_Permits	REFVENDOR_NM	TOTAL_AMOUNT_PER_MONTH_PER_COUNTY
6020056	DISTRICT	ITEM QUANTITY	SP500_Index	DowJones_Avg	NaturalGas_PPI
6020058	NonResConst_Spend	ITEM QUANTITY	HighwaySpend_Mil	TOTAL_AMOUNT_PER_YEAR_PER_REGION	CPI_Northeast
6020200	ITEM QUANTITY	Num of Items	Number_Bidders	REFVENDOR_NM	NUM_CONTRACTS_PER_YEAR_PER_REGION
6020512	MI_Building_Permits	MortgageRate_30Yr	NUM_CONTRACTS_PER_QUARTER_PER_REGION	MONTH_NUM	NUM_CONTRACTS_PER_QUARTER_STATE

Item Number	Top Five Important Factors				
6020514	Const_Mach_PPI	ITEM QUANTITY	PowerCrane_PPI	MI_Building_Permits	HighwaySpend_Mil
6020524	ITEM QUANTITY	PowerCrane_PPI	MI_Building_Permits	CONTRACT DESCRIPTION	NewRes_Building_Permits
6020600	ITEM QUANTITY	ReadyMix_Concrete_PPI	M1_Currency_Bil	TotalConst_Spend	Num of Items
6030015	ITEM QUANTITY	NUM_CONTRACTS_PER_YEAR_PER_COUNTY	Number_Bidders	TOTAL_AMOUNT_PER_YEAR_PER_COUNTY	MONTH_NUM
6030020	ITEM QUANTITY	Num of Items	TOTAL_AMOUNT_PER_YEAR_PER_COUNTY	NUM_CONTRACTS_PER_YEAR_PER_REGION	TOTAL_AMOUNT_PER_QUARTER_PER_COUNTY
6030030	ITEM QUANTITY	CONTRACT DESCRIPTION	MortgageRate_30Yr	Num of Items	REFVENDOR_NM
6030048	ITEM QUANTITY	TranspWare_AvgEarn	DISTRICT	AWARDED AMOUNT	SP500_Index
6030050	Household_Est_Thou	ITEM QUANTITY	MI_Gasoline_Price	CPI_Gasoline_12MChg	Const_Unemployment_Pct
6030052	ITEM QUANTITY	TOTAL_AMOUNT_PER_MONTH_STATE	Household_Est_Thou	NUM_CONTRACTS_PER_QUARTER_STATE	MI_Building_Permits
6030080	ITEM QUANTITY	US_Consumer_Conf	CONTRACT DESCRIPTION	TOTAL_AMOUNT_PER_QUARTER_PER_COUNTY	Num of Items
6030090	ITEM QUANTITY	US_Consumer_Conf	TOTAL_AMOUNT_PER_MONTH_STATE	REFVENDOR_NM	PRIMARY COUNTY
6030100	ITEM QUANTITY	DISTRICT	NUM_CONTRACTS_PER_MONTH_STATE	Const_Avg_Hrs	TOTAL_AMOUNT_PER_YEAR_PER_REGION
6030101	NUM_CONTRACTS_PER_YEAR_PER_COUNTY	ITEM QUANTITY	DISTRICT	TOTAL_AMOUNT_PER_MONTH_PER_REGION	ColdSteel_Bar_PPI
7040001	TotalPrivate_AvgEarn	Const_Mach_PPI	ITEM QUANTITY	US_Consumer_Conf	CONTRACT DESCRIPTION
7040002	TOTAL_AMOUNT_PER_MONTH_PER_REGION	TOTAL_AMOUNT_PER_QUARTER_PER_COUNTY	Num of Items	ITEM QUANTITY	CONTRACT DESCRIPTION

Item Number	Top Five Important Factors				
7050030	HighwaySpend_Mil	CONTRACT DESCRIPTION	NUM_CONTRACTS_PER_MONTH_PER_COUNTY	NaturalGas_PPI	TOTAL_AMOUNT_PER_YEAR_PER_REGION
7050034	NUM_CONTRACTS_PER_MONTH_PER_REGION	ITEM QUANTITY	DowJones_Avg	MortgageRate_30Yr	HotSteel_Bar_PPI
7060003	HighwaySpend_Mil	TOTAL_AMOUNT_PER_MONTH_PER_COUNTY	ITEM QUANTITY	TOTAL_AMOUNT_PER_YEAR_PER_COUNTY	TOTAL_AMOUNT_PER_YEAR_PER_REGION
7060010	ITEM QUANTITY	Num of Items	CONTRACT DESCRIPTION	AWARDED AMOUNT	DowJones_Avg
7060011	REFVENDOR_NM	CPI_FuelOil_USAvg	ITEM QUANTITY	TOTAL_AMOUNT_PER_QUARTER_PER_REGION	NUM_CONTRACTS_PER_MONTH_STATE
7060013	ITEM QUANTITY	TOTAL_AMOUNT_PER_QUARTER_PER_REGION	REFVENDOR_NM	TOTAL_AMOUNT_PER_YEAR_PER_REGION	ResConst_Spend
7060050	REFVENDOR_NM	ITEM QUANTITY	TOTAL_AMOUNT_PER_MON_PER_COU	ColdSteel_Bar_PPI	Num of Items
7060092	ITEM QUANTITY	TOTAL_AMOUNT_PER_YEAR_PER_COUNTY	NonResConst_Spend	ColdSteel_Bar_PPI	NUM_CONTRACTS_PER_YEAR_PER_REGION
7060100	ITEM QUANTITY	Number_Bidders	REFVENDOR_NM	TOTAL_AMOUNT_PER_QUARTER_PER_COUNTY	AWARDED AMOUNT
7060101	ITEM QUANTITY	NonResConst_Spend	CPI_Northeast	NUM_CONTRACTS_PER_MONTH_PER_REGION	NUM_CONTRACTS_PER_YEAR_PER_COUNTY
7060113	MI_Building_Permits	REFVENDOR_NM	DISTRICT	CONTRACT DESCRIPTION	TOTAL_AMOUNT_PER_YEAR_PER_COUNTY
7060117	Asphalt_PPI	ResConst_Spend	DISTRICT	CONTRACT DESCRIPTION	MI_Building_Permits
7070051	PRIMARY COUNTY	Const_Unemployment_Pct	CONTRACT DESCRIPTION	ITEM QUANTITY	NUM_CONTRACTS_PER_MONTH_STATE

Item Number	Top Five Important Factors				
7070060	ITEM QUANTITY	ResConst_Spend	Num of Items	NUM_CONTRACTS_PER_YEAR_PER_REGION	NUM_CONTRACTS_PER_MONTH_PER_REGION
7070061	ITEM QUANTITY	Number_Bidders	NUM_CONTRACTS_PER_YEAR_PER_COUNTY	HotSteel_Bar_PPI	TOTAL_AMOUNT_PER_QUARTER_PER_REGION
7070120	CONTRACT DESCRIPTION	Unemployment_Pct	TOTAL_AMOUNT_PER_QUARTER_PER_COUNTY	NUM_CONTRACTS_PER_YEAR_PER_REGION	Number_Bidders
7120004	ITEM QUANTITY	TOTAL_AMOUNT_PER_YEAR_PER_COUNTY	TotalConst_Spend	REFVENDOR_NM	HighwaySpend_Mil
7120007	ITEM QUANTITY	SP500_Index	CPI_Northeast	REFVENDOR_NM	US_Consumer_Conf
7120017	ITEM QUANTITY	Const_Emp_Thou	REFVENDOR_NM	ColdSteel_Bar_PPI	Asphalt_PPI
7120022	TranspWare_AvgEarn	ITEM QUANTITY	CPI_Inflation	NewRes_Building_Permits	CPI_Northeast
7120025	REFVENDOR_NM	Gasoline_PPI	ITEM QUANTITY	MortgageRate_30Yr	Num of Items
7120027	AWARDED AMOUNT	Oil_Price_Barrel	TOTAL_AMOUNT_PER_YEAR_PER_REGION	NewRes_Building_Permits	TOTAL_AMOUNT_PER_MONTH_PER_COUNTY
7120071	PRIMARY COUNTY	CPI_Northeast	TOTAL_AMOUNT_PER_YEAR_PER_COUNTY	ITEM QUANTITY	Num of Items
7120076	REFVENDOR_NM	ITEM QUANTITY	MortgageRate_30Yr	CONTRACT DESCRIPTION	Unemployment_Pct
7120100	ITEM QUANTITY	DISTRICT	NUM_CONTRACTS_PER_MONTH_STATE	Num of Items	TOTAL_AMOUNT_PER_QUARTER_PER_COUNTY
7120112	ITEM QUANTITY	REFVENDOR_NM	Num of Items	NUM_CONTRACTS_PER_YEAR_PER_REGION	DISTRICT
7120120	ITEM QUANTITY	DISTRICT	REFVENDOR_NM	US_Consumer_Conf	TOTAL_AMOUNT_PER_YEAR_PER_REGION

Item Number	Top Five Important Factors				
7130010	Unemployment_Pct	ITEM QUANTITY	AWARDED AMOUNT	Num of Items	US_Consumer_Conf
7130030	HighwaySpend_Mil	NUM_CONTRACTS_PER_QUARTER_PER_COUNTY	TOTAL_AMOUNT_PER_MONTH_PER_REGION	CONTRACT DESCRIPTION	NUM_CONTRACTS_PER_YEAR_PER_REGION
7130031	TOTAL_AMOUNT_PER_MONTH_PER_COUNTY	TOTAL_AMOUNT_PER_QUARTER_STATE	HotSteel_Bar_PPI	CONTRACT DESCRIPTION	REFVENDOR_NM
7130070	CPI_Gasoline_12M Chg	ITEM QUANTITY	NewRes_Building_Permits	TOTAL_AMOUNT_PER_YEAR_PER_COUNTY	ColdSteel_Bar_PPI
7130071	ITEM QUANTITY	Asphalt_PPI	US_Consumer_Conf	AWARDED AMOUNT	Number_Bidders
7130080	ITEM QUANTITY	Const_Unemployment_Pct	NUM_CONTRACTS_PER_YEAR_PER_COUNTY	TOTAL_AMOUNT_PER_MONTH_PER_COUNTY	REFVENDOR_NM
7130082	Gasoline_PPI	Const_Unemployment_Pct	CONTRACT DESCRIPTION	Num of Items	TOTAL_AMOUNT_PER_QUARTER_PER_COUNTY
7180121	NaturalGas_PPI	NUM_CONTRACTS_PER_QUARTER_PER_REGION	NUM_CONTRACTS_PER_YEAR_PER_REGION	TOTAL_AMOUNT_PER_MONTH_PER_REGION	NUM_CONTRACTS_PER_YEAR_STATE
8010005	DISTRICT	ResConst_Spend	ITEM QUANTITY	REFVENDOR_NM	Const_Mach_PPI
8010007	Const_Mach_PPI	PowerCrane_PPI	NUM_CONTRACTS_PER_YEAR_PER_COUNTY	MI_Gasoline_Price	Const_Materials_PPI
8020010	MI_Const_Emp_Earnings_Thou	ITEM QUANTITY	Num of Items	AWARDED AMOUNT	CONTRACT DESCRIPTION
8020016	ITEM QUANTITY	TotalPrivate_AvgEarn	Num of Items	DISTRICT	CPI_Northeast
8020023	CPI_Northeast	ITEM QUANTITY	Num of Items	SP500_Index	DowJones_Avg
8020031	ITEM QUANTITY	NonResConst_Spend	PowerCrane_PPI	Num of Items	DISTRICT
8020036	ITEM QUANTITY	DieselFuel_PPI	AWARDED AMOUNT	HighwaySpend_Mil	Num of Items
8020038	ITEM QUANTITY	NewRes_Building_Permits	Num of Items	CPI_Northeast	NonResConst_Spend

Item Number	Top Five Important Factors				
8020040	ITEM QUANTITY	CPI_Northeast	Num of Items	AWARDED AMOUNT	HighwaySpend_Mil
8020050	NonResConst_Spend	HighwaySpend_Mil	TranspWare_AvgEarn	TOTAL_AMOUNT_PER_MONTH_PER_COUNTY	Num of Items
8030011	CONTRACT DESCRIPTION	ITEM QUANTITY	Num of Items	NUM_CONTRACTS_	PRIMARY COUNTY
8030030	Num of Items	ITEM QUANTITY	AWARDED AMOUNT	CONTRACT DESCRIPTION	PRIMARY COUNTY
8030034	Num of Items	ITEM QUANTITY	DISTRICT	DowJones_Avg	AWARDED AMOUNT
8030036	Num of Items	Const_Avg_HrlyEarn	ITEM QUANTITY	DISTRICT	Const_Avg_Earn
8030044	ITEM QUANTITY	Num of Items	MI_Building_Permits	HighwaySpend_Mil	AWARDED AMOUNT
8030046	Num of Items	MI_Const_Emp_Thou	ITEM QUANTITY	CPI_Northeast	TOTAL_AMT_PER_QUARTER_PER_REGIO
8032002	Num of Items	ITEM QUANTITY	Number_Bidders	NUM_CONTRACTS_PER_QUARTER_PER_COUNT	MI_Gasoline_Price
8060040	ITEM QUANTITY	Const_Materials_PPI	MI_Const_Emp_Earnings_Thou	MI_Const_Emp_Thou	TOTAL_AMOUNT_PER_MON_PER_COUNT
8070000	ITEM QUANTITY	ColdSteel_Bar_PPI	NUM_CONTRACTS_PER_YEAR_PER_REGION	Num of Items	NewRes_Building_Permits
8070002	SP500_Index	ColdSteel_Bar_PPI	ITEM QUANTITY	HotSteel_Bar_PPI	TOTAL_AMOUNT_PER_QUARTER_PER_REGION
8070004	ResConst_Spend	ITEM QUANTITY	FabMetal_PPI	ReadyMix_Concrete_PPI	ENR_Labor_Index
8070044	US_Consumer_Conf	AWARDED AMOUNT	Num of Items	Household_Est_Thou	TotalConst_Spend
8080002	ITEM QUANTITY	TranspWare_AvgEarn	Num of Items	MI_Building_Permits	TOTAL_AMOUNT_PER_QUARTER_STATE
8100104	Const_Avg_HrlyEarn	Household_Est_Thou	ReadyMix_Concrete_PPI	ResConst_Spend	Concrete_PPI
8100250	NaturalGas_PPI	TOTAL_AMT_PER_MON_PER_REGION	NUM_CONTRACTS_PER_YEAR_STATE	WTI_Oil_Price	TOTAL_AMOUNT_PER_QUARTER_STATE

Item Number	Top Five Important Factors				
8100280	ITEM QUANTITY	Household_Est_Thou	CONTRACT DESCRIPTION	NUM_CONTRACTS_PER_YEAR_PER_COUNTY	TOTAL_AMOUNT_PER_YEAR_PER_COUNTY
8100330	HighwaySpend_Mil	NUM_CONTRACTS_PER_YEAR_PER_REGION	Oil_Price_Barrel	Const_Unemployment_Pct	MI_Const_Emp_Thou
8100360	Unemployment_Pct	Number_Bidders	CONTRACT DESCRIPTION	Num of Items	TOTAL_AMOUNT_PER_QUARTER_PER_COUNTY
8100361	ReadyMix_Concrete_PPI	ITEM QUANTITY	REFVENDOR_NM	NUM_CONTRACTS_PER_MONTH_PER_REGION	NUM_CONTRACTS_PER_YEAR_PER_COUNTY
8100371	Household_Est_Thou	ITEM QUANTITY	SP500_Index	Num of Items	CONTRACT DESCRIPTION
8100380	ITEM QUANTITY	ColdSteel_Bar_PPI	Num of Items	DISTRICT	REFVENDOR_NM
8100382	HighwaySpend_Mil	TOTAL_AMT_PER_YEAR_PER_COUNT	REFVENDOR_NM	TOTAL_AMOUNT_PER_MONTH_PER_REGION	CONTRACT DESCRIPTION
8100391	Const_Unemployment_Pct	TOTAL_AMOUNT_PER_QUARTER_PER_COUNTY	REFVENDOR_NM	CONTRACT DESCRIPTION	NUM_CONTRACTS_PER_YEAR_PER_COUNTY
8100392	ColdSteel_Bar_PPI	TOTAL_AMOUNT_PER_MONTH_PER_COUNTY	SP500_Index	TranspWare_AvgEarn	Const_Equip_PPI
8100398	HighwaySpend_Mil	NUM_CONTRACTS_PER_YEAR_PER_COUNTY	ITEM QUANTITY	Num of Items	Const_Unemployment_Pct
8100399	CPI_Northeast	CONTRACT DESCRIPTION	NUM_CONTRACTS_PER_MON_STATE	ITEM QUANTITY	REFVENDOR_NM
8100403	ITEM QUANTITY	Num of Items	Const_Mach_PPI	REFVENDOR_NM	CONTRACT DESCRIPTION
8100404	ITEM QUANTITY	CPI_Northeast	NonResConst_Spend	SP500_Index	AWARDED AMOUNT
8100405	ITEM QUANTITY	CPI_Northeast	NewRes_Building_Permits	CONTRACT DESCRIPTION	Household_Est_Thou

Item Number	Top Five Important Factors				
8100425	Num of Items	ITEM QUANTITY	SP500_Index	REFVENDOR_NM	CONTRACT DESCRIPTION
8100616	HighwaySpend_Mil	CONTRACT DESCRIPTION	ITEM QUANTITY	Num of Items	PRIMARY COUNTY
8110024	ITEM QUANTITY	Num of Items	AWARDED AMOUNT	TOTAL_AMOUNT_PER_MONTH_PER_COUNTY	TOTAL_AMOUNT_PER_QUARTER_PER_COUNTY
8110039	Num of Items	ColdSteel_Bar_PPI	Asphalt_PPI	ITEM QUANTITY	AWARDED AMOUNT
8110040	Num of Items	ITEM QUANTITY	AWARDED AMOUNT	TOTAL_AMOUNT_PER_QUARTER_PER_COUNTY	NUM_CONTRACTS_PER_MONTH_STATE
8110041	Num of Items	ITEM QUANTITY	TOTAL_AMOUNT_PER_YEAR_PER_REGION	TOTAL_AMOUNT_PER_MONTH_PER_COUNTY	AWARDED AMOUNT
8110045	ITEM QUANTITY	AWARDED AMOUNT	PowerCrane_PPI	TOTAL_AMOUNT_PER_MONTH_PER_COUNTY	Num of Items
8110051	ITEM QUANTITY	AWARDED AMOUNT	TOTAL_AMOUNT_PER_MONTH_PER_COUNTY	Num of Items	PowerCrane_PPI
8110063	Const_Mach_PPI	ITEM QUANTITY	NewRes_Building_Permits	AWARDED AMOUNT	Num of Items
8110068	ITEM QUANTITY	AWARDED AMOUNT	Const_Equip_PPI	Num of Items	NewRes_Building_Permits
8110071	NewRes_Building_Permits	ITEM QUANTITY	AWARDED AMOUNT	Num of Items	NonResConst_Spend
8110074	ColdSteel_Bar_PPI	ITEM QUANTITY	Num of Items	PRIMARY COUNTY	AWARDED AMOUNT
8110093	ITEM QUANTITY	PowerCrane_PPI	CPI_Northeast	REFVENDOR_NM	NonResConst_Spend
8110110	Num of Items	ITEM QUANTITY	Number_Bidders	REFVENDOR_NM	Concrete_PPI
8110114	ITEM QUANTITY	Const_Materials_PPI	CPI_Northeast	DISTRICT	NewRes_Building_Permits
8110153	ITEM QUANTITY	Num of Items	AWARDED AMOUNT	REFVENDOR_NM	Number_Bidders
8110154	ITEM QUANTITY	Num of Items	CONTRACT DESCRIPTION	TOTAL_AMOUNT_PER_QUARTER_PER_REGION	Number_Bidders

Item Number	Top Five Important Factors				
8110159	Num of Items	ITEM QUANTITY	MONTH_NUM	AWARDED AMOUNT	ColdSteel_Bar_PPI
8110253	ITEM QUANTITY	Num of Items	REFVENDOR_NM	AWARDED AMOUNT	TOTAL_AMOUNT_PER_MON_PER_COUNT
8110294	ITEM QUANTITY	Const_Mach_PPI	Num of Items	Household_Est_Thou	AWARDED AMOUNT
8110343	ITEM QUANTITY	MI_Const_Emp_Earnings_Thou	MI_Const_Emp_Thou	CONTRACT DESCRIPTION	NewRes_Building_Permits
8110450	ITEM QUANTITY	Concrete_PPI	MortgageRate_30Yr	Num of Items	Household_Est_Thou
8110501	FabMetal_PPI	TotalConst_Spend	Num of Items	US_Consumer_Conf	Asphalt_PPI
8110505	FabMetal_PPI	Unemployment_Pct	CPI_Gasoline_12MChg	Num of Items	SteelMill_PPI
8110550	HighwaySpend_Mil	ITEM QUANTITY	PRIMARY COUNTY	FabMetal_PPI	Household_Est_Thou
8120012	AWARDED AMOUNT	DISTRICT	Num of Items	TOTAL_AMOUNT_PER_MONTH_PER_COUNTY	NaturalGas_PPI
8120013	MI_Const_Emp_Earnings_Thou	AWARDED AMOUNT	TOTAL_AMOUNT_PER_YEAR_PER_COUNTY	REFVENDOR_NM	DISTRICT
8120026	DISTRICT	AWARDED AMOUNT	TOTAL_AMOUNT_PER_MONTH_PER_COUNTY	TOTAL_AMOUNT_PER_MONTH_STATE	CONTRACT DESCRIPTION
8120031	Number_Bidders	ITEM QUANTITY	CPI_Gasoline_12MChg	TOTAL_AMOUNT_PER_QUARTER_PER_REGION	DISTRICT
8120035	AWARDED AMOUNT	Num of Items	REFVENDOR_NM	CONTRACT DESCRIPTION	TOTAL_AMOUNT_PER_MONTH_PER_COUNTY
8120081	ITEM QUANTITY	REFVENDOR_NM	DISTRICT	AWARDED AMOUNT	TOTAL_AMOUNT_PER_MONTH_PER_REGION
8120082	ITEM QUANTITY	REFVENDOR_NM	Num of Items	AWARDED AMOUNT	CONTRACT DESCRIPTION
8120083	ITEM QUANTITY	HighwaySpend_Mil	CONTRACT DESCRIPTION	NUM_CONTRACTS_PER_YEAR_PER_REGION	TOTAL_AMOUNT_PER_MONTH_PER_COUNTY

Item Number	Top Five Important Factors				
8120140	AWARDED AMOUNT	Num of Items	TOTAL_AMOUNT_PER_YEAR_PER_REGION	NUM_CONTRACTS_PER_YEAR_PER_REGION	CONTRACT DESCRIPTION
8120180	AWARDED AMOUNT	REFVENDOR_NM	ITEM QUANTITY	CONTRACT DESCRIPTION	TOTAL_AMOUNT_PER_MONTH_PER_COUNTY
8120235	Num of Items	ITEM QUANTITY	TOTAL_AMOUNT_PER_MONTH_PER_REGION	TOTAL_AMOUNT_PER_MONTH_PER_COUNTY	AWARDED AMOUNT
8120240	ITEM QUANTITY	CONTRACT DESCRIPTION	Num of Items	REFVENDOR_NM	TOTAL_AMOUNT_PER_YEAR_PER_COUNTY
8120241	ITEM QUANTITY	REFVENDOR_NM	Num of Items	CONTRACT DESCRIPTION	TOTAL_AMOUNT_PER_YEAR_PER_COUNTY
8120245	REFVENDOR_NM	Num of Items	ITEM QUANTITY	TOTAL_AMOUNT_PER_YEAR_PER_REGION	TOTAL_AMOUNT_PER_MONTH_PER_COUNTY
8120246	Num of Items	ITEM QUANTITY	REFVENDOR_NM	TOTAL_AMOUNT_PER_MONTH_PER_COUNTY	CONTRACT DESCRIPTION
8120250	AWARDED AMOUNT	DISTRICT	Num of Items	ITEM QUANTITY	CONTRACT DESCRIPTION
8120252	TOTAL_AMOUNT_PER_MONTH_PER_COUNTY	AWARDED AMOUNT	CONTRACT DESCRIPTION	PRIMARY COUNTY	Num of Items
8120270	AWARDED AMOUNT	TOTAL_AMOUNT_PER_QUARTER_PER_REGION	REFVENDOR_NM	TOTAL_AMOUNT_PER_YEAR_PER_COUNTY	TOTAL_AMOUNT_PER_YEAR_PER_REGION
8120330	AWARDED AMOUNT	Num of Items	DISTRICT	TOTAL_AMOUNT_PER_MONTH_PER_COUNTY	CONTRACT DESCRIPTION
8120332	AWARDED AMOUNT	DISTRICT	Num of Items	CONTRACT DESCRIPTION	TOTAL_AMOUNT_PER_MONTH_PER_COUNTY

Item Number	Top Five Important Factors				
8120350	DISTRICT	TOTAL_AMOUNT_PER_YEAR_PER_REGION	AWARDED AMOUNT	ITEM QUANTITY	Num of Items
8120351	DISTRICT	REFVENDOR_NM	Num of Items	CONTRACT DESCRIPTION	PRIMARY COUNTY
8120352	DISTRICT	TOTAL_AMOUNT_PER_YEAR_PER_COUNTY	AWARDED AMOUNT	TOTAL_AMOUNT_PER_MONTH_PER_COUNTY	CONTRACT DESCRIPTION
8122000	CONTRACT DESCRIPTION	TOTAL_AMOUNT_PER_MONTH_PER_COUNTY	ITEM QUANTITY	Num of Items	TOTAL_AMOUNT_PER_QUARTER_PER_REGION
8122002	TOTAL_AMOUNT_PER_YEAR_PER_COUNTY	NUM_CONTRACTS_PER_YEAR_PER_COUNTY	TOTAL_AMOUNT_PER_MONTH_PER_REGION	Num of Items	REFVENDOR_NM
8130010	ITEM QUANTITY	Const_Avg_Earn	DISTRICT	Const_Unemployment_Pct	TOTAL_AMOUNT_PER_YEAR_PER_REGION
8130011	ITEM QUANTITY	Const_Materials_PPI	Const_Emp_Thou	Const_Mach_PPI	Const_Unemployment_Pct
8130015	HighwaySpend_Mil	TOTAL_AMOUNT_PER_YEAR_PER_COUNTY	AWARDED AMOUNT	ITEM QUANTITY	NUM_CONTRACTS_PER_QUARTER_PER_COUNTY
8130020	ITEM QUANTITY	SP500_Index	NUM_CONTRACTS_PER_MONTH_PER_REGION	NUM_CONTRACTS_PER_QUARTER_PER_COUNTY	TOTAL_AMOUNT_PER_MONTH_PER_COUNTY
8160027	ITEM QUANTITY	MI_Building_Permits	CONTRACT DESCRIPTION	Asphalt_PPI	ABI_Index
8160061	ITEM QUANTITY	Asphalt_PPI	DowJones_Avg	CPI_Northeast	PowerCrane_PPI
8160062	ITEM QUANTITY	Unemployment_Pct	Number_Bidders	Asphalt_PPI	HighwaySpend_Mil
8160100	ITEM QUANTITY	REFVENDOR_NM	Num of Items	NaturalGas_PPI	NUM_CONTRACTS_PER_MONTH_STATE
8160101	ITEM QUANTITY	Num of Items	AWARDED AMOUNT	TOTAL_AMOUNT_PER_QUARTER_PER_COUNT	CONTRACT DESCRIPTION

Item Number	Top Five Important Factors				
8160102	ITEM QUANTITY	Num of Items	REFVENDOR_NM	Number_Bidders	TOTAL_AMOUNT_PER_QUARTER_STATE
8190029	ITEM QUANTITY	HighwaySpend_Mil	Num of Items	PRIMARY COUNTY	AWARDED AMOUNT
8190032	ITEM QUANTITY	TotalConst_Spend	NewRes_Building_Permits	DowJones_Avg	SP500_Index
8190260	ResConst_Spend	Household_Est_Thou	HighwaySpend_Mil	Num of Items	Const_Materials_PPI
8190602	ITEM QUANTITY	TotalConst_Spend	Number_Bidders	MI_Const_Emp_Earnings_Thou	CONTRACT DESCRIPTION
8190604	ITEM QUANTITY	Num of Items	TotalPrivate_AvgEarn	TotalConst_Spend	CONTRACT DESCRIPTION
8200029	REFVENDOR_NM	TOTAL_AMOUNT_PER_YEAR_PER_REGION	NUM_CONTRACTS_PER_YEAR_PER_COUNTY	MortgageRate_30Yr	PRIMARY COUNTY
8200032	NUM_CONTRACTS_PER_YEAR_PER_COUNTY	AWARDED AMOUNT	Num of Items	REFVENDOR_NM	ITEM QUANTITY
8200045	Household_Est_Thou	Const_Mach_PPI	NonResConst_Spend	PRIMARY COUNTY	Concrete_PPI
8200100	REFVENDOR_NM	NewRes_Building_Permits	TOTAL_AMOUNT_PER_YEAR_PER_COUNTY	US_Consumer_Conf	TOTAL_AMOUNT_PER_YEAR_PER_REGION
8200105	Const_Mach_PPI	REFVENDOR_NM	CPI_Northeast	PRIMARY COUNTY	CONTRACT DESCRIPTION
8200121	Household_Est_Thou	REFVENDOR_NM	CONTRACT DESCRIPTION	TOTAL_AMOUNT_PER_YEAR_PER_COUNTY	Number_Bidders
8200135	TranspWare_AvgEarn	REFVENDOR_NM	TotalConst_Spend	DISTRICT	NonResConst_Spend
8200140	CPI_Northeast	Num of Items	ITEM QUANTITY	TOTAL_AMOUNT_PER_MONTH_PER_COUNTY	Household_Est_Thou
8200142	NonResConst_Spend	HighwaySpend_Mil	NUM_CONTRTS_PER_YEAR_PER_COY	Number_Bidders	TOTAL_AMOUNT_PER_YEAR_PER_COTY
8200186	Num of Items	DISTRICT	TOTAL_AMOUNT_PER_QUARTER_PER_COUNTY	TOTAL_AMOUNT_PER_YEAR_PER_REGION	TOTAL_AMOUNT_PER_YEAR_PER_COUNTY

Item Number	Top Five Important Factors				
8200345	CONTRACT DESCRIPTION	Household_Est_Thou	Num of Items	PRIMARY COUNTY	AWARDED AMOUNT
8200380	MONTH_NUM	ITEM QUANTITY	US_Diesel_Price	REFVENDOR_NM	FFR_Rate
8200422	Num of Items	Const_Materials_PPI	NUM_CONTR_PER_MON_PER_COTY	PRIMARY COUNTY	CONTRACT DESCRIPTION
8200425	Unemployment_Pct	Number_Bidders	ColdSteel_Bar_PPI	Asphalt_PPI	TOTAL_AMOUNT_PER_QUARTER_STATE
8200444	ITEM QUANTITY	TOTAL_AMOUNT_PER_QUARTER_PER_COUNTY	CONTRACT DESCRIPTION	CPI_Gasoline_12MChg	TOTAL_AMOUNT_PER_QUARTER_PER_REGION
8200460	TotalConst_Spend	ITEM QUANTITY	NUM_CONTRACTS_PER_MONTH_PER_COUNTY	PRIMARY COUNTY	REFVENDOR_NM
8200461	SteelMill_PPI	Household_Est_Thou	Num of Items	FabMetal_PPI	CONTRACT DESCRIPTION
8200462	HotSteel_Bar_PPI	SteelMill_PPI	FabMetal_PPI	TOTAL_AMOUNT_PER_QUARTER_PER_REGION	NUM_CONTRACTS_PER_YEAR_STATE
8200470	Const_Equip_PPI	NonResConst_Spend	Num of Items	AWARDED AMOUNT	ABI_Index
8200480	ResConst_Spend	ITEM QUANTITY	Num of Items	CONTRACT DESCRIPTION	DISTRICT
8220001	ITEM QUANTITY	REFVENDOR_NM	Concrete_PPI	TOTAL_AMOUNT_PER_YEAR_PER_REGION	DowJones_Avg
8220013	ITEM QUANTITY	CONTRACT DESCRIPTION	REFVENDOR_NM	AWARDED AMOUNT	TOTAL_AMOUNT_PER_QUARTER_PER_REGION
8220025	ITEM QUANTITY	CONTRACT DESCRIPTION	PRIMARY COUNTY	Asphalt_PPI	US_Consumer_Conf
8230156	ITEM QUANTITY	MI_Building_Permits	CONTRACT DESCRIPTION	AWARDED AMOUNT	Num of Items
8230166	CPI_Northeast	PRIMARY COUNTY	CONTRACT DESCRIPTION	NUM_CONTRACTS_PER_YEAR_PER_COUNTY	MONTH_NUM