DEVELOPMENT OF AN INTERACTIVE DASHBOARD WITH FORECASTING FOR CONSTRUCTION MATERIAL PRICES ANALYSIS IN THE UK

(14,726 words)

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Abstract

This study developed an interactive dashboard and predictive models to assist UK construction project managers in understanding, analysing, and forecasting construction material prices (CMPs). Historical price data for 15 key construction materials from October 2019 to June 2024 was collected and analysed. The project focused on transforming complex construction industry data into an accessible format for non-specialist audiences. Multiple linear regression (MLR) models identified significant economic indicators influencing material prices, while Autoregressive Integrated Moving Average (ARIMA) models were developed to forecast future prices, with most materials showing forecast errors below 5%. Key findings include significant price volatility since 2020, with some materials like flexible pipes showing over 17% annual increases. The sterling exchange rate, employment figures, and construction output price index are common factors that potentially affect materials' price. Therefore, an interactive Tableau dashboard was created to visualise these historical trends, economic indicators, and price forecasts. The dashboard's design prioritised user-friendly interfaces and intuitive data exploration features, allowing project managers to gain deeper insights into market dynamics without requiring specialised data analysis skills for improving cost estimation and risk assessment in their construction projects.

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Chapter 1: Introduction

1.1 Background

The construction industry is a vital sector of the UK economy, which contributes approximately 6% to the GDP and employs around 2.7 million people in 2018 (Rhodes, 2019). Construction costs for mega projects have become a major concern, due to their high prices and numerous design modifications during their long construction durations. Contractors have also been struggled to create accurate cost estimates as a result of this issue. Since the construction material prices (CMPs) can account for up to one-fourth of overall project costs (Hwang et al., 2012). The industry is highly susceptible to fluctuations in material prices, which can impact project costs, timelines, and overall feasibility. The latest data from the Department for Business and Trade shows that the cost of construction materials in the UK rose by 36% since May 2020, the last 12 months has seen a 3.3% fall in prices (Cladco, 2024). Moreover, the data shows variations in some materials' price such as pre-cast concrete products increased by 63% since May 2020, while flexible pipes and fittings saw a 55% price hike in the same period. The significant price volatility was due to major events such as COVID-19 and Brexit, which caused supply chain disruption, raw material shortages, worker shortages, etc (Cladco, 2024). As a result, construction project managers are increasingly seeking innovative solutions to manage risks associated with material costs and improve project planning accuracy.

The adoption of data-driven decision-making tools has become critical for the industry's efficiency and competitiveness. The UK government's Construction 2025 strategy emphasises the importance of digital technologies in improving the sector's performance (gov.uk, 2013). Among these technologies, interactive dashboards and predictive modelling have emerged as powerful aids for construction professionals (João Ribeirinho et al., 2020). These tools provide a forward-looking perspective on material prices and forecast future price trends based on historical data and relevant economic indicators, using methods like time series analysis, regression models, and machine learning algorithms (Rafiei and Adeli, 2018). This predictive capability allows project managers to anticipate potential cost fluctuations and adjust their strategies accordingly.

The integration of interactive dashboards and predictive models represents a significant step towards digital transformation in the construction industry, offering numerous benefits for project managers in the context of material price management. These dashboards visualise complex data for helping managers make real-time decisions, improve communication among stakeholders, and customise views according to specific needs (Yigitbasioglu and Velcu, 2012). When predictive models are integrated with these dashboards, they provide additional benefits like forecast future prices, identify influencing factors affecting price fluctuations, enable scenario planning, and assist in developing more effective risk management strategies (Hwang et al., 2017). The combination of these tools helps project managers to navigate the challenges posed by material price volatility more effectively, helping them to improve project planning, cost estimation, and overall project performance.

As the construction sector continues to evolve, the effective use of these data-driven tools is becoming increasingly important for maintaining competitiveness and ensuring project success in an uncertain economic environment. This report explored the development and implementation of interactive Tableau dashboards and predictive models for construction material prices in the UK which aimed to provide insights into how these tools can be used by project managers to support decision-making processes and improve project outcomes.

1.2 Aim and objectives

The aim of this research is to develop and implement an interactive dashboard using Tableau and predictive models to assist UK construction project managers in understanding, analysing, and forecasting construction prices. This aim aligns with the growing need for data-driven decision-making in the construction industry, as highlighted by the UK government's Construction 2025 strategy (gov.uk, 2013). To achieve this aim, the following objectives have been established:

1. Design and develop an interactive dashboard using Tableau that visualises historical and current trends in UK construction material prices (CMPs).
2. Identify key factors that influence CMPs fluctuations in the UK market.
3. Develop forecasting models that can forecast future CMPs based on historical data and identified influencing factors.
4. Integrate the forecasting models with the Tableau dashboard to create a comprehensive decision support tool for project managers.
5. Evaluate the effectiveness of the interactive dashboard in improving decision-making processes for material procurement and cost management in construction projects.

1.3 Research questions

1. How can an interactive dashboard improve construction project managers' understanding of material price trends in the UK?
2. What key factors influence CMPs fluctuations in the UK market?
3. How can the integration of historical pricing data and predictive analytics enhance project budget planning?
4. What limitations exist in creating an accurate analytics tool for CMPs analysis?
5. To what extent can predictive models accurately forecast future CMPs?
6. How can the dashboard and predictive models be designed to accommodate the diverse needs of different types and scales of construction projects?

1.4 Problem statement

Due to the material price volatility, the lack of advanced analytical tools like interactive dashboards and predictive models make project managers struggle with vast amount of disorganised pricing data, leading to reduced productivity and missed trends (Bilal et al., 2016). This inefficient data management is compounded by the absence of real-time, easily accessible data visualisation tools, which slows down the decision-making process, causing to missed opportunities and high costs (Olawale and Sun, 2015). Without robust forecasting model, project managers rely heavily on historical data and personal experience for cost estimation, which results in significant discrepancies between estimated and actual cost (Akintoye & Fitzgerald, 2000). The inaccurate forecasting of material prices exposes construction projects to financial risks and leads to project failure. Additionally, companies that lack advanced analytics tools may put themselves at a competitive disadvantage in bidding processes and project execution (Agarwal et al., 2016). Finally, the inability to forecast prices of sustainable materials may interrupt informed decision-making of balancing cost considerations and environmental impact (Kibert, 2016).

These issues show the critical need for innovation solutions that provide construction project managers with material price insights and accurate forecasting capabilities. The development of an interactive dashboard and predictive models for material price analysis could enhance decision-making process, improve cost estimation accuracy and contribute to more successful project outcomes in the UK construction industry.

1.5 Rational

Recent technology advancements in data analytics and visualisation present an opportunity to revolutionise traditional approaches to material price monitoring and forecasting (Bilal et al., 2016). Therefore, unprecedented market volatility in recent years has made sophisticated price analysis and prediction tools not only beneficial, but also necessary. These tools aim to streamline decision-making processes, which reduce project delays and improve project outcome. Moreover, by enhancing the accuracy of cost estimations, they can mitigate financial risks associated with construction projects.

Construction companies which take advantage of data analysis for bidding and project management are likely to gain a significant edge in this competitive industry, also moving towards sustainability more easily (Agarwal et al., 2016). This development aligns with the broader trend of Construction 4.0, which promotes digitalisation in the industry (Dallasega et al., 2018). Furthermore, these technologies help address the current skills shortage by simplifying complex data analysis, and also enhance the industry's ability to adapt market changes, which are affected by Brexit and global supply chain disruption (CITB, 2023). Ultimately, the study aims to contribute to the modernisation and optimisation of the UK construction industry by representing a necessary step towards a more data-driven efficient construction sector.

1.6 Research structure

This study is organised into five chapters, each addresses specific aspects of the research project on developing an interactive dashboard and predictive models for construction material price analysis in the UK.

Chapter 1: Introduction

- Outlines the problem in UK construction material price management.
- Articulates the purpose and primary goals of the study.
- Emphasises the importance of the research for the construction industry.

Chapter 2: Literature Review

- Explores literature on construction material pricing in the UK, current methods for price monitoring and forecasting, and application of data analytics in construction.

Chapter 3: Methodology

- Explains data collection and preprocessing methods.
- Outlines dashboard design and development process.
- Details predictive model selection and implementation.
- Discusses evaluation metrics and validation methods.

Chapter 4: Results and Analysis

- Presents key findings from the data analysis.
- Reports on predictive model performance.
- Showcases results in the dashboard with features and functionality.

Chapter 5: Conclusion

- Summarises the study’s findings and benefits of the dashboard for project managers.
- Discusses study limitations.
- Recommendations for project managers and future research.

Chapter 2: Literature Review

2.1 Reasons for construction material price volatility

The UK construction sector has been coping with significant price volatility in recent years, driven by an interplay of various factors. This affects heavily to project budgets, timelines, and overall sector stability. Therefore, understanding causes of this volatility is important for stakeholders in the construction industry to navigate these challenging times effectively.

Firstly, economic challenges have been at the forefront of driving price volatility. Akanni et al., 2014 highlighted the critical role of exchange rate fluctuations, especially for countries relying heavily on imported materials. Inflation has also been a key factor, which increases the cost of goods and reduces the profitability of building material suppliers. An article from BuildPartner (2024) showed some factors like rising energy costs, interest rates, and wages contribute to higher prices for construction materials. These economic pressures create a challenging environment for cost prediction and project planning.

Secondly, the impact of energy costs on material prices is another factor identified in the literature. Danso and Obeng-Ahenkora (2018) emphasised the significance of crude oil prices, which affect both transportation costs and overall energy costs for production. This was further supported by Pablo C. W. (2024), who highlighted the construction industry's heavy dependence on fuel. Political instability in key oil-producing regions and global economic cycles contribute to oil price fluctuations. For example, the conflict in Ukraine and economic sanctions on Russia have led to surges in oil prices, hence, directly affecting construction costs. Thirdly, supply chain disruptions have significantly impacted material availability and prices. Mullane (2024) reported a notable decline in the availability of key construction materials, with deliveries of bricks and blocks dropping by 9.3% and 3.7% annually as of May 2024. These shortages have led to price increases across various materials. Furthermore, Mullane (2024) noted a decrease of 244,000 workers compared to three years ago, showing labour shortages in the industry. As a result, this has increased costs as companies compete for the limited workforce.

Finally, government policies and legislation play a significant role in shaping the construction materials market. Both Akanni et al. (2014) and Danso and Obeng-Ahenkora (2018) highlighted how changes in policies, taxes, and regulations can affect material prices. Harle (2024) pointed out that a reduction in the number of tenderers for projects has led to higher premiums being charged by those willing to take on work. The reluctance of contractors to engage in high-risk projects due to market instability further contributes to price volatility, creating a self-reinforcing cycle of increased costs. While there is cautious optimism about future stabilisation as noted by Harle (2024), current government policies and some economic factors continue to influence material prices. The unpredictable nature of these factors makes price forecasting challenging for project managers. Therefore, the development of interactive dashboards and predictive models shows promise in improving the ability to predict and manage these price fluctuations and offers a potential solution for navigating the complex landscape of CMPs.

2.2 Dashboards in construction cost management

Dashboards have become increasingly important in various industry for synthesising and presenting complex data in an easily digestible format. Dong et al. (2020) showed the value of dashboards in the COVID-19 pandemic for summarising large amounts of information to the public through tools like Johns Hopkins University COVID-19 tracker. Few (2006) mentioned that the importance of dashboards comes from their ability to summarise large amounts of information into graphical forms, providing at-a-glance visibility into business performance. Nadj et al. (2020) highlighted that dashboards can serve as effective decision support systems (DSS) for operational decision-makers. Because it can fulfil both the urgency of fast-paced environments by offering real-time data support and tracking of performance metrics against enterprise-wide strategic objectives based on historical data, which enhances situation awareness (SA) among construction professionals. As Negash and Gray (2008) noted, dashboards are considered as one of the most effective analysis tools available.

Several studies highlighted the value of data-driven approaches and visualisation for construction cost management. Bilal et al. (2019) investigated the use of big data analytics for analysing project profitability, which demonstrates how visualisations of cost data could reveal insights to improve financial performance. Chen (2022) proposed a construction project cost management system using big data, which emphasises the importance of data extraction and visual presentation for effective cost control. These studies underscore the potential for dashboards to transform how managers interact and derive value from project cost data. For CMP analysis, dashboards can aggregate data from multiple sources to provide a comprehensive view of market trends and price fluctuations. Liang et al. (2021) developed a case-based reasoning model for forecasting construction expenditures, which could be integrated into visual dashboards to aid in cost prediction. By visualising historical and forecasted price data, managers can identify cost risks and opportunities for procurement optimisation.

When building effective dashboards, Nadj et al. (2020) showed several key components that should be considered:

1. **Visual features**: A good dashboard design requires a balance between information utility and visual complexity, using elements like colours, chart types, and data-ink ratios for presenting data clearly and efficiently.
2. **Interactive features**: Interactive capabilities such as drill-down, roll-up, and filtering allow users to explore data in more depth. These features can help managers understand complex relationships within the data.
3. **Data integration**: Dashboards should synthesise data from multiple sources to provide a holistic view of factors influencing project costs and material prices.
4. **User-centred design**: Dashboards should be designed for the specific needs and technical capabilities of project managers, with intuitive interfaces and relevant metrics.

In conclusion, data visualisation dashboards represent a promising tool for construction project managers to gain insights into CMPs. By integrating diverse data sources, providing interactive and user-friendly interfaces and incorporating analytical features, dashboards can significantly enhance decision-making capabilities in construction cost management.

2.3 Forecasting methods for construction material prices

The volatility of construction material prices has long been a challenge for project managers and cost estimators in the construction industry. Over the years, researchers have developed and refined various forecasting methods to improve cost estimation and project planning. Some considerable models are currently available in practice based on such techniques as, regression analysis, neural network (NN), machine learning algorithms and time series models. The relative merits and demerits of these techniques were analysed by experts and are well-documented.

Regression analysis has been a foundational approach in cost prediction for construction projects. Researchers like Li et al. (2005) and Trost and Oberlender (2003) applied various forms of regression models to predict costs for different types of buildings and projects. Abu Hammad et al. (2010) further extended this approach by incorporating multiple explanatory parameters into a probabilistic regression model for public building projects. While regression methods are relatively straightforward to implement and interpret, as noted by Moghayedi and Windapo (2021), they may struggle to capture complex, non-linear relationships that often characterise construction material prices.

Artificial Neural Networks (ANNs) have shown significant promise in predicting construction costs and material prices, due to their ability to capture complex, non-linear relationships in data. Siqueira (1999) applied ANNs to predict costs for low-rise pre-fabricated structural steel buildings in Canada, using data from 75 building projects collected over a 3-month period. This study demonstrated the potential of ANNs to learn from historical project data and make accurate cost predictions. Moreover, the superiority of ANNs over traditional regression methods was demonstrated in a study by Günaydın (2022). When applied to cost estimation for low-rise steel structures, the ANN model reduced the error rate by approximately 4% compared to regression methods. This improvement in accuracy shows the potential of ANNs to enhance cost prediction in the construction industry. Shiha et al. (2020) further advanced this approach by presenting three models that employ ANNs to estimate future costs of major building materials like steel reinforcing bars and cement, with a 6-month forecast horizon. These models incorporated historical price data with macroeconomic indices, demonstrating the ability of ANNs to integrate diverse data types for improved prediction accuracy.

In recent years, more sophisticated machine learning techniques have been explored. These include Support Vector Machines (SVM), Decision Trees (DT), Random Forests (RF), and XGBoost. SVMs are powerful machine learning algorithms, which are capable of handling high-dimensional data and complex decision boundaries. As Vapnik (2006) explained, SVM is a supervised machine learning technique that is used to find the optimal hyperplane for maximising the margin between different classes in the feature space, thereby minimising misclassification. However, Osuna and Girosi (1998) pointed out that SVMs can be computationally expensive, especially when working with massive datasets or high-dimensional feature spaces. As the number of training instances and the dimensionality of the data increase, SVMs require more memory and training time.

Another supervised machine learning model is Decision Tree (DT), which uses a recursive splitting method to separate input data into hierarchical rules at each tree node. Perner, Zscherpel, and Jacobsen (2001) highlighted that DTs can determine the relevance of data attributes using generated logic statements and interpretable rules. One advantage of DTs, as noted by Prasad, Iverson, and Liaw (2006), is their ability to avoid the curse of dimensionality while offering high-performance processing efficiency due to their splitting process. However, Curram and Mingers (1994) pointed out that DTs may struggle when dealing with time series, noisy, or nonlinear data. Additionally, Dietterich and Kong (1995) mentioned that DTs are known to have high variation, making them sensitive to even small changes in the training data.

Random Forest (RF) is an ensemble learning model based on bagging, as described by Breiman (2001). RF algorithms create bootstrap samples to build a forest of trees based on random feature subsets, which produce accurate performance without experiencing overfitting problems. But Aria, Cuccurullo, and Gnasso (2021) noted that RF can be complex, especially when working with high-dimensional data or many trees. As the number of trees increases, interpreting the specific contributions of each tree and understanding the underlying decision-making process are more challenging. Finally, XGBoost, as described by Chen and Guestrin (2016), is a large-scale machine learning system that can construct a highly scalable end-to-end ensemble tree-boosting system. XGBoost uses parallel computing to lower computational complexity and accelerate learning efficiently. Elmousalami (2020) conducted a comparison of 20 AI techniques and found that XGBoost was the most accurate method, which had a mean absolute percentage error (MAPE) of 9.091% and an adjusted R-squared of 0.929. However, Qin et al. (2021) point out that XGBoost requires careful tuning of several hyperparameters for optimal performance.

Time series models are also considered in construction material price forecasting due to their ability to capture temporal dependencies in price data. The Autoregressive Integrated Moving Average (ARIMA) model and its variants have been widely applied in this context. Ilbeigi et al. (2017) compared four univariate time series forecasting models, which includes Holt Exponential Smoothing (ES), Holt-Winters ES, ARIMA, and Seasonal ARIMA for predicting asphalt and cement prices. They found that all four time series models could predict prices with better accuracy than current approaches such as Monte Carlo simulation. Notably, ARIMA models achieved errors of less than 2%. Ashuri and Lu (2010) also successfully applied a seasonal ARIMA model to forecast the construction cost index over a 12-month period. The effectiveness of ARIMA models in capturing both short-term fluctuations and long-term trends was further highlighted by Faghih and Kashani (2018). They introduced a Vector Error Correction (VEC) model, which is an extension of the ARIMA framework, for estimating construction material prices in the United States. This model addressed a gap in the literature by forecasting both short-term and long-term movements of specific construction materials.

Additionally, Kissi et al. (2018) extended the application of ARIMA models by incorporating exogenous variables. They used an ARIMAX (Autoregressive Integrated Moving Average with Exogenous Variables) model to forecast the Tender Price Index (TPI) in Ghana. Their results showed that the ARIMAX model outperformed single-method forecasts, which emphasises the importance of integrated model approaches in forecasting construction-related indices.

Many researchers have employed various methodologies to improve accuracy and reliability of forecasting. Sonmez et al. (2007) developed a comprehensive model incorporating 14 independent components to anticipate cost contingency in international projects. This approach demonstrated the potential of multiple linear regression (MLR) in capturing the complexity of construction costs. As mentioned, Abu Hammad et al. (2010) designed a probabilistic regression model to predict the cost of public building projects by utilising explanatory parameters such as project area and duration. These studies show the value of incorporating multiple relevant factors in cost estimation models. However, they have limitations when dealing with time-varying variables and representing different time lags between influencing elements. This shortcoming is relevant in the context of construction material prices, which often exhibit temporal dependencies and autocorrelation. Therefore, researchers have turned to time-series approaches. These methods predict future values of a variable based on its historical values and other relevant factors, making them well-suited for handling time-related problems in construction cost estimation. According to Wong et al. (2005), time-series models are designed to forecast trends in a systematic and time-related manner, which allows the generation of useful projections based on historical trends. This is valuable in the construction industry, where material price volatility can have significant impacts on project costs and timelines. Despite the advantages of time-series models, the ability of MLR to incorporate multiple explanatory variables makes it well-suited for identifying and quantifying the impact of various economic indicators on CMPs. Hence, this capability is important in this study, where the aim is to understand the complex interplay of economic factors affecting CMPs in the UK.

Chapter 3: Methodology

This study employed a comprehensive approach to develop an interactive dashboard and predictive models for construction material prices in the UK. Figure 1 presents the process map of the procedure employed in this study. We began with clearly defining the scope and objectives and researching how to provide insights and forecasts for project managers. Following this, an extensive data collection phase was undertaken by gathering historical data on CMP and relevant economic indicators in the UK market. Then, the dataset went through pre-processing to ensure quality and consistency. This involved cleaning the dataset, handling missing values, and addressing any outliers. An exploratory data analysis was conducted to uncover initial trends, patterns, and relationships within the data for determining long-term price trends of construction materials. Moreover, we developed regression model for each construction material for identifying the most relevant indicators influencing price changes over time. This began with defining dependent and independent variables, which determines statistically significant factors, estimating the model, and calculating coefficients.

Another core of the research involved developing forecasting models of construction material price (CMP). We selected the Autoregressive Integrated Moving Average (ARIMA) method as a powerful time series analysis technique. This process included checking for stationarity, differencing the series if necessary, identifying model parameters, estimating the model, and performing diagnostic checks. Additionally, the prediction from regression models was developed for comparing and validating the forecasting results from ARIMA models. This ensured that the forecasting model offered the reliable results for project managers and also providing insights into when economic indicators might be important for forecasting and when time series analysis alone might suffice.

The ultimate goal of this research was the development of an interactive dashboard, which presents historical price trends, forecasting model outputs, and key economic indicators in a visually appealing and user-friendly interface. The integration of data visualisation techniques with the forecasting models created a tool that allows construction project managers to gain valuable insights and make informed decisions regarding material costs.

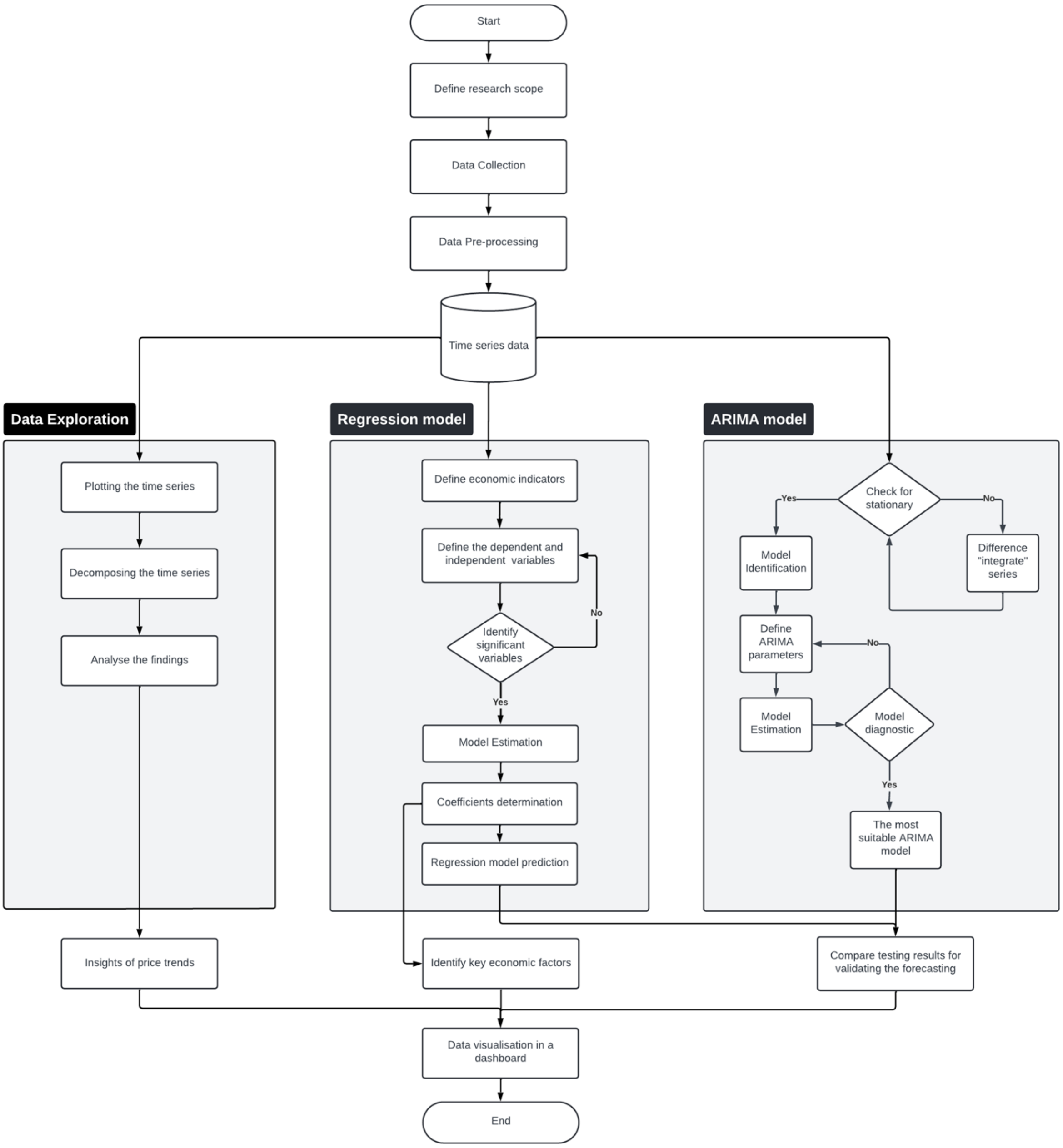


Figure 1: Process map of the procedure

3.1 Data collection

To provide insights and predictions on construction material prices in the UK, this study relied on publicly accessible data, primarily from the Office for National Statistics (ONS). The ONS serves as the authoritative source for comprehensive construction material price data in the UK, which is the backbone of our analysis. We collected monthly price indices for a range of construction materials from October 2019 to June 2024, encompassing a five-year period. This timeframe was chosen to ensure sufficient historical context for trend analysis and predictive modelling. The materials in our dataset include:

1. Cement
2. Pre-cast concrete products
3. Pre-cast concrete: blocks, bricks, tiles and flagstones
4. Ready-mixed concrete
5. Fabricated structural steel
6. Metal doors and windows
7. Pipes and fittings (rigid)
8. Pipes and fittings (flexible)
9. Plastic doors and windows
10. Paint (aqueous)
11. Paint (non-aqueous)
12. Screws
13. Builder woodworks
14. Wood doors and windows
15. Sand, clays, gravel and kaolin

These datasets were provided by the Department for Business and Trade. The data collection process involved accessing the ONS website and retrieving relevant datasets from their construction statistics section. It is important to note that the dataset uses Construction Material Price Indices (CMPIs), which measure the notional trend of input costs to contractors in terms of changes in the cost of building materials. These indices represent factory gate prices charged by materials manufacturers. They do not account for current market conditions experienced by contractors on specific projects when purchasing from sub-contractors, merchants, or factors. This means that materials discounts or premiums paid for resources in short supply are not reflected in these indices. The weightings used to calculate the CMPIs are derived by multiplying the appropriate materials proportion (materials only index divided by the combined building index) by the relevant value of construction output at the sector level. Currently, the indices are set at 100 for the base year of 2015 in order to align with other government statistics.

Moreover, to enhance our understanding of price fluctuations and market conditions, we also collected data of CMPIs across various sectors such as new housing work, repair and maintenance work, and other work, for helping project managers understand the overall trend into CMPs in the UK. Furthermore, for supporting the predictive modelling phase, we gathered 20 economic indicators from various sources like ONS and Bank of England. These supplementary datasets included macroeconomic indicators such as GDP, producer price index, currency exchange rates, etc. The full list of indicators and their source is shown in the Table 1. By incorporating these diverse data points, we aimed to capture both industry-specific factors and wider economic influences that may impact construction material prices. All collected data was systematically organised into a structured database. Data integrity was carefully maintained with relevant metadata such as publication dates and revision histories. Then, the compiled data underwent cleaning and validation processes to ensure accuracy and consistency. In this process, we checked for missing values and outliers and standardised formats across different datasets.

Table 1: Indicators and their data source

No.	Indicator	Source
1	Consumer Price Index (CPIH)	Office for National Statistics (ONS)
2	Input Producer Price Index (Input PPI)	Office for National Statistics (ONS)
3	Output Producer Price Index (Output PPI)	Office for National Statistics (ONS)
4	Construction Output Price Index (OPI)	Office for National Statistics (ONS)
5	Interest Rate	Bank of England
6	Sterling Exchange Rate to Euro	Bank of England
7	Sterling Exchange Rate to US Dollar	Bank of England
8	Index of Production (IOP) for All Industries	Office for National Statistics (ONS)
9	Index of Production (IOP) for Manufacturing	Office for National Statistics (ONS)
10	Index of Production (IOP) for Energy Supply	Office for National Statistics (ONS)
11	Index of Production (IOP) for Water and Waste Management	Office for National Statistics (ONS)
12	House Price Index	Office for National Statistics (ONS)
13	FTSE 100 Index	London Stock Exchange
14	Gross domestic product (GDP)	Office for National Statistics (ONS)
15	GDP from Construction	Office for National Statistics (ONS)
16	Unemployment Rate	Office for National Statistics (ONS)

17	Employment rate	Office for National Statistics (ONS)
18	Wage (Average Weekly Earnings (AWE))	Office for National Statistics (ONS)
19	Money Supply (M4)	Bank of England
20	Purchasing managers index (PMI) from Construction	S&P Global

3.2 Data exploration

After the data preparation stage, we began with a comprehensive data exploration to provide project managers with insights into UK construction material price trends and patterns. This stage helped to create the interactive dashboard, which allowed for in-depth analysis of the collected data. Tableau was selected as the primary visualisation and analysis tool for creating the interactive dashboard, after consideration of various options, including Microsoft Power BI. Tableau excels in handling large datasets and performing complex calculation efficiently, which is essential for our analysis over an extended time period. While Microsoft Power BI offers wide range of visualisation options, Tableau provides greater flexibility in customising visualisation. This allows us to create tailored views that precisely match the needs of construction project managers, especially for complex visualisations like multi-layered time series comparisons.

Our data exploration methodology began with an analysis of overall CMPIs. We created an interactive line chart displaying CMPIs across various sectors such as all work, new housing work, repair and maintenance work, and other work. This visualisation allows for overlaying multiple CMPIs from different sectors for comparison and includes options to adjust the time range. This helped to identify long-term trends, seasonality, and cyclical patterns in material prices across different construction sectors in the UK. Furthermore, we performed seasonal decomposition for CMPIs across sectors to uncover cyclical and seasonal patterns, which helped us in the anticipation of recurring price fluctuations. To visualise rolling volatility of CMPIs across various sectors, we created a line chart showing the percentage change in CMPIs compared to the previous year. This approach helped to identify year-to-year changes and investigate events that affected these changes over time.

Next, we focused on individual material prices. We constructed a bar chart showing the percentage change for price indices of individual construction materials on the previous year to June 2024 (the most recent data point). This visualisation helps to identify which specific materials have been most subject to price fluctuations. Additionally, we created a line chart showing trends of all individual material CMPIs to highlight periods of high volatility across all materials, which provides context for market-wide instability.

3.3 Multiple regression analysis for factor influence assessment

Multiple Linear Regressions (MLR) is a linear statistical strategy for investigating the relationships between a dependent variable and two or more independent variables. This method is employed to investigate the relationships between CMPs and various economic indicators. When one of the independent variables is changed while the other independent variables remain constant, regression analysis can help you understand how the typical value of the dependent variable varies. Therefore, MLR provides insights into the factors influencing material prices, which helps construction project managers to have a deeper understanding of market dynamics.

Through an extensive literature review, a set of 20 indicators were identified as potentially influential on CMPs. These indicators were carefully selected based on their theoretical relevance and data availability. The data for this study was sourced from reputable public databases and official websites, as detailed in Table 1. This approach ensures data reliability and reproducibility of the research. The collected data was categorised into two main groups: dependent variables (raw prices of construction materials) and independent variables (economic and industry-specific indicators). The general form of the multiple regression model used in this study is shown in Equation 1:

$$Y = C + b_1X_1 + b_2X_2 + b_3X_3 + \cdots + b_nX_n \quad (1)$$

Where Y denotes the dependent variable (material price), C denotes the constant term, $b_1, b_2, \ldots, b_n$ denote regression coefficients, and $X_1, X_2, \ldots, X_n$ denote independent variables (economic indicators). Hence, this model helps to estimate the unique effect of each independent variable on the material price. SAS Enterprise Guide was employed for the model development. Key steps in the analysis process included correlation analysis, variable selection, model fitting, and diagnostic testing. The analysis ensured the model met key assumptions of multiple regression:

1. Linearity: The dependent variable y is a linear combination of the independent variables $X_1, X_2, \ldots, X_n$.

2. Independence: Observations are chosen from the population independently and randomly.
3. Normality: Observations are distributed regularly.
4. Variance homogeneity: All observations have the same variance.

From the literature review, some analysts suggest indicators that potentially influence construction material prices. Hence, we concluded and listed 20 indicators in the Table 1 and explained these below:

1. **Consumer Price Index (CPIH)**: CPIH is the most comprehensive measure of inflation, that extends CPI to include a measure of the costs associated with owning, maintaining and living in one's own home. CPIH potentially affects construction material prices because it reflects overall inflationary pressures in the economy. As general price levels rise, the cost of inputs for construction materials (like raw materials, energy, and labour) tends to increase, and driving up the prices of finished construction materials.
2. **Input Producer Price Index (Input PPI)**: Input PPI measures the price changes of materials and fuels bought by UK manufacturers for processing. It represents the cost pressures at the earliest stage of the production process. This index can directly impact CMPs as it reflects changes in the cost of raw materials and energy used in manufacturing construction products.
3. **Output Producer Price Index (Output PPI)**: Output PPI measures changes in the prices of goods produced by UK manufacturers, often referred to as "factory gate prices". It represents the price of products sold by manufacturers before any additional costs like retail markup are added. Therefore, output PPI can affect construction material prices as it directly reflects price changes at the manufacturing level.
4. **Construction Output Price Index (OPI)**: Construction OPI measures the price level of construction work being executed in a given period. It provides a direct indicator of cost trends within the construction industry. This index can influence construction material prices by reflecting overall cost pressures in the sector.
5. **Interest Rate:** Interest rate, which is set by the Bank of England, influences the rates that banks charge for borrowing and pay on savings. Higher interest rates increase borrowing costs for manufacturers and construction companies, leading to higher material prices to cover these increased costs. Additionally, interest rates can impact overall economic activity and construction demand, indirectly affecting material prices through changes in supply and demand dynamics.

6. **Sterling Exchange Rate to Euro**: This represents the value of the British pound relative to the Euro. The exchange rate can impact construction material prices, especially for materials imported from other European countries. A weaker pound makes imports more expensive, potentially driving up the cost of European-sourced construction materials in the UK market. Conversely, a stronger pound could make imports cheaper, potentially lowering material costs.
7. **Sterling Exchange Rate to US Dollar**: Similarly, this represents the value of the pound against the US dollar. It affects the cost of materials and resources imported from dollar-denominated markets, including many global commodities used in construction.
8. **Index of Production (IOP) for All Industries**: IOP measures the volume of production of the manufacturing, mining and quarrying, and energy supply industries. It provides a broad indicator of economic activity in production industries. This can affect construction material prices by reflecting overall industrial output levels.
9. **Index of Production (IOP) for Manufacturing**: This IOP focuses on the manufacturing sector, which is relevant to construction material prices as many construction materials are manufactured products. Changes in manufacturing output can indicate supply conditions, production capacity, and potentially, pricing pressures for construction materials.
10. **Index of Production (IOP) for Energy Supply**: This IOP component measures output in the energy supply sector. As energy is an important input in the production of many construction materials, changes in energy production can affect energy prices, which in turn can impact the production costs and the prices of construction materials.
11. **Index of Production (IOP) for Water and Waste Management**: This measures output in the water supply and waste management sectors, which can reflect overall industrial activity and environmental factors. Changes in water and waste management practices or costs could indirectly affect the production processes and costs for certain construction materials.
12. **House Price Index**: This tracks changes in residential property prices. It's a key indicator of the housing market, which is closely tied to construction activity. Rising house prices often correlate with increased construction activity, which can drive up demand for construction materials and potentially their prices.
13. **FTSE 100 Index**: This is a share index of the 100 largest companies by market capitalisation listed on the London Stock Exchange. While not directly tied to construction, it serves as a broad indicator of economic health and investor sentiment.

A rising FTSE 100 may indicate strong economic conditions, which could lead to increased construction activity and demand for materials and affecting prices.

14. **Gross domestic product (GDP)**: GDP is the market value of all finished goods and services produced within the UK in a specific time period. It's the broadest measure of economic activity. GDP growth often correlates with increased construction activity and overall demand in the economy, which can drive up demand for construction materials and their prices.
15. **GDP from Construction**: The specific sector directly reflects the level of activity in the construction industry. Higher GDP from construction indicates more construction activity, which means higher demand for construction materials and leading to price increases.
16. **Unemployment Rate**: This measures the percentage of the labour force that is jobless. It's a key indicator of economic health and can affect construction material prices indirectly. Lower unemployment generally indicates a stronger economy, which can lead to increased construction activity and demand for materials.
17. **Employment Rate**: This measures the proportion of the working-age population in employment. Similarly, it's an indicator of economic health as higher employment rates often correlate with increased economic activity.
18. **Wage (Average Weekly Earnings (AWE))**: This measures the mean weekly pay of employees in the UK. Higher wages increase production costs, which manufacturers may pass on through higher prices. They also indicate greater consumer purchasing power, which can drive demand for housing and construction, potentially increasing material demand and prices.
19. **Money Supply (M4)**: M4 is a measure of the money supply that includes cash and checking deposits (M1) as well as savings deposits, money market securities, mutual funds, and other time deposits. Changes in the money supply can lead to inflation, which could drive up construction material prices. It also reflects overall economic liquidity, which can impact construction activity and material demand.
20. **Purchasing managers index (PMI) from Construction**: This is an index based on surveys of purchasing managers in the construction industry. It provides insight into current and future construction activity levels. A higher PMI indicates higher demand for construction materials, leading to price increases.

3.4 ARIMA Model for Forecasting of Construction Material Prices

The accurate forecasting of CMPs is an important practice in the UK construction industry, where high price fluctuation can adversely affect the success of projects. This study aims to develop a robust system capable of predicting changes in material prices with a high degree of accuracy, thereby providing valuable insights for project planning and budgeting. Therefore, we employed the Autoregressive Integrated Moving Average (ARIMA) model, also known as the Box-Jenkins approach, as an advanced and powerful time series forecasting technique.

This method is particularly well-suited for short-term forecasting and is capable of realistically describing dynamic change patterns in time series data. The ARIMA methodology differs from conventional forecasting methods in that it does not assume any particular pattern in the historical data. Instead, it uses an iterative approach to identify a suitable model from a general class of models. As the procedure of ARIMA modelling is depicted in the Figure 1, the iterative process involves three key stages: model identification, parameter estimation, and diagnostic checking.

In the model identification stage, we first assessed whether the time series data is stationary. If the data was non-stationary, we would transform it by using techniques such as differencing to achieve stationarity. An Autoregressive Moving Average (ARMA) model is a combination of a model with autoregressive terms and a model with moving average terms. The autoregressive (AR) model has the appearance of a regression model with lagged values of the dependent variable in the independent variable positions. Hence, the model provides forecast as linear function of a finite number of past values. Whereas, moving average (MA) model provides forecast based on a linear combination of finite number of past errors. Therefore, moving average refers that the deviation of the response from its mean is a linear combination of current and past errors, as time moves forward, the errors move forward as well. The order of the autoregressive component (p), and the order of the moving average component (q) are then determined. This is done by examining the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots. The autocorrelation function (ACF) measures the correlation between a time series and its lags. It provides insights into the internal structure of the time series and helps identify patterns such as trends and seasonality. The ACF plot displays these correlations graphically, with the lag number on the horizontal axis and the correlation coefficient on the vertical axis. In the context of ARIMA modelling, the ACF is useful for identifying the order of the moving average (MA) component. A significant spike in the ACF at a particular lag suggests the presence of an MA term at that order. On the other hand, the partial autocorrelation function (PACF) measures the correlation between a time series and its lags while controlling for the effects of all shorter lags. This helps isolate the "direct" relationship between an observation and its lag, removing the indirect effects of intermediate observations. The PACF plot is important for determining the order of the autoregressive (AR) component in the ARIMA model. A significant spike in the PACF at a particular lag indicates the potential need for an AR term of that order.

When interpreting these plots:

1. For an AR (p) process, the ACF tails off gradually, while the PACF cuts off after lag p.
2. For an MA (q) process, the ACF cuts off after lag q, while the PACF tails off gradually.
3. For an ARMA (p, q) process, both the ACF and PACF tail off gradually.

The order of differencing (d) is typically determined before examining the ACF and PACF plots. The series is differenced until it appears stationary, and this number of differencing operations is the d value. By analysing these plots, we could find some appropriate orders for our autoregressive integrated moving average (ARIMA) model with ARIMA (p, d, q) notation.

Next, the parameter estimation stage is to develop the most suitable ARMA form to model the stationary series after determining the correct order of differencing required to make the series stationary. For finding the most significant ARMA model, we employed two widely-used criteria: the Akaike Information Criterion (AIC) (Akaike, 1974) and the Schwarz Bayesian Criterion (SBC) (Schwarz, 1978). These criteria balance model fit against complexity, helping to avoid overfitting. Therefore, for each type of material, the best model was chosen based on the value of AIC value and SBC value. As lower values of AIC and SBC indicate better models, the procedure followed in this study was to first create a model with the lowest AIC and SBC values.

Finally, the diagnostic checking is the formal evaluation of the selected ARIMA model thorough an examination of various diagnostic tests. This process ensures that the selected model adequately captures the data's characteristics and meets the assumptions of ARIMA modelling. A variety of diagnostic techniques are available to ensure that an acceptable model is created. Key diagnostic techniques include residual analysis, autocorrelation checks, normality tests, parameter significance evaluations, and the use of information criteria such as AIC and SBC. Firstly, a useful diagnostic check is plotting the estimated model's residuals. This should highlight any outliers that may have an impact on parameter estimations, as well as any potential autocorrelation or heteroscedasticity issues. Secondly, plotting the residual correlation diagnostics provide another test of model adequacy. This includes ACF and PACF plots for remaining correlation in the residuals. Ideally, the residuals should be 'white noise', which means there is no significant autocorrelation at any lag. Hence, this test is used to check the assumption that residuals are independently distributed (i.e., no autocorrelation).

Thirdly, the assumption of normally distributed residuals is assessed through histograms and Quantile-Quantile (Q-Q) plots. While perfect normality is rare in real-world data, substantial deviations may indicate model inadequacy. Finally, parameter significance is evaluated by examining t-statistics and p-values associated with each model parameter (AR and MA terms) to ensure they contribute meaningfully to the model's explanatory power. If a model fails these tests, we iterate through models with the next lowest AIC and SBC values until finding one that satisfies all diagnostic criteria.

Once an ARIMA (p, d, q) model, which is determined with appropriate orders, passes all the diagnostic tests. In prediction forms, the ARIMA model could be expressed using Equation 2:

$$Y_t = c + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q} + \varepsilon_t \quad (2)$$

Where Y_t denotes the differenced series and the "predictor" on the right hand side include both lagged values of Y_t and lagged errors. C denotes the constant term, p denotes the order of autoregressive component (AR), q denotes the order of the moving average component (MA), ϕ is the coefficient of the autoregressive model, θ is the coefficient of the moving average model, and finally, ε_t denotes the error term.

We utilised SAS Enterprise Guide, a software application specifically designed for time series analysis. We based our models on monthly price data of construction materials over a four-year period from October 2019 to December 2023. Once a suitable model was identified and validated, we used it to forecast material prices for the first five months of 2024 (January to June). The accuracy of the prediction is evaluated by the Mean Absolute Percentage Error (MAPE) as the primary judgement criterion, with a value of 10% or less generally considered acceptable in prediction models (Fan et al., 2010). MAPE is calculated using the Equation 3:

$$MAPE = \frac{1}{n} \sum_{t=1}^{n} \left| \frac{Y_t - f_t}{Y_t} \right| \times 100 \quad (3)$$

Since the multiple linear regression (MLR) model's ability to forecast is contingent on having future values for all independent variables, which are often unknown and can be difficult to predict themselves, the MLR is more useful for understanding the relationships between various economic indicators and material prices, rather than for direct future price prediction. However, we also employed the MLR model as a benchmark to validate the forecasting ability of the Box-Jenkins (ARIMA) model. This comparison allows us to assess whether the forecasting of certain materials is heavily dependent on economic indicators or can be adequately captured by time series analysis alone. To facilitate this comparison, separate regression models for the prediction were developed for each construction material and tested on the same forecasting period (January 2024 to June 2024). Their MAPE values were calculated and used to compare with the MAPE values from the ARIMA models. These comparisons quantitatively assessed the relative performance of the two models across different material types, providing insights into when economic indicators might be crucial for accurate forecasting and when time series analysis alone might suffice.

Chapter 4: Results and Analysis

4.1 Data Exploration

Firstly, the exploration of CMPIs revealed significant trends and patterns across different types of construction work in the UK market from 2019 to 2024. Figure 2 presents a line chart of monthly CMPIs for various sectors such as all work, new housing, repair and maintenance work, and other new work, using 2015 as the base year (index = 100). From October 2019 to October 2020, CMPIs across all construction types remain relatively stable, hovering around 110 to 115. However, from October 2020, a steep and consistent upward trend is observed across all sectors, continuing until July 2022. This period marks a significant inflationary phase in CMPs. The indices reach their peak around July 2022, with values ranging from approximately 155 to 165, which represent a 50-65% increase from the 2015 baseline. From July 2022, there is a slight decline followed by a stabilisation period, with indices settling around 155 to 160 by June 2024. While all sectors follow similar trends, other new work type consistently shows the highest index values.

We further analysed the volatility of prices in Figure 3, which illustrates the percentage change in CMPIs compared to the previous year. Before 2020, annual changes are minimal, normally ranging between -5% to 5%, showing a relatively stable market. Then, a sharp incline is evident in late 2020, likely corresponding to the economic shock of the COVID-19 pandemic and post-Brexit in the UK. The period from late 2020 to early 2023 shows the high volatility of prices, with the peak occurred in May 2022 (increased by 26.8% for all work, 24.0% for new housing, 30.5% for repair and maintenance work, and 24.7% for other new work). Finally, from 2024, the market shows signs of cooling as all work decreased by 0.9%, new housing increased by 0.7%, repair and maintenance rose by 0.7%, and other new work decreased by 2.3% from June 2023 to June 2024. These recent figures suggest a gradual stabilisation of material prices, though with variations across different construction sectors. Hence, this cooling trend may indicate a potential return to more normal market conditions.

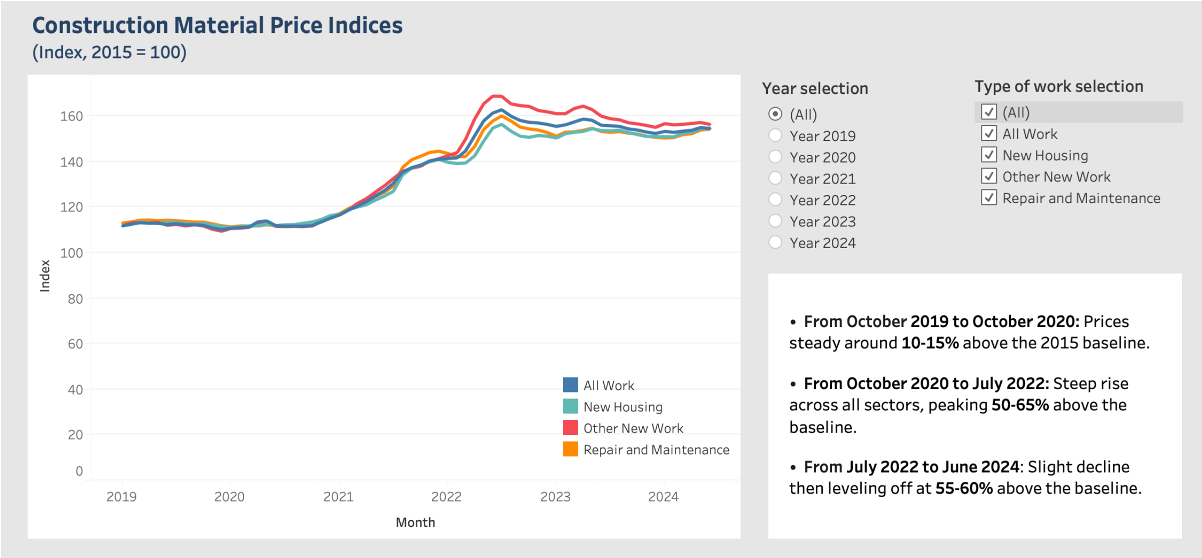


Figure 2:Interactive line chart of CMP indices across types of construction work.

(Base year: 2015 = 100)

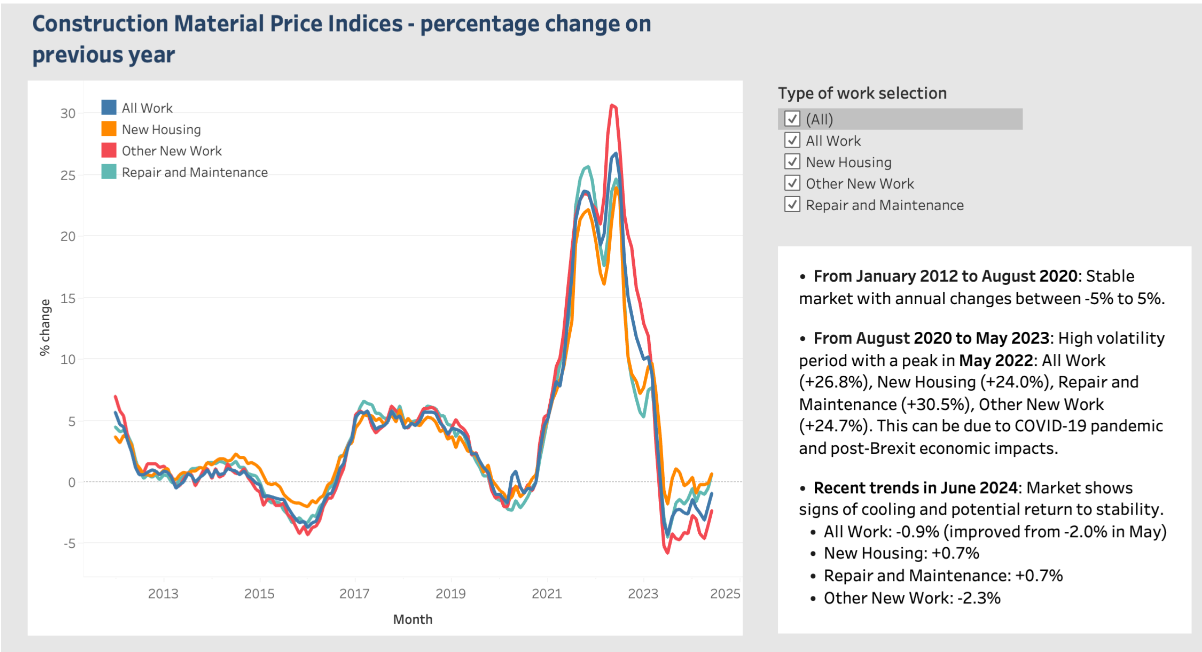


Figure 3: Interactive line chart of percentage change for CMP indices on previous year

Secondly, the analysis of individual construction materials revealed a complex and varied landscape of price changes. Figure 4 provides the percentage change in price indices for various construction materials in the year to June 2024. Most notably, flexible pipes and fittings, and metal doors and windows see more than 10% annual growth in the year to June 2024 (17.4% and 16.1% respectively). Figure 5, which illustrates the monthly price indices for these materials, showed a gradual increase from June 2021 to October 2023, followed by a sharp spike. For flexible pipes and fittings, there was a dramatic jump from an index of 142.8 to 171.9

in just one month. Similarly, metal doors and windows saw a sudden increase from 151.2 to 172 between June and July 2023. These abrupt changes suggest potential supply chain disruptions or sudden shifts in demand for these specific materials.

Conversely, fabricated structural steel and gravel, sand, clays and kaolin experience the most significant price decreases, with annual drops of 16.2% and 12.8% respectively (shown in Figure 4). The line chart of monthly price indices for these materials (shown in Figure 6), reveals highly volatile trends characterised by sharp fluctuations. This behaviour could be attributed to factors such as changes in global commodity prices, shifts in construction activity, or alterations in supply chain dynamics. Other construction materials in Figure 4 display moderate price changes such as pre-cast concrete blocks, bricks, tiles and flagstones (5.41%), pre-cast concrete products (3.68%), ready-mixed concrete (3.25%), wood doors and windows (1.82%), screws etc. (-2.14%), aqueous paint (-4.10%), and rigid pipes and fittings (-5.33%). Figure 7 illustrates the trends for these materials, showing more stable patterns compared to the extreme cases mentioned earlier, but still having noticeable variations over time. Lastly, cement, non-aqueous paint, and plastic doors and windows have the least percentage change of price on year to June 2024 (Shown in Figure 4). Figure 8 shows that these materials show relatively steady growth over the period, with some fluctuations but not having the extreme volatility seen in other categories.

The significant variations across different types of materials highlight the importance of material-specific forecasting and cost management strategies for construction project managers. Moreover, the volatility observed in some materials, such as fabricated structural steel and flexible pipes and fittings, also emphasises the need for flexible procurement strategies and robust risk management practices in construction projects. Hence, we conducted a deeper investigation into the factors that potentially influence these diverse patterns. This analysis aims to provide project managers with a more comprehensive understanding of the volatility in CMP, thereby enhancing their ability to manage risks and improve forecasting accuracy.

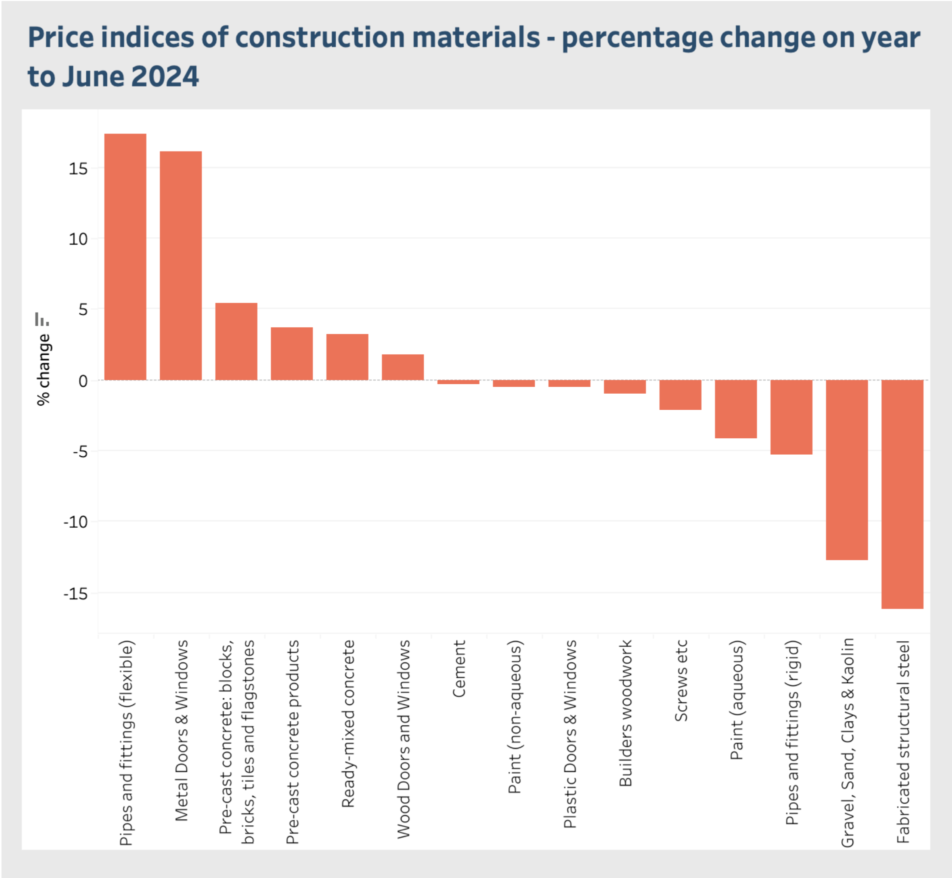


Figure 4: Percentage change in price indices for construction materials on year to June 2024

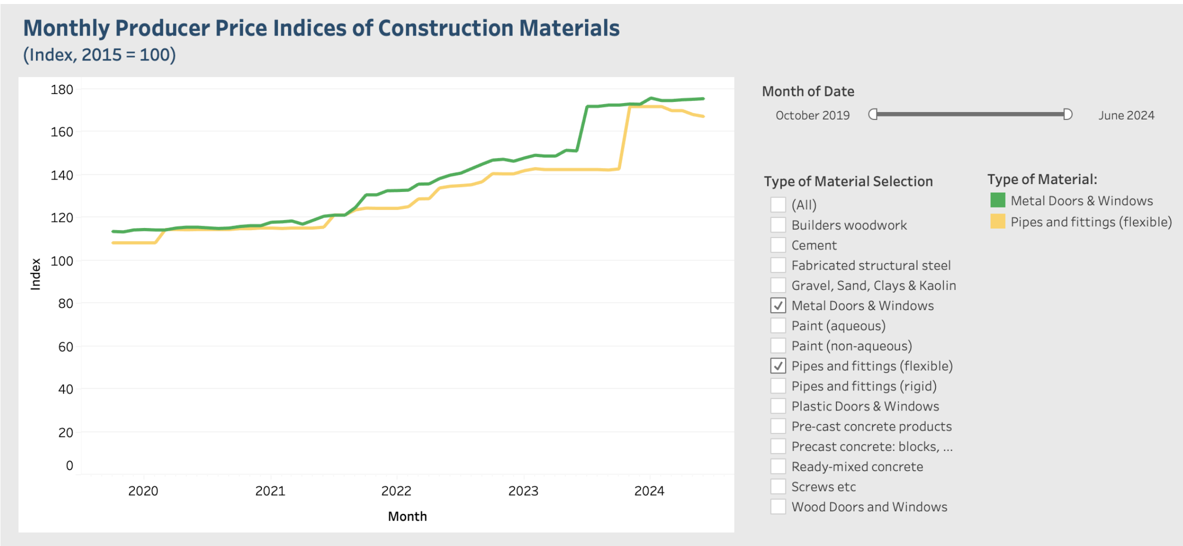


Figure 5: Monthly price indices for metal doors and windows, and flexible pipes and fittings

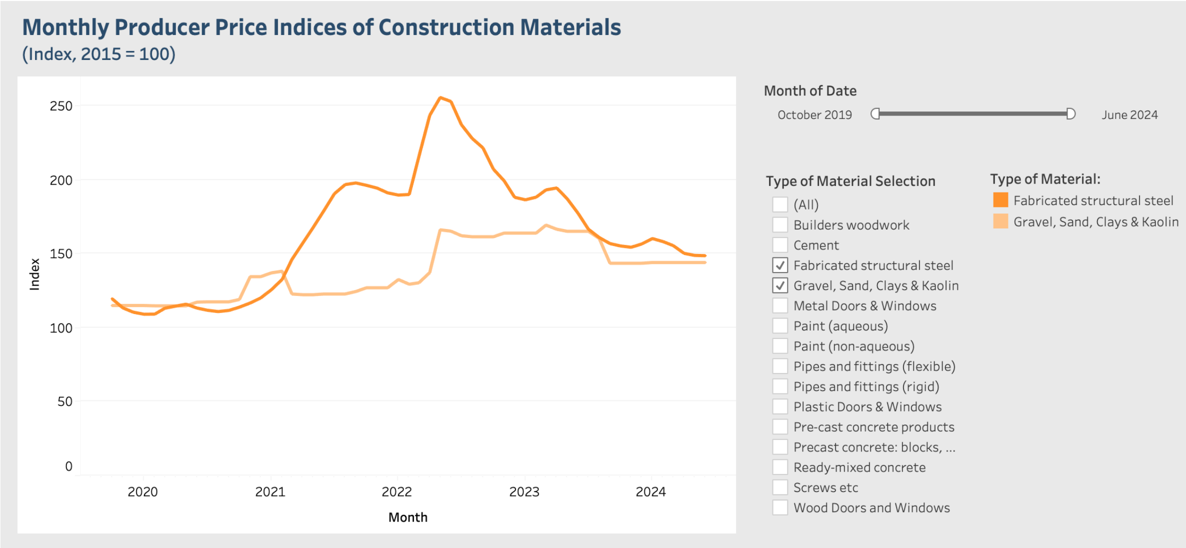


Figure 6: Monthly price indices for fabricated structural steel, and gravel, sand, clay and kaolin

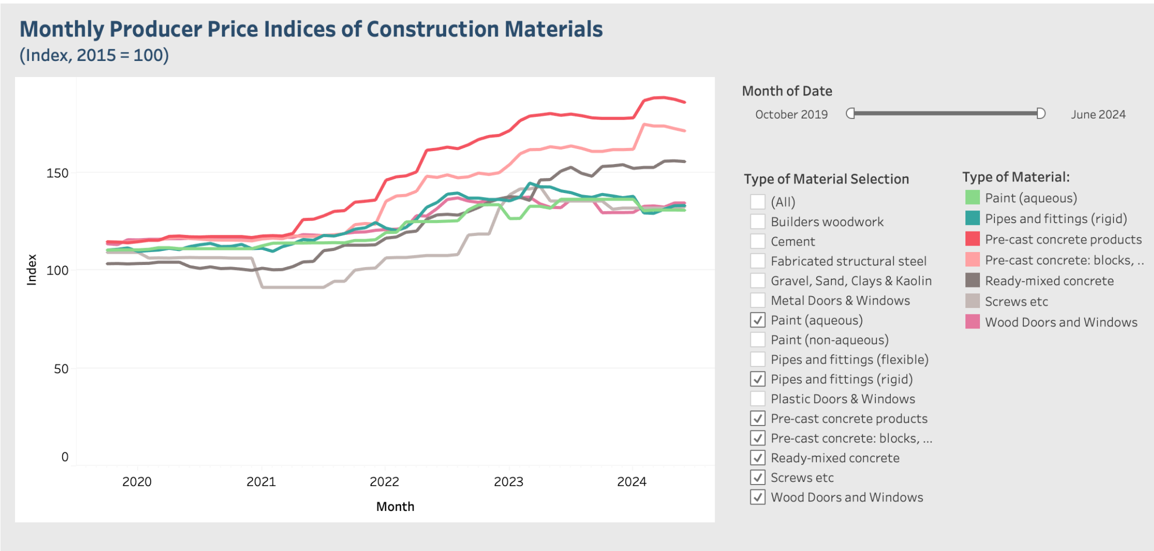


Figure 7: Monthly price indices for aqueous paint, rigid pipes and fittings, pre-cast concrete products, pre-cast concrete blocks, bricks, tiles and flagstones, ready-mixed concrete, screws etc, and wood doors and windows.

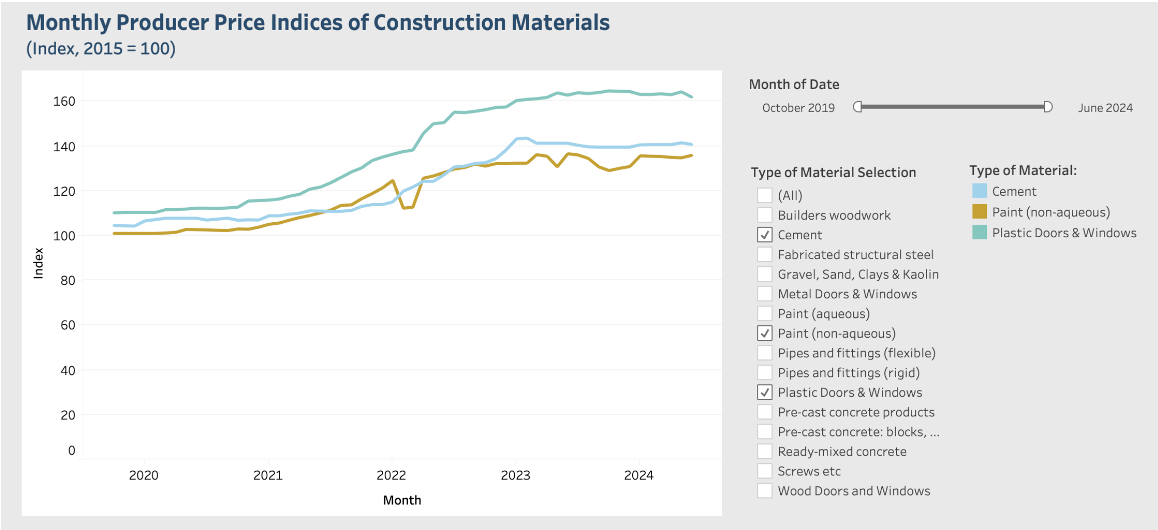


Figure 8: Monthly price indices for cement, non-aqueous paint, and plastic doors and windows.

4.2 Results of Multiple Regression Modelling

4.2.1 Estimated Models Coefficients

The aim of the research using MLR models is to find out whether it is possible to describe the relationship between prices and the influencing indicators through some equations. After that, prediction models are created using only significant indicators i.e., indicators with their p-value of less than 0.05 are used in the prediction process. As a result, the final model may not include all of the indicators we selected. These tests of significance are useful for determining if each explanatory variable is required in the model, assuming that the others are already present.

SAS Enterprise Guide software was used for building linear regression model of each construction material. The actual price index is the (Y) dependent variable in the regression analysis. The independent variables (X) that have been assigned are shown in Table 1. For example, in the case of cement, the "p-value" column in Table 2 represents the significant level. Among the 20 indicators, 9 indicators such as consumer price index (CPIH), output producer price index (PPI), interest rate, sterling exchange rate to us dollar, index of production (IOP) for all industries, IOP for manufacturing, IOP for energy supply, employment rate and money supply (M4) had p-value of 0.0004, 0.0084, 0.0003, <.0001, 0.0027, 0.027, 0.0394, 0.0115, 0.0003 and 0.0001 respectively, which were < 0.05. This result told us that these indicators add a significant contribution to explaining the change in cement prices from October 2019 to December 2023. (The full table of MLR models' result for all material prices is shown in the Appendices).

Table 2: Coefficient value and p-value from the MLR model for the cement price index.

Model	Cement	
	Coefficient	P-value
Constant	-477.87987	**0.0004**
CPIH	-1.15976	**0.0084**
Input PPI	-0.53652	0.0777
Output PPI	2.17616	**0.0003**
Construction OPI	0.18501	0.4666
Interest Rate	4.49088	**<.0001**
Sterling Exchange Rate to Euro	-31.55170	0.0844
Sterling Exchange Rate to USD	42.54684	**0.0027**
IOP for All Industries	-1.39242	**0.0270**
IOP for Manufacturing	1.17625	**0.0394**
IOP for Energy Supply	0.27766	**0.0115**
IOP for Water and Waste Management	-0.00648	0.9727
House Price Index	-0.25087	0.0658
FTSE 100 Index	-0.00046813	0.6123
GDP	0.01616	0.9417
GDP from Construction	-0.09138	0.4874
Unemployment Rate	3.33952	0.0602
Employment Rate	5.92587	**0.0003**
Wage (AWE)	-0.07570	0.1154
Money Supply (M4)	0.00004258	**0.0001**
PMI from Construction	-0.08144	0.2433

General forms of the equations for predicting cement prices were obtained from Table 2. When all other independent variables are held constant, coefficients show how much the dependent variable varies with an independent variable. The regression coefficient provides the prospective change in the dependent variable for an increase of one unit in the independent variable. From the Table 2, the sterling exchange rate to US dollar had the largest positive impact on cement prices with the coefficient of 42.54684, which indicated that even a small change in the exchange rate could have a considerable effect on the cement price. Hence, this strong relationship suggested that the UK cement industry may be heavily reliant on imports from dollar-denominated markets. The employment rate, interest rate and output producer price index also had positive effects on cement prices. This could imply that higher employment, manufacturing cost and growing economy potentially led to cement demand and increasing price. Surprisingly, the consumer price index (CPIH) shows a negative relationship with cement prices, which reflected complex interactions between various economic factors. For instance, periods of high inflation might coincide with reduced construction activity, leading to lower demand for cement. Lastly, the negative relationship between the index of production for all industries and the cement price showed that overall industrial efficiency might lead to lower cement prices. Therefore, the regression equation of the cement price index is:

$$Y = -477.87987 - 1.15976X_1 + 2.17616X_2 + 4.49088X_3 + 42.54684X_4 - 1.39242X_5 + 1.17625X_6 + 0.27766X_7 + 5.92587X_8 + 0.00004258X_9$$

4.2.2 Determine the Suitability of the Models

The values of R^2 and adjusted R^2 were used to determine the appropriateness of the regression models for the data. The value of R^2, the coefficient of determination, indicates the proportion of variance in the dependent variable that can be explained by the independent variables. For the cement model, as displayed in the R^2 column of the Table 3, a value of 0.9961 shows that our independent variables account for 99.61 percent of the variability in our dependent variable, which implies a good level of predictability. Although R-squared appears to be a simple statistic that measures how well a regression model fts a set of data, it does not provide us with a good ending. R^2 value must be associated with residual plots, other statistics, and an in-depth understanding of the topic area to get the entire picture. Moreover, R-squared tends to increase as more predictors are added to the model, even if these additional variables don't actually improve the model's predictive power. This can lead to overfitting, especially with smaller sample sizes. Adjusted R-squared, on the other hand, will decrease if any superfluous variable is included and increase if any beneficial variable is introduced. Therefore, adjusted R-squared helps to guard against overfitting and also compensate for the number of terms in a model. For the cement price index prediction, in the Table 5, the result of 0.9935 shows that the predictors that should be kept in the model explain true 99.35 percent of the variance in the outcome variable.

Table 3: Significant indicators, R-squared value, and adjusted R-squared value from MLR models for all construction materials.

Material type	Model summary		
	Significant indicators	R square	Adjusted R square
Cement	CPIH, Output PPI, Interest Rate, Sterling Exchange Rate to USD, IOP for All Industries, IOP for Manufacturing, IOP for Energy Supply, Employment Rate, Money Supply (M4)	0.9961	0.9935
Pre-cast concrete products	Construction OPI	0.9978	0.9964
Pre-cast concrete: blocks, bricks, tiles and flagstones	Construction OPI	0.9944	0.9906
Ready-mixed concrete	CPIH, Unemployment Rate	0.9947	0.9911
Fabricated structural steel	Construction OPI, Interest Rate, IOP for Energy Supply, Money Supply (M4), PMI from Construction	0.9820	0.9699
Metal doors and windows	Unemployment Rate, Employment Rate	0.9772	0.9620
Pipes and fittings (rigid)	Construction OPI	0.9828	0.9713
Pipes and fittings (flexible)	Construction OPI, Sterling Exchange Rate to Euro, House Price Index, Unemployment Rate	0.9417	0.9028
Plastic doors and windows	CPIH, Construction OPI, FTSE 100, Money Supply (M4), Unemployment Rate, PMI from Construction	0.9989	0.9982
Paint (aqueous)	Input PPI, Sterling Exchange Rate to Euro	0.9852	0.9753
Paint (non-aqueous)	Construction OPI	0.9783	0.9638
Screws	Construction OPI, Interest Rate, IOP for Energy Supply, Money Supply (M4), PMI from Construction	0.9731	0.9552

Builder woodworks	Construction OPI, Unemployment Rate, Money Supply (M4)	0.9967	0.9946
Wood doors and windows	CPIH, Input PPI, Output PPI, Unemployment Rate, Employment Rate	0.9763	0.9605
Sand, clays, gravel & kaolin	CPIH, Construction OPI, Unemployment Rate	0.9611	0.9352

From the Table 3, most materials have the adjusted R-squared value of more than 0.95 which shows a strong predictive power of the MLR. Moreover, examining the significant indicators in the Table 3 reveals that Construction OPI is the most common, appearing in 9 out of 15 models. CPIH, Unemployment Rate, and Money Supply (M4) are also frequent significant indicators. Some materials like cement have many significant indicators (9), while others like pre-cast concrete products have only one. This variation in the number of significant indicators suggests that price dynamics differ significantly across material types.

Finally, the histogram of residuals for the constructed model of the cement as an example is shown in Figure 9. This histogram provides a visual representation of how well the residuals conform to a normal distribution, which is a key assumption in linear regression analysis. The histogram displays the frequency distribution of residuals, with the horizontal line representing the residual values and the vertical line showing the percentage of occurrences. Overlaid on the histogram are two curves: a blue line representing the theoretical normal distribution and a red line showing the kernel density estimate of the actual distribution. The shape of histogram approximates a bell curve, which is characteristic of a normal distribution. There are also slight deviations in the tails of the distribution, with a bit more data in the right tail than would be expected in a perfect normal distribution. While not perfect, the actual distribution (represented by the histogram bars and the red kernel density line) follows the theoretical normal distribution (blue line) reasonably well. Overall, we concluded that residuals are roughly normally distributed, indicating that the assumption of homoscedasticity or equality of variances has been realised.

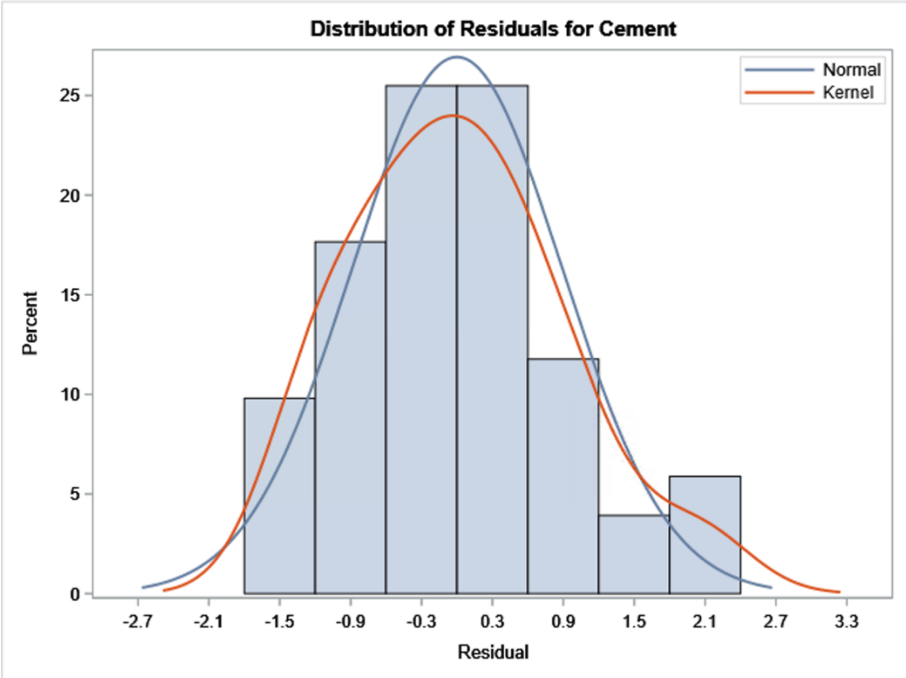


Figure 9: Histogram of residuals for the MLR model of cement price index.

4.3 Results of ARIMA Modelling

4.3.1 Stationary Test

Firstly, we needed to ensure the stationarity of the time series data, as ARIMA models require stationary input. To assess stationarity, we utilised SAS Enterprise Guide to perform trend and correlation analyses for each construction material. These analyses include time series plots, Autocorrelation Function (ACF), Partial Autocorrelation Function (PACF), and Inverse Autocorrelation Function (IACF) for the raw data.

For example, in the Figure 10, the ACF plot reveal autocorrelation coefficients significantly different from zero for the initial lags, gradually decreasing towards zero as the number of lags increased. This pattern indicates a trend-cycle in the raw data, suggesting non-stationarity. Similarly, ACF plots from all other materials such as pre-cast concrete (blocks, bricks, tiles, flagstones and general products), ready-mixed concrete, fabricated structural steel, doors and windows (metal, plastic, wood), pipes and fittings (rigid and flexible), paint (aqueous and non-aqueous), builder woodworks, screws, and sand, clays, gravel and kaolin, show that they are all non-stationary in the first inspection. To address this non-stationarity, we applied the differencing technique, which removes the trend from the series. After the first-order differencing, we observed a marked improvement in the stationarity of all material price series. As shown in Figure 11, the autocorrelation coefficients for each material type rapidly decline to zero after the second or third lag, indicating that the differenced time series has achieved stationarity. This transformation is an important step for ensuring that the ARIMA modelling met all necessary assumptions.

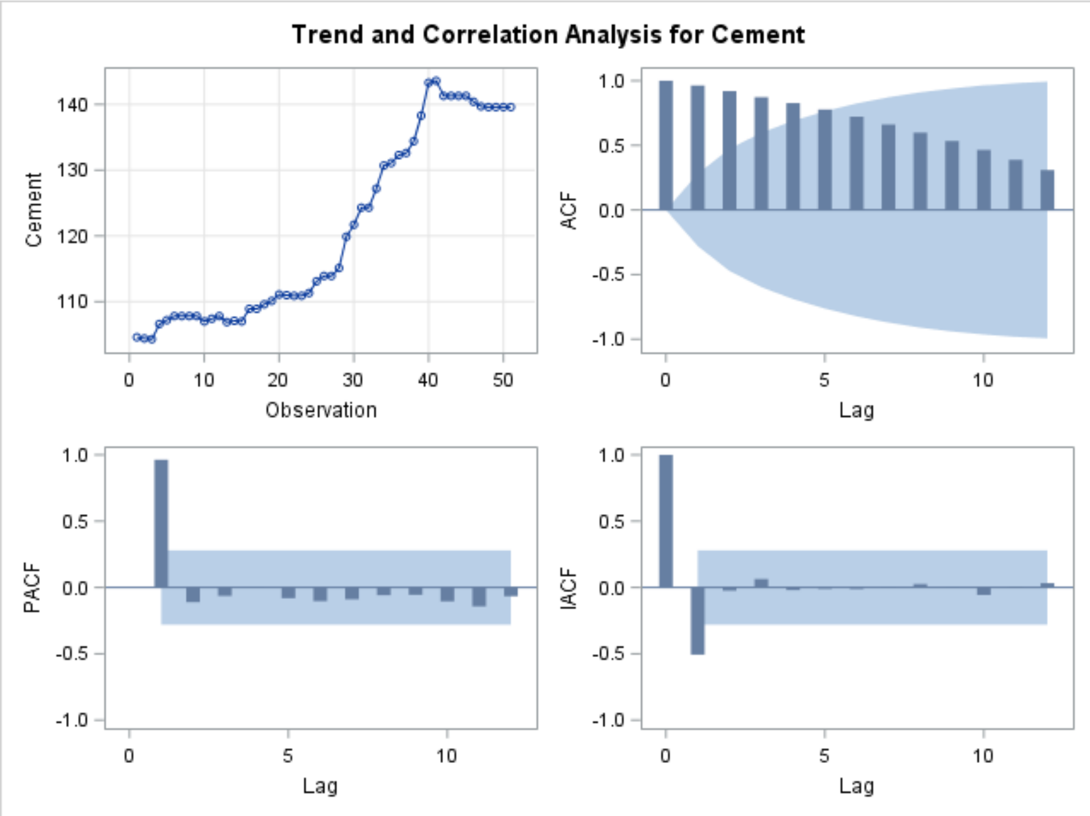


Figure 10: Time series, ACF, PACF and IACF plots for the cement price index raw data.

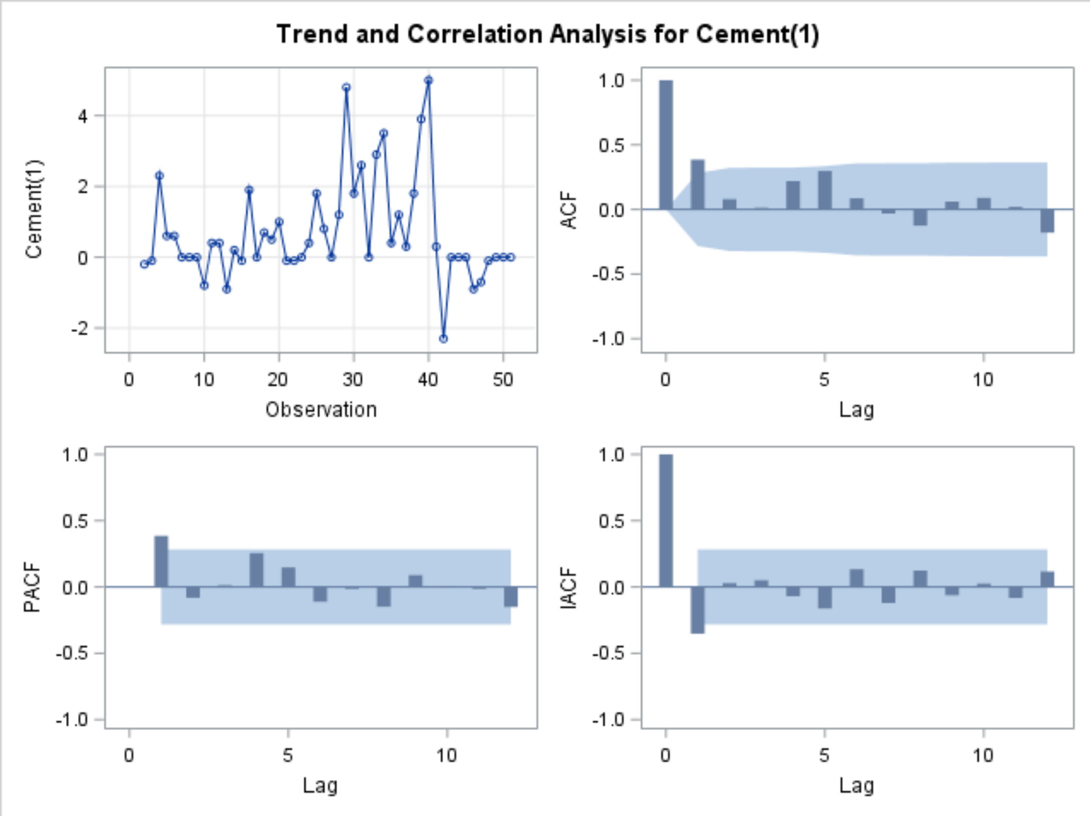


Figure 11: Time series, ACF, PACF and IACF plots for the cement price index after the first differencing.

4.3.2 Model Identification

The next step is to develop a suitable ARMA form to model the stationary series after determining the correct order of differencing required to make the series stationary. This involves determining the orders of the autoregressive (AR) and moving average (MA) components of the model from the careful examination of ACF and PACF plots to identify potential model structures. We utilised SAS Enterprise Guide to generate these plots for all material types after the first differencing. For finding the most significant ARMA model, two criteria, the Akaike Information Criterion (AIC) and the Schwarz Bayesian Criterion (SBC) (Schwarz, 1978) were used for evaluating. As lower values of AIC and SBC indicate better models, the procedure followed in this study was to first create a model with the lowest AIC and SBC values.

As an illustrative example, we detail the model identification process for cement prices. Based on the ACF, PACF and IACF plots for the first differencing of the cement data (shown in Figure 11), we could find some order for the AR and MA components for the ARIMA modelling. The PACF plots showed a significant spike at lag 1, with no other significant spikes beyond the confidence intervals. This suggested an AR (1) component for the ARIMA model. On the other hand, the ACF plot shows a significant spike at lag 1, with no other significant spikes beyond the confidence intervals. This suggested an MA (1) component would be suitable for the model. Hence, we tried to run multiple ARIMA (p, d, q) models with different orders such as ARIMA (1, 1, 1), ARIMA (1, 1, 0), ARIMA (0, 1, 1) and also ARIMA (0, 1, 0) as a baseline simple random walk model. The ARIMA (1, 1, 1) model is likely to be a good model as it captures the most prominent spikes in both ACF and PACF plots. However, it's worth noting that the correlations, while significant at lag 1, are not extremely strong, and most other lags fall within the confidence intervals. Therefore, we compared these models, using the mentioned criteria (AIC and SBC) to determine the most significant model for improving forecasting accuracy. In the Table 4, ARIMA (1, 1, 0) was selected as the most significant model with the lowest AIC and SBC value. This suggests that cement prices are best predicted by considering their first difference (rate of change) and the previous period's deviation from the mean.

Table 4: AIC and BSC values from ARIMA models for cement price index forecasting

	ARIMA (0, 1, 0)	ARIMA (1, 1, 0)	ARIMA (0, 1, 1)	ARIMA (1, 1, 1)
AIC	178.4311	172.3391	172.6901	174.0636
SBC	180.3431	176.1631	176.5142	179.7996

4.3.3 Model diagnostic

The formal evaluation of each of the time series models will be the next stage. This will entail a thorough examination of each model's diagnostic tests, which include residual analysis, autocorrelation checks, normality tests, parameter significance evaluations, and the use of information criteria such as AIC and SBC. If a model failed these tests, we would iterate through models with the next lowest AIC and SBC values until finding one that satisfies all diagnostic criteria.

For the cement price index example, we applied these diagnostic techniques to the ARIMA (1, 1, 0) model. The residuals plot in the Figure 12 shows randomly distributed residuals around the zero line, which suggests that the model is capturing the main trends and patterns in the data. Additionally, there is no clear trend in the variability of residuals over time, showing the model successfully addressed the non-stationarity in the raw data. The consistent spread of residuals satisfies the homoscedasticity assumption, with most residuals falling within a range of -2 and +2, even though there are a few noticeable spikes in the residuals, particularly around

January 2022 and January 2023. These could represent unusual events or shocks in the cement market that the model could not fully capture. Overall, this result still indicates a well-fitted model.

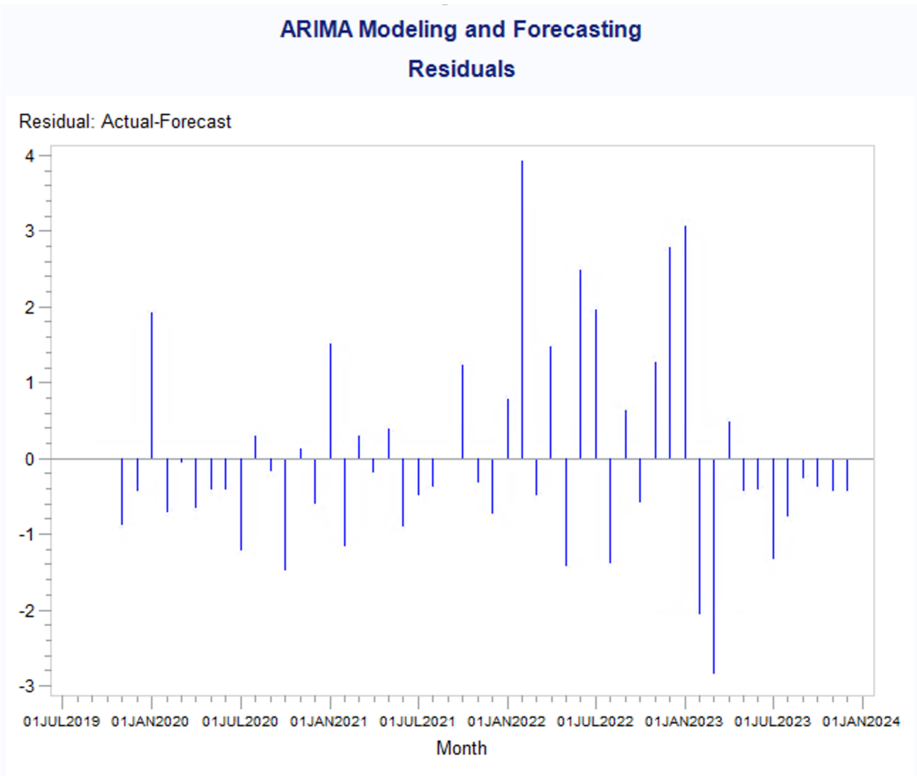


Figure 12: Estimated model's residuals of cement price index forecasting.

In the Figure 13, the residual correlation diagnostic plots reveal no significant spikes beyond the confidence intervals (blue shaded area) for lags greater than 0 in both ACF and PCAF plots of residuals, showing that there is no significant autocorrelation and partial autocorrelation remaining. This suggests the model has adequately captured the time series dependencies. Furthermore, the white noise probability plot confirms that residuals behave like white noise, with p-values above the conventional significance levels (0.05 and 0.01) for all lags.

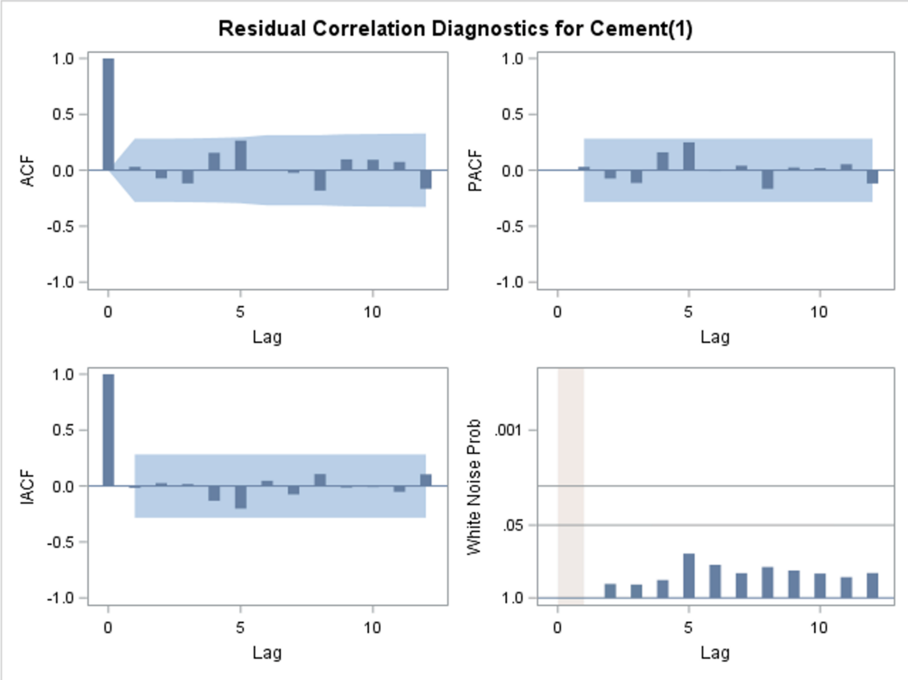


Figure 13: Residual correlation diagnostics for cement price index forecasting.

For normality checks, the histogram in the Figure 14 shows the distribution of residuals overlaid with a normal curve (blue line) and a kernel density estimate (red line), suggesting that the symmetric and bell-shaped of the distribution has proved its consistency with normality. The Q-Q plot in the Figure 14 compares the quantiles of the residuals against the quantiles of a theoretical normal distribution. Since most points fall close to the diagonal line, there is a good alignment with normality. Although there are minor deviations from perfect normality, particularly in the tails of the distribution, this is common in real-world data.

Lastly, a table in the Figure 15 shows both model parameters have p-values (0.0305 and 0.0055) below 0.05, which means their significance were at the 5% level. Hence, these parameters are both significant for the model. After all diagnostic checks, the selected ARIMA (1, 1, 0) model has adequately captured the data's characteristics of cement price and met all assumptions of the model. Therefore, from the table in the Figure 15, the ARIMA (1, 1, 0) model for cement price index forecasting is specified as:

$$u_t - 0.67342 = 0.38783(u_{t-1} - 0.67342) + e_t$$

Where $u_t = y_t - y_{t-1}$ is the differenced cement data at time point t and y_t is the raw data (cement price index) at time point t. e_t is the error term unexplained by the model.

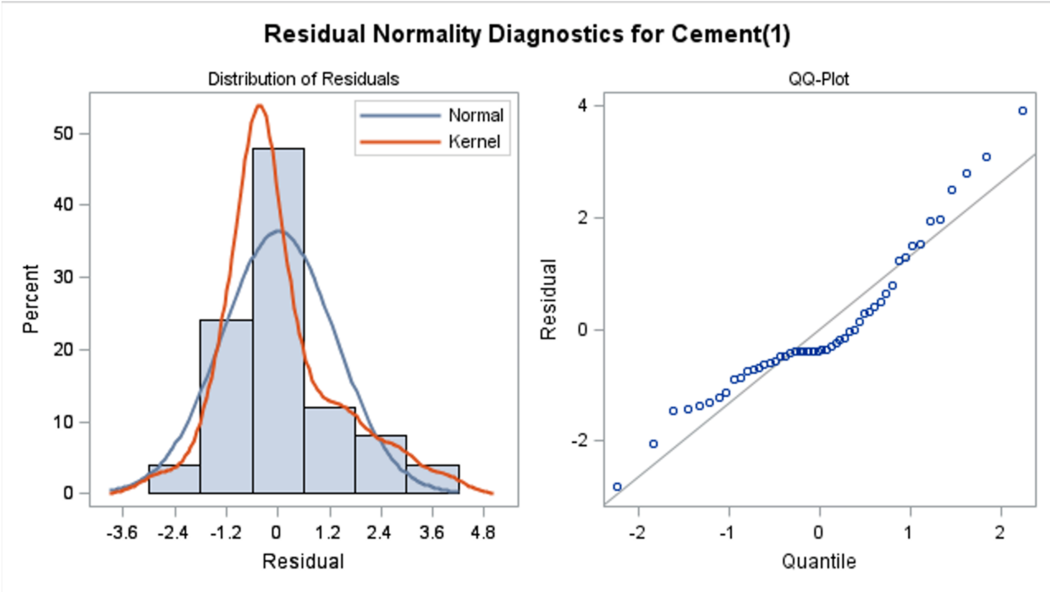


Figure 14: Residual normality diagnostics for cement price index forecasting.

Conditional Least Squares Estimation					
Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	0.67342	0.30209	2.23	0.0305	0
AR1,1	0.38782	0.13345	2.91	0.0055	1

Figure 15: Conditional Least Square Estimation table for the ARIMA (1,1,0) model of cement price forecasting.

Similarly, we iterated the procedure of ARIMA modelling for other construction materials and selected the most significant model for each type of material in the Table 5.

Table 5: Selected ARIMA models for all construction materials

Model	AIC	SBC
Cement. ARIMA (1,1,0)	172.3391	176.1631
Pre-cast concrete products. ARIMA (1,1,1)	236.5752	242.3112
Pre-cast concrete: blocks, bricks, tiles and flagstones. ARIMA (0,1,1)	228.267	232.091
Ready-mixed concrete. ARIMA (1,1,0)	227.1241	230.9482
Fabricated structural steel. ARIMA (1,1,2)	312.7905	320.4386
Metal doors and windows. ARIMA (0,1,0)	256.0263	257.9384
Pipes and fittings (rigid). ARIMA (1,1,0)	215.3377	219.1618
Pipes and fittings (flexible). ARIMA (0,1,0)	288.5888	290.5009

Plastic doors and windows. ARIMA (0,1,0)	183.8355	185.7475
Paint (aqueous). ARIMA (0,1,2)	208.3174	214.0534
Paint (non-aqueous). ARIMA (0,1,2)	243.0515	248.7875
Screws. ARIMA (0,1,0)	275.7884	277.7004
Builder woodworks. ARIMA (1,1,1)	165.967	171.7031
Wood doors and windows. ARIMA (0,1,0)	203.6989	205.611
Sand, clays, gravel and kaolin. ARIMA (0,1,0)	322.2656	324.1776

Based on the selected ARIMA models from the Table 5, we forecasted the price for all materials in the next subsequent 18 months (July 2024 to December 2025). In the Figure 16, the majority of materials are expected to experience gradual price increases over this 18-month period, even though the rates of increase vary significantly across different materials. Several materials are forecasted to see steeper price increases, with the increase of approximately 7-8% by June 2025. This group includes pre-cast concrete products, pre-cast concrete blocks, bricks, tiles and flagstones, ready-mixed concrete, flexible pipes and fittings, cement, gravel, sand, clays and kaolin, and plastic doors and windows. These materials show the most substantial upward price pressure, which could impact construction costs for projects heavily reliant on these items. Interestingly, fabricated structural steel displays a unique trend that diverges from the general pattern. The forecast shows an initial sharp increase of about 5.5% in the next months, followed by a steady decline. By June 2025, the price index for fabricated structural steel is decreased by 8%. This behaviour highlights the importance of material-specific forecasting and the need for flexible procurement strategies. Other materials are expected to experience low price increases, ranging from about 1% to 3% by June 2025. However, actual market conditions are influenced by unforeseen economic events, which are not captured in the historical data used for the ARIMA models.

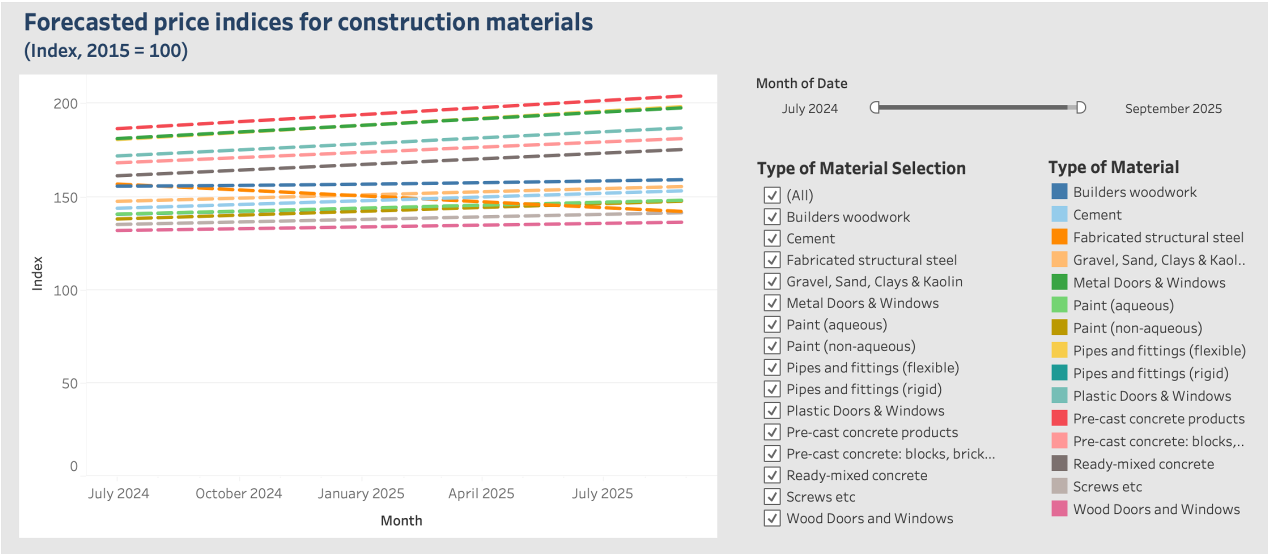


Figure 16: Line chart of forecasted price indices for all materials

4.4 Comparison of ARIMA and regression prediction

In order to validate the proposed time series models, the forecasting accuracy of the ARIMA models were compared to MLR models. The actual material prices series were used as a basic. The validity of each model was tested using the actual and the predicted values for the six-month out-sample from January to June 2024. According to the values of the mean absolute variable percentage error (MAPE) in the Table 6, the small forecast error in both models might state that both models performed well in terms of CMP forecasting.

It's important to note that while the MLR model shows strong performance in explaining historical price variations, its forecasting ability is inherently limited by the need for future values of independent variables. These economic indicators are often unknown and can be challenging to predict accurately. Consequently, the primary value of the MLR model lies in its ability to explain the relationships between various economic factors and material prices, rather than in direct future price prediction. By employing the MLR model as a benchmark against the ARIMA model, we gain insight into whether the price dynamics of certain materials are more closely tied to broader economic indicators or if they can be adequately captured by time series analysis alone.

The ARIMA model outperformed the MLR model for several material types, including sand, clays, gravel, and kaolin; cement; fabricated structural steel; pipes and fittings (both rigid and flexible); paint (non-aqueous); screws; and builder woodworks. This superiority of ARIMA for these materials suggests that their price movements may be more influenced by their own historical patterns and trends rather than by broader economic indicators. Conversely, the MLR model showed better performance for general pre-cast concrete products, pre-cast concrete products (blocks, bricks, tiles, and flagstones), ready-mixed concrete, metal doors and windows, plastic doors and windows, wood doors and windows, and paint (aqueous). The superior performance of MLR for these materials indicates that their prices may be more sensitive to various economic factors captured by the regression model.

Additionally, notable observations include the higher MAPE values for fabricated structural steel and pipes and fittings (both rigid and flexible) compared to other materials. This can be explained as these materials have more volatile and less predictable price movements (shown in Figure 6). The difference in performance between ARIMA and MLR models across materials highlights the importance of selecting the appropriate forecasting method based on the specific characteristics of each material. This suggests that construction project managers should adopt tailored forecasting strategies for different materials rather than applying a one-size-fits-all approach.

Table 6: MAPE values from ARIMA model and MLR model for all construction materials

Material Type	MAPE from ARIMA Model	MAPE from Multiple Regression Model
Cement	**0.693**	1.254
Pre-cast concrete products	2.164	**1.912**
Pre-cast concrete: blocks, bricks, tiles and flagstones	3.858	**2.829**
Ready-mixed concrete	2.244	**1.293**
Fabricated structural steel	**4.216**	9.536
Metal doors and windows	1.433	**0.944**
Pipes and fittings (rigid)	**4.959**	8.448
Pipes and fittings (flexible)	**3.831**	10.952
Plastic doors and windows	3.105	**2.983**
Paint (aqueous)	5.337	**4.281**
Paint (non-aqueous)	**0.831**	3.212
Screws	**1.101**	2.541
Builder woodworks	**1.108**	1.697
Wood doors and windows	1.624	**0.982**

Sand, clays, gravel & kaolin	**1.042**	7.3

4.5 Implementing the dashboard

The aim of the research is the development of an interactive dashboard that represents historical price trends, predictive model outputs, and key economic indicators that influenced the CMPs in a visually appealing and user-friendly interface. This dashboard integrates data visualisation techniques with the predictive models, creating a powerful tool that allows construction project managers to gain valuable insights and make informed decisions regarding material costs. We utilised Tableau for creating interactive and customisable dashboards due to the Tableau's superior handling of large datasets and greater flexibility in customising visualisations. The interactive dashboard is fully displayed on Figure 18, Figure 19, and Figure 20.

4.5.1 Interactive line charts of monthly price indices for different types of construction work

Firstly, the dashboard shows an interactive line chart displaying historical price trends across different types of construction works (shown in Figure 2). As the chart breaks down the CMPIs data into sectors like all work, new housing, other new work, and repair and maintenance, project managers are able to focus on the most relevant data for their specific project types, understand how different construction sectors are affected by price changes. Moreover, this includes interactive features such as selecting specific years for detailed analysis and choosing different types of construction work simultaneously. This allows users to examine the volatility of CMP on a month-by-month basis for each construction work type. Hence, project managers are able to analyse short-term fluctuations by zooming in on specific periods to understand price dynamics and develop more accurate decisions in budgeting and timing for material procurement.

Another interactive chart in the dashboard (shown in Figure 3) presents the percentage change in CMPIs compared to the previous year. This visualisation is important for project managers as it highlights periods of high volatility, allowing for better risk assessment in long-term projects. The chart also provides context for current price movements by comparing them to historical volatility, helping to identify trends that may indicate broader economic or industry-specific changes. Therefore, by understanding these year-to-year changes, project managers can improve their forecasting of future price movements based on historical patterns, make more robust plans and negotiate more effectively with suppliers.

4.5.2 Interactive line charts of price indices for individual construction materials

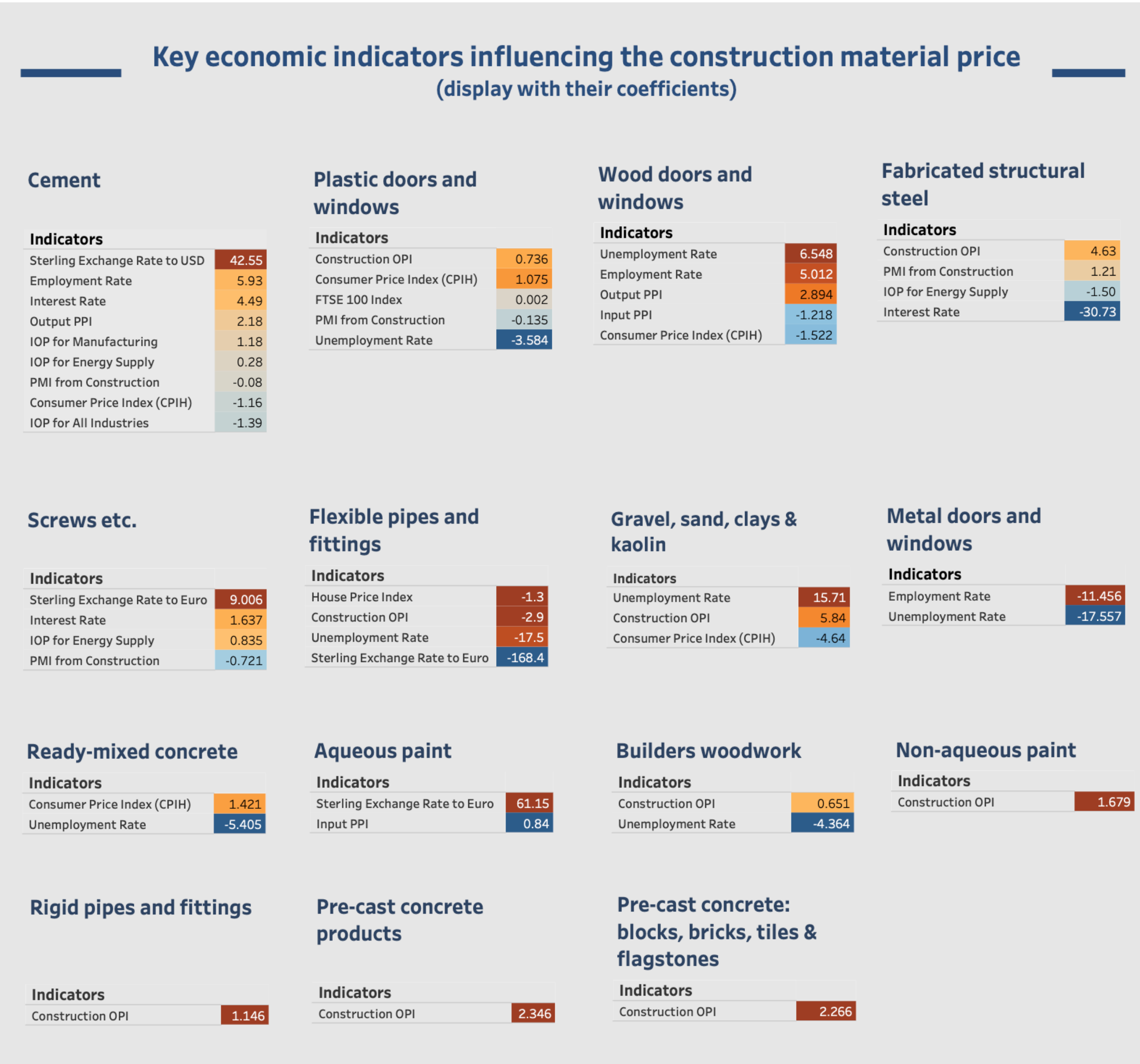
After having an overview of CMP for different construction sectors, the dashboard shows the price indices of individual construction material. By showing the percentage change in price indices for various construction materials in the year to June 2024, as shown in the Figure 4, users are able to see easily the volatility of different materials over the past year. This helps project managers to identify which material has the high volatility of price, so they focus on these potentially problematic materials. For helping them to track more detailed, an interactive line chart of monthly price indices for individual construction materials is shown in the dashboard. Users can adjust the time range for more detailed observation and select different construction materials simultaneously to see multiple CMP trends. For example, when users select 'metal doors and windows' and 'flexible pipes and fittings' options (shown in Figure 5), they can obverse the price movements of these material and notice similarities in trends and patterns, such as they both have a sharp incline in one month. Furthermore, the dashboard provides insights that highlight the percentage change of prices on the base year to June 2024. This additional context helps project managers to quickly understand the price trend of each construction material without the need for extensive data analysis. Therefore, this part of the dashboard offers the construction project managers a powerful tool, which involves identifying volatile materials, tracking price movements over time, and understanding historical CMP trends.

4.5.3 Highlight tables of key economic indicators

The next section of the dashboard shows key economic indicators that significantly influence the price of each construction material. These indicators were identified from the MLR models, with the results presented in Table 3 and Table 7. Only indicators with a p-value below 0.05 were considered statistically significant and included as key influencers of CMP. To visualise this finding effectively, highlight tables were employed for each construction material. These tables display key indicators along with their corresponding coefficients, providing project managers with a clear understanding of each indicator's impact on the material's price index. These tables also use a colour-coding scheme to enhance the readability: Positive coefficients are represented by shades of red, while negative coefficients are represented by shades of blue.

The intensity of the colour correlates with the coefficient values, allowing for quick visual assessment of their impact.

Additionally, the indicators of each table are sorted by their coefficient values. This arrangement helps project managers to easily identify the most impactful indicators for each material. As illustrated in Figure 17, these highlight tables are also organised in the dashboard in descending order based on number of significant indicators per material. This layout helps to rapidly point out which construction materials are potentially most influenced by economic indicators. Overall, this visualisation approach offers project managers an efficient tool to analyse the complex relationship between economic factors and CMPs in the UK.



Key economic indicators influencing the construction material price
(display with their coefficients)

Cement

Indicators	
Sterling Exchange Rate to USD	42.55
Employment Rate	5.93
Interest Rate	4.49
Output PPI	2.18
IOP for Manufacturing	1.18
IOP for Energy Supply	0.28
PMI from Construction	-0.08
Consumer Price Index (CPIH)	-1.16
IOP for All Industries	-1.39

Plastic doors and windows

Indicators	
Construction OPI	0.736
Consumer Price Index (CPIH)	1.075
FTSE 100 Index	0.002
PMI from Construction	-0.135
Unemployment Rate	-3.584

Wood doors and windows

Indicators	
Unemployment Rate	6.548
Employment Rate	5.012
Output PPI	2.894
Input PPI	-1.218
Consumer Price Index (CPIH)	-1.522

Fabricated structural steel

Indicators	
Construction OPI	4.63
PMI from Construction	1.21
IOP for Energy Supply	-1.50
Interest Rate	-30.73

Screws etc.

Indicators	
Sterling Exchange Rate to Euro	9.006
Interest Rate	1.637
IOP for Energy Supply	0.835
PMI from Construction	-0.721

Flexible pipes and fittings

Indicators	
House Price Index	-1.3
Construction OPI	-2.9
Unemployment Rate	-17.5
Sterling Exchange Rate to Euro	-168.4

Gravel, sand, clays & kaolin

Indicators	
Unemployment Rate	15.71
Construction OPI	5.84
Consumer Price Index (CPIH)	-4.64

Metal doors and windows

Indicators	
Employment Rate	-11.456
Unemployment Rate	-17.557

Ready-mixed concrete

Indicators	
Consumer Price Index (CPIH)	1.421
Unemployment Rate	-5.405

Aqueous paint

Indicators	
Sterling Exchange Rate to Euro	61.15
Input PPI	0.84

Builders woodwork

Indicators	
Construction OPI	0.651
Unemployment Rate	-4.364

Non-aqueous paint

Indicators	
Construction OPI	1.679

Rigid pipes and fittings

Indicators	
Construction OPI	1.146

Pre-cast concrete products

Indicators	
Construction OPI	2.346

Pre-cast concrete: blocks, bricks, tiles & flagstones

Indicators	
Construction OPI	2.266

Figure 17: Highlight tables of key economic indicators for construction material price (CMP)

4.5.4 Interaction line chart of forecasting construction material price

The final section of our dashboard presents an interactive line chart that visualised the forecasting results from the selected ARIMA models for each construction material. The line chart shows the forecasted prices for the subsequent 18 months (July 2024 to December 2025) are shown as a dashed line for clearly distinguishing between actual and predicted values (shown in Figure 16). Users can also adjust the time range and select one or multiple specific materials from a list menu, allowing them perform comparison and individual analysis of some material's price forecasts. The interactive nature of the forecast visualisation transforms it from a mere display of data into a dynamic tool for strategic planning and risk assessment. By allowing users to interact and customise the data presentation, the dashboard empowers project managers to derive deeper insights and make more informed decisions regarding cost management of construction materials. The dashboard combines the historical data analysis with the predictive capabilities of our ARIMA models, this offers project managers a comprehensive view of past trends and future projections. However, it is important to remember that these forecasts should be used as general guidance as CMPs are also influenced by unforeseen economic events or supply chain disruptions not captured in the historical data used for the ARIMA models. Project managers should use these forecasts as a starting point for planning but remain adaptable to changing market conditions.

Chapter 5: Conclusion

5.1 Summary of findings and benefits of the dashboard

The study has developed an interactive dashboard and predictive models to assist UK construction project managers in understanding, analysing and forecasting construction material prices. The interactive dashboard has provided a visual representation of historical price trends, which allows construction project managers to easily identify patterns and fluctuations in material prices over time. Moreover, the ability to compare different materials and adjust time ranges could enhance their understanding of market dynamics. The dashboard has revealed significantly volatility in CMP over the past 5 years, with notable increases across most materials since late 2020. Some materials like cement, plastic doors and windows, and non-aqueous paint showed relatively steady growth, while other materials like fabricated structural steel and gravel, sand, clays and kaolin showed highly volatile trends with sharp fluctuations. The study identified various temporal patterns in material prices: Firstly, a period of relative stability from October 2019 to October 2020; Secondly, a steep and consistent upward trend from October 2020 to July 2022, which can be explained by major economic events like Brexit and the COVID-19 pandemic; Finally, a slight decline followed by stabilisation from July 2022 to June 2024. By visualising the complex data into a digestible format of different historical price trends, project managers can understand the volatility of material prices more easily. Furthermore, the interactive nature of the dashboard allows them to customise for specific project needs.

Through the multiple regression analysis, we identified key economic indicators that influenced material prices. For example, the cement price was found to be significantly influenced by sterling exchange rate to US dollar, employment rate and interest rate. The construction output price index (OPI) is the most common significant factor that appeared in 9 out of 15 material price models. Other frequently significant indicators are consumer price index (CPIH), employment rate, and unemployment rate. By visualising the relationship between economic indicators and material prices in the dashboard, the project managers can gain a deep understanding of the factors that drove price fluctuations, which allows them to anticipate potential price changes based on economic trends. This knowledge also helps project managers conduct more accurate risk assessment by monitoring relevant economic indicators. For example, if a project heavily relies on cement, managers can pay closer attention to fluctuations in the sterling exchanging rate and employment figures to analyse the price risk.

The study compared the forecasting accuracy of ARIMA and MLR models and showed that some materials like general pre-cast concrete products, pre-cast concrete products like blocks, bricks, tiles, and flagstones, ready-mixed concrete, metal doors and windows, plastic doors and windows, wood doors and windows, and aqueous paint show better forecasting performance in MLR models, which implied that these materials' prices are sensitive to various economic factors captured by the regression model. Fortunately, most materials showed forecast errors (measured by MAPE) below 5%, which indicates good predictive performance. However, some materials with high volatile prices, such as fabricated structural steel and pipes and fittings, had higher error rates. Overall, the dashboard has showed the 18-month price forecasts for 15 construction materials. This helps project managers use these forecasts to create more accurate budgets for upcoming projects and also being able to assess financial risks associated with material costs.

5.2 Limitations

While this study provides valuable insights and tools for construction project managers, it still contains some limitations and challenges. Firstly, the research relies primarily on publicly available data, which may not capture all events that caused the rapid change in the construction material market, such as regional variations, specific supply chain disruptions and effects from major events like Brexit and COVID-19 pandemic, since their data were not publicly available for analysing. Therefore, the forecasting's accuracy from the ARIMA and MLR models is also impacted by these unforeseen events, reducing the reliability of the dashboard for project managers. Secondly, the scope of our study was limited to a specific set of materials and economic indicators. Other factors that could influence prices, such as technological advancements or environmental regulations, were not included in our models, that may limit their comprehensiveness. Thirdly, the effective use of the dashboard and interpretation of its outputs require a certain level of data literacy and understanding of economic principles, which may present a challenge for some users. Lastly, while our models provide forecasts for up to 18 months. Hence, longer-term predictions become increasingly uncertain and should be used with caution. These limitations show the need for users to approach the dashboard and its forecasts as decision-support tools rather than definitive predictors, and also to continually update and refine their strategies based on emerging data and market conditions.

5.3 Recommendations for project managers and future research

For project managers, it is essential to use the insights provided by the interactive dashboard and forecasting models to enhance decision-making processes. Regular monitoring of the dashboard will enable more accurate budget planning and risk assessment for upcoming projects. Moreover, particular attention should be paid to the economic indicators identified as significant for each material. For instance, when planning projects heavily reliant on cement, closely tracking changes in the sterling exchange rate to US dollar and employment rates could provide valuable insights. While the forecasting feature of the dashboard is useful for short to medium-term planning, managers should be aware of its limitations, especially for materials showing high volatility like fabricated structural steel and pipes and fittings.

Another use of the dashboard is that project managers can use its insights to negotiate better terms with suppliers or explore alternative materials when prices for certain items are predicted to increase significantly. Finally, integrating the use of the dashboard into regular team meetings and reporting processes can ensure all stakeholders are aware of potential price risks and opportunities, fostering a more proactive approach to cost management in construction projects.

For future research, several indicators could be explored to build upon this study and further enhance the utility of the dashboard for the construction industry. Incorporating more data such as regional price variations and specific supply chain disruptions, could improve the accuracy of price forecasts. Moreover, expanding the range of materials covered like newer sustainable alternatives, would provide a more comprehensive dashboard for project managers. The predictive models could also be enhanced by investigating the application of more advanced machine learning techniques, such as deep learning or ensemble methods. This could improve forecasting accuracy, especially for highly volatile materials. Another recommendation is that developing features, that allow users to input project-specific information (e.g., scale, location, timeline) to receive more tailored price forecasts and risk assessments, would increase the tool's relevance to individual projects.

Finally, investigating methods to automate the data collection process and provide real-time updates to the dashboard could enhance its value for day-to-day decision-making in the fast-paced construction industry. By pursuing these research directions, the capabilities of a dashboard for the construction industry can continue to be refined and expanded, further supporting effective cost management and decision-making in construction projects.

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7. Appendices

7.1 Full view of the interactive dashboard

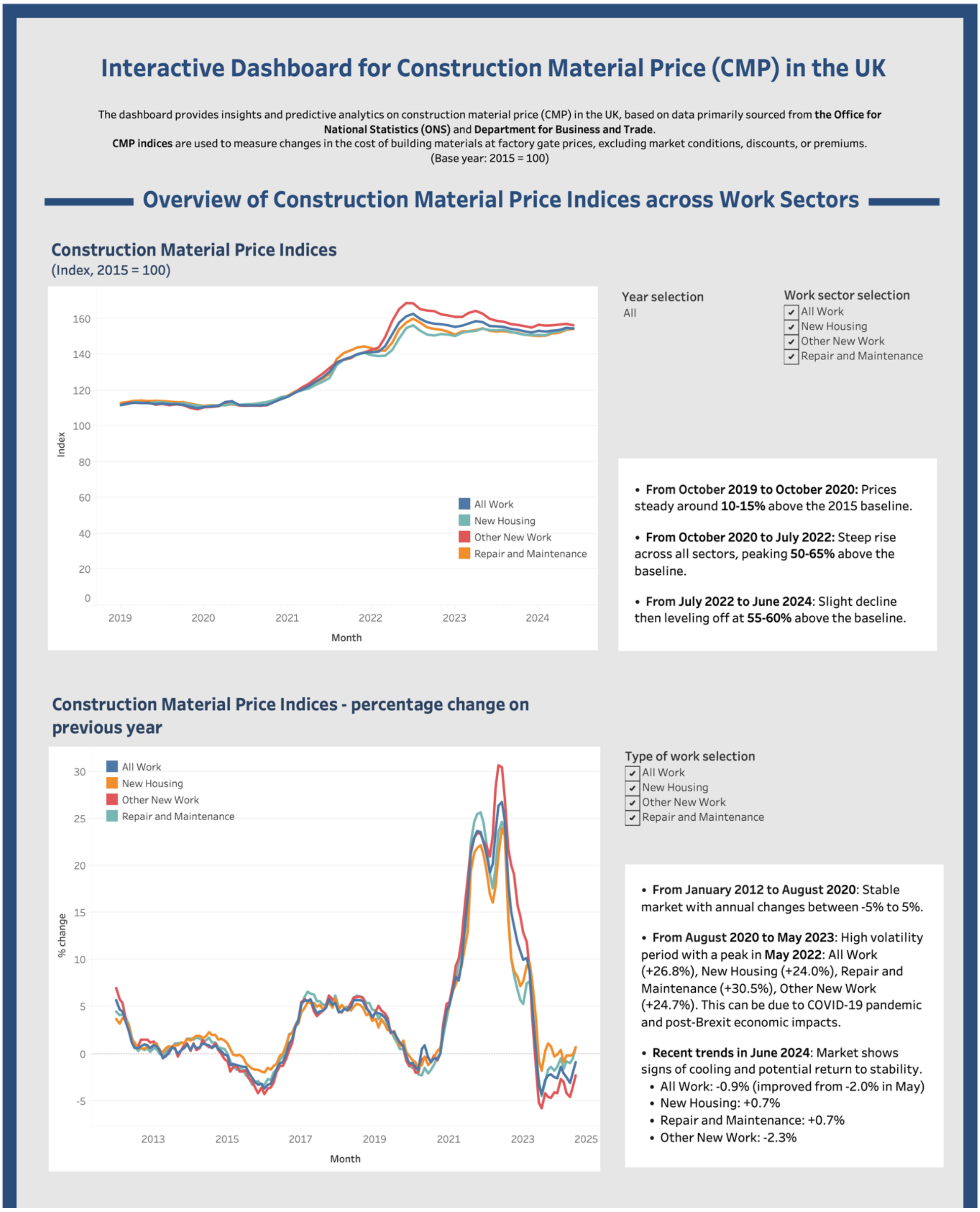

Figure 18: The first section of the interactive dashboard.

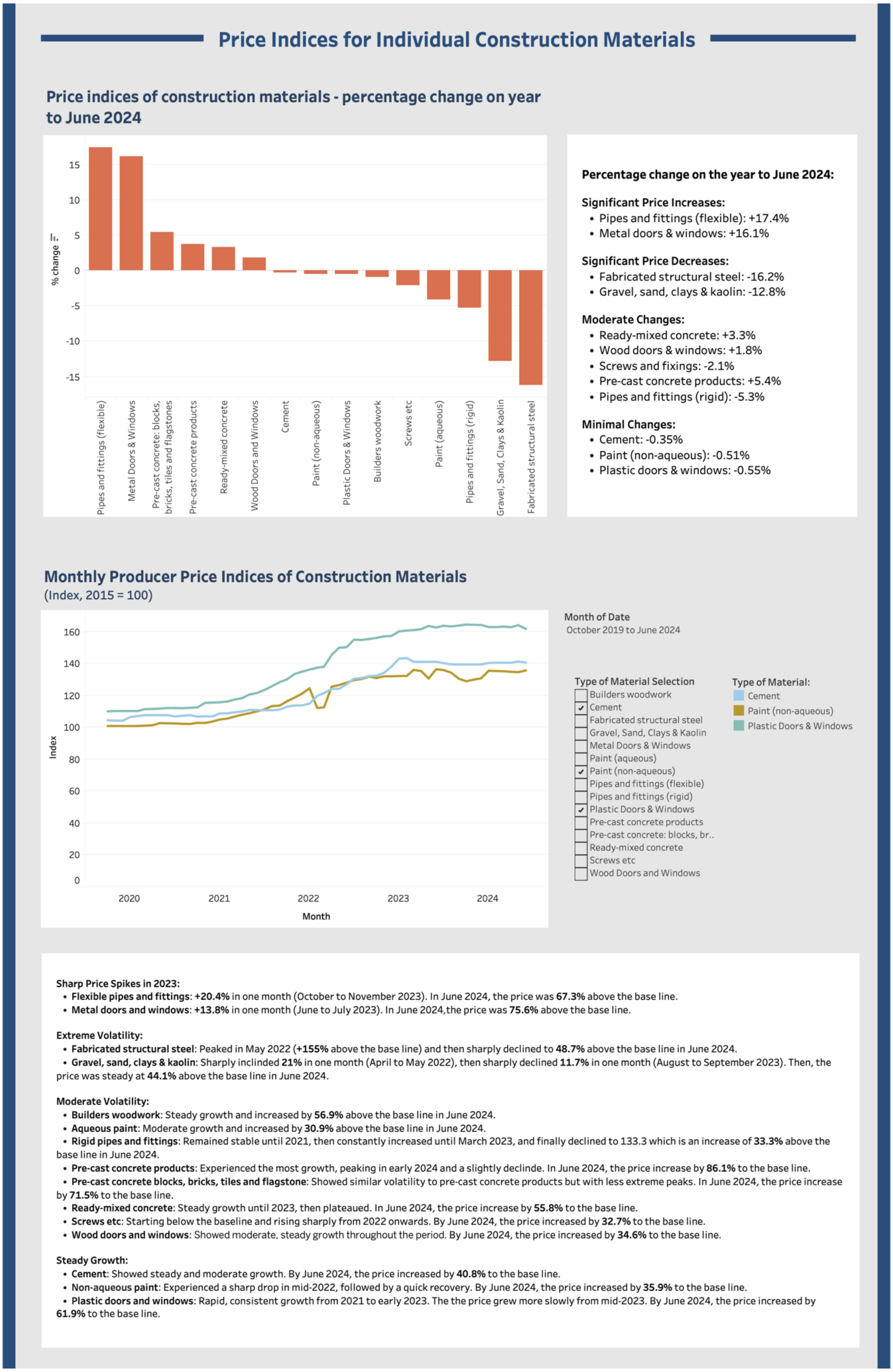

Figure 19: The second section of the interactive dashboard.

Figure 20: The third and fourth section of the interactive dashboard.

7.2 Results from the multiple linear regression models

Table 7: Coefficient and p values for all indicators of all construction material prices

Model	Gravel, sand, clays & Kaolin		Cement		Pre-cast concrete products	
	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
Constant	-140.88906	0.7925	-477.87987	**0.0004**	-356.15047	**0.0374**
CPIH	-4.63775	**0.0154**	-1.15976	**0.0084**	-0.37408	0.5063
Input PPI	0.18616	0.8862	-0.53652	0.0777	0.21627	0.5905
Output PPI	0.20606	0.9302	2.17616	**0.0003**	-0.26967	0.7103
Construction OPI	5.83937	**<.0001**	0.18501	0.4666	2.34561	**<.0001**
Interest Rate	-1.88993	0.6330	4.49088	**<.0001**	0.52912	0.6643
Sterling Exchange Rate to Euro	-6.76505	0.9311	-31.55170	0.0844	2.95972	0.9024
Sterling Exchange Rate to USD	-37.80842	0.5137	42.54684	**0.0027**	17.05740	0.3410
IoP for All Industries	0.49221	0.8529	-1.39242	**0.0270**	0.14916	0.8553
IoP for Manufacturing	-0.03367	0.9889	1.17625	**0.0394**	-0.10106	0.8922
IoP for Energy Supply	-0.05425	0.9055	0.27766	**0.0115**	0.19692	0.1686
IoP for Water and Waste Management	0.38839	0.6411	-0.00648	0.9727	-0.15960	0.5348
House Price Index	0.72706	0.2174	-0.25087	0.0658	-0.01658	0.9263
FTSE 100 Index	0.00672	0.1044	-0.00046813	0.6123	-0.00142	0.2600
GDP	-1.50842	0.1274	0.01616	0.9417	0.10163	0.7342
GDP from Construction	0.70906	0.2238	-0.09138	0.4874	-0.07822	0.6598
Unemployment Rate	15.70651	**0.0451**	3.33952	0.0602	-4.44535	0.0643
Employment Rate	1.56856	0.8073	5.92587	**0.0003**	1.73493	0.3843
Wage (AWE)	-0.16700	0.4219	-0.07570	0.1154	0.08104	0.2096
Money Supply (M4)	-0.0000392	0.3689	0.00004258	**0.0001**	0.00002608	0.0583
PMI from Construction	-0.26285	0.3888	-0.08144	0.2433	-0.00447	0.9618

Model	Pre-cast concrete: Blocks, bricks, tiles & flagstones		Ready-mixed concrete		Fabricated structural steel	
	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
Constant	-192.47496	0.3373	165.07689	0.3789	112.90080	0.8874
CPIH	-0.37465	0.5809	1.42092	**0.0312**	0.89525	0.7414
Input PPI	0.53407	0.2745	-0.55618	0.2254	3.94223	0.0491
Output PPI	-0.62431	0.4776	0.89404	0.2801	-1.58011	0.6528
Construction OPI	2.26622	**<.0001**	0.49321	0.2086	4.63207	**0.0084**
Interest Rate	0.26465	0.8571	0.20758	0.8801	-30.73294	**<.0001**
Sterling Exchange Rate to Euro	50.91643	0.0881	-19.85559	0.4685	-50.59810	0.6649
Sterling Exchange Rate to USD	19.90820	0.3569	28.63882	0.1609	28.34741	0.7417
IoP for All Industries	0.19808	0.8410	1.30020	0.1663	2.30779	0.5604
IoP for Manufacturing	-0.14652	0.8707	-1.03905	0.2232	-3.76160	0.3009
IoP for Energy Supply	0.35398	0.0441	-0.30679	0.0612	-1.49591	**0.0343**
IoP for Water and Waste Management	-0.19057	0.5391	-0.56741	0.0575	-0.39321	0.7512
House Price Index	-0.25732	0.2400	-0.25869	0.2079	-0.49524	0.5689
FTSE 100 Index	-0.00107	0.4810	-0.00194	0.1748	-0.00741	0.2247
GDP	-0.33791	0.3526	0.14833	0.6612	1.05697	0.4666
GDP from Construction	0.17294	0.4218	0.02165	0.9140	-0.64369	0.4551
Unemployment Rate	-3.94948	0.1677	-5.40481	**0.0475**	18.46681	0.1093
Employment Rate	-0.44681	0.8518	-2.68828	0.2355	-0.66000	0.9451
Wage (AWE)	0.07917	0.3076	0.04941	0.4945	0.08463	0.7837
Money Supply (M4)	0.00002115	0.1959	-0.00001124	0.4585	-0.00021773	**0.0019**
PMI from Construction	-0.01096	0.9226	0.01493	0.8875	1.20908	**0.0113**

Model	Metal doors & windows		Pipes and fittings (rigid)		Pipes and fittings (flexible)	
	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
Constant	903.67878	**0.0292**	-106.47096	0.6299	1024.61741	**0.0487**
CPIH	1.59122	0.2450	0.93399	0.2188	3.14665	0.0733
Input PPI	-0.44726	0.6444	-0.87000	0.1122	-0.42037	0.7311
Output PPI	0.51320	0.7695	1.15085	0.2408	2.71051	0.2260
Construction OPI	-0.98265	0.2399	1.14552	**0.0172**	-2.88637	**0.0091**
Interest Rate	3.17976	0.2837	-3.00657	0.0724	1.22863	0.7408
Sterling Exchange Rate to Euro	24.54105	0.6738	-4.36082	0.8925	-168.38255	**0.0281**
Sterling Exchange Rate to USD	15.85445	0.7120	-33.22148	0.1691	73.84993	0.1796
IoP for All Industries	1.04296	0.5979	-1.24059	0.2616	-0.53947	0.8287
IoP for Manufacturing	-0.77999	0.6650	1.13493	0.2600	1.35873	0.5511
IoP for Energy Supply	-0.21741	0.5235	0.07411	0.6941	-0.27369	0.5250
IoP for Water and Waste Management	-0.31074	0.6161	0.37835	0.2745	-0.77824	0.3232
House Price Index	0.16672	0.7003	-0.18906	0.4329	-1.29535	**0.0234**
FTSE 100 Index	-0.00236	0.4357	0.00177	0.2937	0.00166	0.6622
GDP	-0.23497	0.7449	0.31625	0.4314	0.32466	0.7220
GDP from Construction	0.05325	0.9010	-0.22829	0.3396	-0.26844	0.6204
Unemployment Rate	-17.55736	**0.0037**	1.69458	0.5881	-17.50494	**0.0189**
Employment Rate	-11.45604	**0.0220**	0.30923	0.9071	-10.74771	0.0829
Wage (AWE)	0.19113	0.2198	-0.10091	0.2419	-0.18269	0.3506
Money Supply (M4)	-0.00001238	0.7012	-1.40296E-7	0.9937	0.00003551	0.3861
PMI from Construction	0.13395	0.5535	-0.04644	0.7104	-0.36598	0.2049

Model	Plastic doors and windows		Paint (aqueous)		Paint (non-aqueous)	
	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
Constant	-96.55588	0.3182	89.20457	0.5883	-196.29440	0.4649
CPIH	1.07458	**0.0024**	0.89032	0.1187	0.49643	0.5860
Input PPI	-0.31249	0.1867	0.84172	**0.0420**	-0.99319	0.1339
Output PPI	0.50861	0.2335	-1.29181	0.0816	0.43055	0.7146
Construction OPI	0.73563	**0.0008**	-0.30132	0.3806	1.67887	**0.0048**
Interest Rate	-0.65981	0.3549	1.81574	0.1418	-1.67686	0.3985
Sterling Exchange Rate to Euro	4.34237	0.7572	61.15157	**0.0156**	42.17011	0.2857
Sterling Exchange Rate to USD	-5.90401	0.5690	-19.49256	0.2762	-46.39113	0.1151
IoP for All Industries	-0.20468	0.6674	1.07110	0.1952	-1.37943	0.3025
IoP for Manufacturing	0.32294	0.4584	-1.15469	0.1276	1.25875	0.3020
IoP for Energy Supply	0.01573	0.8477	-0.06261	0.6560	0.13035	0.5689
IoP for Water and Waste Management	0.14398	0.3379	-0.02263	0.9294	0.79964	0.0618
House Price Index	0.05417	0.6043	0.20452	0.2577	0.17992	0.5374
FTSE 100 Index	0.00173	**0.0226**	-0.00193	0.1281	0.00372	0.0735
GDP	-0.02314	0.8941	-0.39227	0.1945	0.06506	0.8933
GDP from Construction	0.03707	0.7197	0.33428	0.0663	-0.06021	0.8343
Unemployment Rate	-3.58383	**0.0124**	0.58952	0.8001	-0.56479	0.8814
Employment Rate	-1.02339	0.3777	-1.07713	0.5865	0.30990	0.9232
Wage (AWE)	-0.02580	0.4882	0.09367	0.1475	-0.12489	0.2325
Money Supply (M4)	0.00002100	**0.0106**	-0.00000150	0.9105	0.00001977	0.3645
PMI from Construction	-0.13511	**0.0178**	0.08513	0.3640	-0.14928	0.3282

Model	Screws		Builders' woodwork		Wood doors and windows	
	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
Constant	-866.72085	**0.0203**	-312.76416	**0.0275**	-382.26174	**0.0436**
CPIH	-0.33962	0.7796	0.04637	0.9202	-1.52239	**0.0195**
Input PPI	0.66021	0.4485	-0.32619	0.3280	-1.21798	**0.0097**
Output PPI	-2.32772	0.1449	0.40705	0.4980	2.89443	**0.0011**
Construction OPI	1.63652	**0.0335**	0.65061	**0.0272**	0.43010	0.2628
Interest Rate	9.00574	**0.0017**	0.03918	0.9689	1.33094	0.3284
Sterling Exchange Rate to Euro	-51.03856	0.3318	37.09524	0.0700	-6.74466	0.8012
Sterling Exchange Rate to USD	-13.25510	0.7305	-2.47846	0.8658	14.37917	0.4680
IoP for All Industries	-0.65357	0.7120	0.35008	0.6046	-0.73406	0.4210
IoP for Manufacturing	1.72158	0.2901	-0.13348	0.8282	0.50823	0.5401
IoP for Energy Supply	0.83465	**0.0096**	-0.00260	0.9822	0.13677	0.3842
IoP for Water and Waste Management	0.53338	0.3396	0.14646	0.4903	0.05378	0.8500
House Price Index	0.01744	0.9641	0.14793	0.3214	0.21074	0.2940
FTSE 100 Index	0.00428	0.1201	0.00001259	0.9902	0.00007406	0.9573
GDP	0.83352	0.2035	0.05268	0.8310	0.03582	0.9140
GDP from Construction	-0.61356	0.1173	0.03901	0.7900	-0.09387	0.6341
Unemployment Rate	-6.67101	0.1926	-4.36392	**0.0295**	6.54808	**0.0161**
Employment Rate	8.04279	0.0681	1.74017	0.2917	5.01172	**0.0287**
Wage (AWE)	-0.15075	0.2788	0.03762	0.4763	-0.06770	0.3421
Money Supply (M4)	0.00011096	**0.0005**	0.00004223	**0.0006**	0.00001428	0.3391
PMI from Construction	-0.72083	**0.0011**	-0.12959	0.1003	0.04247	0.6824