Bindura University of Science Education

Assessing the impact of past inflation rates and project durations on future Bill of quantities BOQ demand levels

By

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A dissertation submitted in partial fulfillment of the requirements for the Bachelor of Science Honors Degree in **Statistics and Financial Mathematics.**

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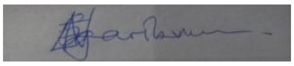
APPROVAL FORM

The undersigned certify that they have read the dissertation titled '**Assessing the impact of past inflation rates and project durations on future BOQ demand levels**' and confirm that it is suitable for submission to the Statistics department, Faculty of Science and Engineering, for assessment.

Signature of student:  Date: **18/06/2025**

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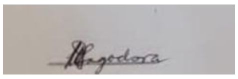
Signature of Chairperson of Department:  Date:**18/06/2025**

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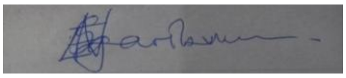
Signature:  Date: **18/06/2025**

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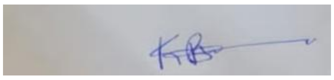
I, **Mr Basira**, declare that I have supervised this thesis and I am satisfied that it can be submitted to the Biological Sciences Department, Faculty of Science and Engineering, at Bindura University of Science Education.

Signature:  Date: **22/06/2025**

DEDICATIONS

I take this time to thank God for guidance and wisdom. I dedicate this dissertation to my lovely family whose love, encouragement and prayers have carried me through every step of this journey, and my parents who taught me the value of hard work, perseverance and kindness. Thank you for believing in my abilities and being there for me every step of the way from day 1. I am confident to say this is our achievement and not mine alone.

ACKNOWLEDGEMENTS

I would like to acknowledge the support and guidance to the professionals and experts in the field who shared their knowledge and understanding to develop and improve my dissertation till it reached this level. Special thanks to my supervisor Mr Basira and coordinator Ms P. Hlupo for their unwavering support. Their knowledge and views upgraded this dissertation to a greater extend. I would also like to thank the whole Bindura department of statistics and mathematics in terms of administrative assistance.

LIST OFABBREVIATIONS

VAR: Vector Auto-regression model.
LRM: Linear regression model
BOQ: Bill of quantity
MSE: Mean squared errors
MAE: Mean absolute errors

ABSTRACT

This study assessed the impact of inflation rate and project duration on Bill of quantities (BOQ) demand within Zimbabwe's construction sector. It applied the Vector auto-regression (VAR) and Linear regression (LR) models to evaluate the causal and predictive relationships between the variables using time series data. The aim of the study was to identify the accurate model when it comes to forecasting BOQ demand and understanding the relative influence of inflation on project durations in a macro economically changing environment. Model performance was assessed through the mean absolute error (MAE) and the Mean squared error (MSE) and it was revealed from the analysis that linear regression model outperformed the Vector auto regression model due to its small MAE and MSE values. The validity was also assessed through the diagnostic tests, including the Jerque-Bera, Portmanteau and Breusch-Pagan. The inflation rate showed a statistically strong positive impact on BOQ demand whilst the project duration variable showed a weak and less consistent impact on BOQ demand. The other assumptions were met except the auto-correlation which might have been caused by omitted variables or consistent macroeconomic changes widespread in Zimbabwe's construction environment.

Contents

LIST OF FIGURES

The Impact of Inflation rates and Project durations on BOQ demand

Chapter 1- Introduction

Introduction

The Bill of quantity (BOQ) is a computerised price list of building materials and labour costs. It has proved to be an important tool in the construction industry these days, for knowing the exact quantity of materials needed and costs to complete a project without disruptions is the key to a detailed and clear project plan from the project managers. The BOQ helps the managers to save time and allocate resources effectively, and it also helps stock managers to know the most demanded materials so as to keep the right quantity of those materials so as to keep up sales. This list estimation for clients also help the company to keep records of the quantity of materials they would have sold and the quantity of materials to be re-stocked, or the materials they must start selling. Factors such as inflation rates and project duration have been pulling some strings in BOQ demand, without the knowledge of their impact on BOQ demand; managers have been providing wrong budgets leading to unwanted costs. In my project I will be looking at how these factors affect the BOQ demand in order to provide a clear insight to the stakeholders for better planning and decision making. For instance if inflation rate is high, building material and labour costs will also be high leading to a demand of BOQ. This is simply because when the costs are high there will be need to know the exact quantity of materials and labour needed to complete a project without fail at the same time avoiding unnecessary costs.

This project will involve steps like data collection, data processing, defining research objectives, literature review and exploratory data analysis.

1.1 Background of the study

In the construction industry, planning is the main key to a successful project. It is important to know the exact quantity of materials to be used and costs that will be incurred during the project and this where the BOQ jumps in to help. It is also important to know that to avoid loses due to under or overstocking issues, a company must know the exact levels of stock to maintain. However, it is of most importance to know that BOQ demand can be influenced by factors such as inflation rate and project duration. For instance, the higher the inflation rate is the lower the demand for BOQ gets.

In the past before the construction companies knew the impact of inflation rate and project duration, contractors would rely on what they call the “Cost-Plus contracts” where clients would agree to pay the contractors for actual costs incurred, plus a mark-up for overhead and profit. This exposed both the contractors and clients to inflation risks, because by the time the project ends the inflation rate might be higher than the expected. Inflation also led to wrong estimations of building material prices and labour costs, disputes and unexpected costs.

This indirect impact of inflation rates on BOQ demand was not looked into until recently in 2025 when the construction industry conducted a research, “Inflation and construction cost trends” by Matt’s. This is when it was known that, high inflation rates reduce the purchasing power of the contractors and clients because materials will be expensive and this will lead to an increase in BOQ demand.

1.2 Statement of problem

Achvalt contractors, a small construction company that also sells building materials is facing overstocking and under-stocking problems leading to huge losses. They also have been making project plans and decisions basing on non numerical trends of possible outcomes. According to Kumur et al. (2023), an increase in inflation leads to a rise in demand for building materials as contractors rush to lock in prices. The assumption of the study is that, lack of knowledge on the effects of inflation rates and project duration on BOQ demand or improper use of this knowledge might be the cause. This study will be applying statistical tools to model the potential impact of inflation rate and project durations on BOQ demand.

1.3. Research Objectives

a) To identify the direction and strength between the dependant variable (Bill of quantities demand) and the independent variables (inflation rate and project duration).

b) To determine the predictive power of both Vector auto-regression and Multiple linear regression models in predicting BOQ demand using the inflation rate and project durations.

c) To identify if past inflation rate and project duration can determine future BOQ demand through the causal relationships between the variables (inflation rate, project duration and BOQ demand.

1.4 Delimitations of the study

Delimitations of the study are boundaries that are set to focus a research and in this study the delimitations were, Specific time frame where the study was restricted to a specific time frame, which was from 2000 to 2024. The second delimitation of the study was assessing just the impact of inflation rate and project durations only on BOQ demand without considering other factors such as material prices that could also influence the level of BOQ demand. Another delimitation of this study was specific geographical scope; this study only focused on the Archvault contractors company in Mutare only. The other delimitation of this study was specific projects where the study was only based on specific construction projects like residential which may not include other categories. Another delimitation was the specification of techniques to be used; The study applied the VAR and MLR only to assess the impact without the use of others like machine learning. Second from last, the study focused on the data provided by the Archvault contractors company only without collecting from other companies in the same industry for variation and comparative advantages. This study is of helps the internal stakeholders only excluding the clients in the industry.

1.5 Assumption of the study

The study assumed that the economy remains relatively stable making consistent analysis of inflation and project duration impacts on BOQ demand impossible, the study also assumed that the data of BOQ demand, inflation rate and project duration are all accurate and can be applied in the real world. The study assumed that, definitions of inflation, project duration and BOQ remains the same across the study, it also assumed that link between the variables are easy to predict to enable effective modelling and forecasting. Second from last the study assumed that the stakeholders make reasonable decisions based on the available data and forecasts that drive BOQ demand and lastly the study assumed that, the effects of both factors, were relatively uniform across various types of construction projects within the defined scope.

1.6 Limitations of the study

The weaknesses of the study that may affect the reliability of outcomes include data limitations, where the accessibility and quality of historical data may limit the accuracy of analysis, the second weakness is specification of the assumption for instance, the Vector auto-regression model assumes that the variables should not be highly correlated with each other and that there should be a low possibility of big outliers. Another limitation includes failure to interpret individual shocks because of correlated error term in the equations.

Whereas the linear relationship assumption by the linear regression model, might also lead to unreliable results if they are not met. The assumption that the predictor variables should not be highly correlated with each other might also lead to biased results by the MLR if not satisfied.

1.7 Significance of the study

To the students: The study will help students in many ways that includes, being a learning tool to the students who are interested in the construction management, giving them more knowledge on the link between BOQ demand, inflation rates and project durations. Secondly the methodologies and outcomes of this study will be reference to other following students who will think of applying the same methodologies to their dissertations. Lastly this study will help students in the construction business career to know methods to use and what to consider when forecasting their demand or when deciding their levels of stock.

To the university: The study will be an upgrade to the university's research reputation, showing its hard work on attending to real world problems in construction. The methodologies and outcomes of my study will also lead to engagements with construction industry partners, providing opportunities for collaborative in-depth research.

To the Archvault construction company: This study will help the AC company to understand the effects of inflation rates and project durations on BOQ demand, to avoid predictions that do not consider the inflation rate and project duration impact. Secondly the study will enable project managers to know the correct steps to plan in order to complete the project without disturbances like the cost overruns. It also enables the stock manager of the company to be aware of the levels of stock to maintain in different economic situations. This study also serves as a work up call to the company that they should start the application of statistical techniques to assess their businesses and for their needed predictions.

To the construction industry: The methodologies and outcomes of this research will provide the construction industry with the knowledge of how project planning and accurate demand forecasting is of help to profit and business boosting. This study will be a competitive advantage to construction companies who will apply statistical methods in their day-to-day businesses.

To the researcher: lastly the study will help the researcher to improve knowledge on how to apply statistical models to forecast different values. It will also help the researcher to get recognition if the dissertation is recognised as useful to the economy. Lastly this research will be an achievement to the researcher.

1.8 Definition of key terms

- ✓ Bill of Quantities (BOQ) is a document of listed materials, parts and labour required that is used in the construction company.
- ✓ Inflation rate is the percentage change in prices of goods and services over a defined period of time.
- ✓ Project duration is the period taken to complete a project.
- ✓ Vector auto-regression model (VAR): It is a multivariate time series model that predicts multiple time series simultaneously.
- ✓ Linear regression model (LRM): It is a statistical technique that is used to model the relationship between a dependant variable and one or more independent variables by fitting a linear equation to the observed data

1.9 Conclusion

This chapter introduced the topic, defining the terms such as BOQ, inflation and many other terms that I will be using in the whole project. It also includes the stating of the objectives indicating the main objective which is to model the impact of inflation and project duration on BOQ demand. In the next chapter I will be looking at the literature review of the study

Chapter 2 Literature Review

2.1 Introduction

The construction industry is naturally sophisticated, with different factors driving the demand for Bill of quantities (BOQ). The two factors that have proven to be significant drivers over the years are inflation rate and project duration. This chapter shows existing literature on the effects of these factors on BOQ demand, giving a firm base to understand the changes at hand.

2.2 Theoretical Literature review

The Vector auto-regressive (VAR) model

The Vector Auto-regression model (developed by a macro-econometrician, Christopher Sims in 1980), is a statistical technique that is used to examine the changing relationships between multiple time series variables. It expands the concept of auto-regression, which models a single time series using its past values as a base, to a system of multiple interacting time series. They treat all variables as endogenous, and this shows that they have an impact on each other and are useful, especially to systems where output of a system is taken back into the system as input, determining future outputs. The Vector auto-regression model expands the concept of auto-regressive models to multiple time series providing a more explained analysis of interlinked systems.

The VAR models can be used to test for causality using the Granger causality test that helps to identify whether one of the time series can help to forecast the other. It is also used for variance decomposition, where the proportion of a variance in each variable that is explained in the system is identified. Advantages of the VAR model include flexibility, where we are saying that they can handle more sophisticated and changing relationships with strong assumptions about the underlying causal structure. They also used observed data to estimate the relationships between variables, leading to good and effective decisions due to evidence. They are also used for prediction of the quantity of building materials to be used in a project until the end. The VAR models are also used to assess the risks related to the project and present them in their results. Lastly these models are applicable in many areas that include mining, engineering and other areas that needs to analyse relationships.

According to Mtiraoui and Slimene (2025) in their research paper "The Bitcoin prediction by VAR", the model is used to model univariate time series data, where the current observed value is assumed to be a function of the past values plus a random shock. The process $\{X_t\}$ is said to be auto-regressive of order p, denoted AR (p) if, $X_t = \varphi_1 X_{t-1} + \varphi_2 X_{t-2} + \ldots\ldots + \varphi_p X_{t-p} + \varepsilon_t$, $\{\varepsilon_t\} \sim N(0, \sigma^2)$, $X - \varphi_1 X_{t-1} + \varphi_2 X_{t-2} + \ldots\ldots + \varphi_p X_{t-p} = \varepsilon_t$ or $(1-\varphi_1 L_1 - \ldots\ldots - \varphi_p L_p) X_t = \varepsilon_t$. The equation indicates that a VAR model is a linear regression of the current value in the time series against one or more previous values in the time series.

According to my variables (inflation rates, project durations and BOQ demand), my parameters with BOQ demand being the dependent variable will be BOQ demand = $\beta_1 X_1 + \beta_2 X_2 + \varepsilon_t$. β_1 and β_2 are my parameters (BOQ demand level) that are being influenced by inflation rate and project duration (X_1 and X_2 respectively).

The methodology of the VAR model include the data collection and processing stage, where the required data is collected to model the VAR model effectively, Stationarity is tested through Augmented Dickey Fuller test ($\Delta y_t = \alpha + \beta t + \rho y_{t-1} + \sum_{i=1}^{p} \emptyset_i \Delta y_{t-i} + \varepsilon_t$), where $\Delta y_t = y_t - y_{t-1}$ (the first time series difference), α is a constant, βt is the trend term, ρ is the coefficient of the lagged level of the series, $\emptyset_i$ are the coefficients of the lagged differences, p represents the lag order and ε_t error term (white noise). The steps include the estimation of the equation using ordinary least squares (OLS), then the stating of the H_0: p = 0 and determine the test statistic and compare it with critical values from the Dickey-Fuller distribution. If H_0 is rejected the series is stationary and if not it may have a unit root and is not stationary.

Under data collection and processing methodology there is also data splitting, were will be dividing data into training and testing sets for model evaluation. Secondly there is the model specification methodology where the lag order selection is done. The lag (ρ) is determined for the model using Akaike information Criterion (AIC). This is where model formulation is done and exogenous variables are considered to be included if they have a notable impact on the system.

The third methodology is model estimation, where parameter estimation and diagnostic checking to ensure no auto-correlation or heteroskedasticity in the residuals. Then the Analysis and interpretation methodology takes over, when the results from the model estimation will be clearly explained. Lastly the forecasting methodology where model validation is also done through the MAE and RMSE results from the model.

However these models include setbacks such as hard time when estimating parameters, as number of variables and lags increase, becoming very large which will then lead to over-fitting and lose of statistical power. Lastly interpretability of VAR models is possible but is challenging.

2.3 Linear regression model

The Linear regression model is a statistical technique that is used to model the relationship between a dependant variable and one or more independent variables by fitting a linear equation to the observed data. It was first developed in the early forms (17^{th} to 18^{th} centuries) where they were seen in the work of Isaac C Newton around 1700. The method of least squares was first applied by Adrien-Marie Legendre in 1805 and Carl Frierich Gauss in 1809.

Also, the "Regression" term was introduced by Sir Francis Galton in the 19th century to describe a "biological phenomenon". The Gauss-Markov theorem was later developed together with the least square theory by Gauss in 1821.

The main theory behind involves finding the best-fitting line that reduces the sum of squared variations between the forecasted and actual values. Its key concepts include, the least squares method for the estimation of parameters of the linear equation. The second concept is the Gauss-Markov theorem that gives conditions under which the least of squares estimator is the best linear unbiased estimator (BLUE). Thirdly there is the Liner equation for model specification, $Y = \beta_0 + \beta_1X_1 + \beta_2X_2 + \ldots .. + \beta_pX_p + \varepsilon$, where Y is the dependent variable, X_i are the independent variables and the coefficients to be estimated are represented by the by β_i and $\varepsilon$is the error term. The model main's assumptions are linearity, independence of errors, homoscedasticity (constant variance of errors), and normality of errors.

The model include the definition of problem where I will state the objectives and identify the variables, collect data the required data and cleaning the data, checking for the assumptions (linearity, independence, homoscedasticity and normality) and identifying and address outliers. Lastly the estimation of parameters (β_0, β_1 and β_2) using the Ordinary Least Squares (OLS)

2.4 Inflation rate on BOQ demand

Inflation is the percentage change in prices of goods and services in an economy over a period of time. Various studies have shown that inflation rate can notably affect construction costs and BOQ demand (AM Abdelalim 2024). Inflation rate has both positive and negative impact on demand, for instance when inflation rate increases, the level of demand for different goods and services either decrease or increase. Due to panic consumers might buy more goods to stock before the prices increase further or due to the same salary they receive goods and services will be come too expensive for them to buy leading to a decrease demand level. Researches have also explored the relationship between inflation and construction demand, indicating the need for correct predictions and cost management (Hwang et al., 2013)

The hyperinflation situation that happened in Zimbabwe in 2008 had a huge negative and positive impact on the demand levels. It led to a decline in real wages and this result eroded the purchasing power of some goods since people were now focusing on basic goods. The situation also led to reduced consumption and dollarization and currency abandonment. High inflation rates also caused loss of confidence to businesses, since they were not certain whether to buy more or less stock, they kept low stock levels which also led to low demand to the supplier of goods and services.

Mankiw (2020) also backed this up with the price effect theory where the higher the prices because of inflation, the lower the quantity demand may go, holding all other factors constant. Alsokrugman and Wells (2018) also proved that through the income effect that says a decrease in buying power of consumers may be the result of inflation which will then lead to decrease demand. (Blanchard and Johnson, 2015) proved that, the more increase in production costs due to inflation, the more suppliers might reduce the quantity supplied or the more they increase the prices.

2.5 Impact of project duration on BOQ demand

Project duration is the time taken to complete a project. The project duration is influenced by factors such as availability of materials, plans being used, the management team skills and the complexity of the project. The time taken to complete a project determines the demand of the items on the Bill of quantity document, it might not be a notable change but it still determines.

Short time lines results in an increase in BOQ demand levels. If the project is short, there will be an increase in demand for more building materials and labour to work on new projects. Also short project durations is equal to speed up projects and sped up projects mostly results in mistakes which will require for more materials and maybe upgraded or increased labour to attend to the mistake effectively.

At the other side, longer project durations lead to lower peak demand for resources. Project durations allow the correct estimation of material and labour quantity which shows the levels of demand in the BOQ. Project duration is an important tool when deciding how to allocate and manage resources effectively throughout the project. It is also a tool to control project costs effectively. Shortened project durations also help to show risks that are linked to material availability or labour shortages and the BOQ can help to quantify the risks. The longer the project the more likely it is for the project to have some design changes, which requires a flexible BOQ structure.

However long project durations provides flexibility in distributing resources and negotiating better prices and it also reduces of risks associate with the shortage of materials for it provides more time to plan and budget for the sufficient quantity of materials.

2.6 Empirical Literature review

The “International electronic journal of mathematics education” is a report by Elizeth Mayrene et al. (2024), applies the Linear regression model to forecast Artificial intelligence use in experimental science. Their results indicated that both AI competencies and digital resources are important forecasters of the usage of AI.

Also the paper “Applications of linear regression models in exploring the relationship between media attention, economic policy uncertainty and cooperate green innovation” is a paper by Yang Xu et al. (2023). It assessed the effect of media attention and economic policy uncertainty on green innovation among A share industrial listed enterprises. It used data from 2011 to 2020 and they concluded from their results that there is a positive impact on green innovation caused by media attention.

Dos Santos Farias et al. (2020) evaluated the performance of linear regression and other machine learning methods for estimating reference evapotranspiration (ETRef) using data from limited weather. Their conclusion was that, though machine learning performed well, linear regression could be a useful too, particularly when dealing with less complex data sets or when finding more simple models.

F Khan (2020) applied the VAR model to model the tree variables (new cases, deaths and recover cases) about COVID-19 in Pakistan. He used the public confirmed data about the new cases, deaths and recover cases for 10 days.

In 1980 Christopher Sims in the paper "Macroeconomics and Reality" examined the effect of the dynamic policy using time series data and Macroeconomic variables. The Vector Auto-regression models were used as the methodology to analyse the changing relationships between economic variables and policy changes. The results indicated that policy changes had a notable effect on economic variables but the effect depended on the specific policy and economic context. The study of comparing US and German data shows variations in the responses of the two countries' economies to the dynamic nature of policy; this showed the importance of considering country specific factors. Lastly in this study, Sims identified high confidence levels in his results with significance levels of 0.0007 for the US and 0.003 for German that backed his discoveries statistically.

"Vector auto-regression for forecasting the number of COVID-19 cases and analysing behavioural indicators in the Philippines" is a study by Khan et al.(2023), that applied Vector auto-regression models to jointly model COVID-19 cases, hospitalisations and deaths. Public hospitalization rate data due to COVID-19 and deaths was used. The Granger causality tests suggest that the relationship of public interest with number of cases changed over time. During the prediction time of August 11-18, only change mobility (P=0.002) improved the prediction of cases, while public interest was also found to Granger-cause the number of cases during September 15-22 (P=0.001) and January 28 to February 4 (P=0.003)

Rajab et al. (2023) applied the VAR model in forecasting the COVID-19 pandemic in the UAE, Saudi Arabia and Kuwait. This study was to test the effectiveness and reliability of the model when it comes to predicting the spread of the pandemic. The results showed Mean absolute error (MAPE) of 0.35%, 2.03% and 3.75% in predicting the number of daily new cases for the three countries respectively. They went on to interpolate their predictions to forecast cumulative number of cases, and they obtain MAPE of o.0017%, 0.002% and 0.024% respectively. The good results indicated that the VAR model is an effective and reliable model to use in the management of the pandemic.

Researchers that include Lanne and Lutkephol (2008), Sims (2020), Brunnermeier et al. (2021) and Lewis (2021) studied the identification of VAR models with non-linearities.

Vector Auto-regression analysis of corruption, economic growth, and foreign direct investment in Ghana by Tiwari and Mutascu (2011) and Blonigen (2005). They applied the Vector auto-regression model to study the impact of FDI inflows on economic growth in developing nations. In their research they investigated the dynamic and causal relationship among corruption, foreign direct investment and economic growth simultaneously using a data set from Ghana. The outcomes proposed that there is a reverse causality among the variables, and it showed that these variables work together rather than against each other.

2.7 Challenges and Gaps in Existing Research

2.7.1 Challenges:

While carrying out the study issues like limited data and quality which may affect effective quantitative analysis were incurred. The sophistication of inflationary impacts because they are not uniform in all construction items was also a challenge and it was because some materials may experience higher volatility than others. Thirdly there is also the challenge due to changes in projects. The unknown changes must be accounted for and the way in which inflation and project duration drives adjustments to the real BOQ. Lastly there is the issue of regional specificity, where the problem is because of the assumption that inflation rates are the same throughout the country, but here we are saying that they differ within Zimbabwe so the inflation rates in the research may not be applicable in Mutare. This shows a potential of biased results.

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2.7.2 Gaps in existing research

Here will be looking at areas that are left out when it comes to the application of the VAR model but are being neglected. These gaps include restricted specificity to construction and BOQ demand, where I am saying that while VAR models have been and are still used to study inflation on economic growth, there is a few or no researches that applies the VAR model to get a clear grasp on how inflation rate and project duration affect the Bill of quantities (BOQ) demand in the construction industry.

Secondly there is also lack of heterogeneity in the inflations' effect, where I am saying that inflation affects various construction materials and labour components differently. Inflation is treated as a single, homogenous factor, ignoring the diverse impact on various BOQ item.

Also there is the issue of insufficient relationship modelling between inflation rates and project durations. Also inflation rates have not been included in the construction industry. In my study I will be applying the VAR model to model the relationship.

Linear regression model is applied in cases where there are limited variables (Inflation and project durations) without considering other factors of BOQ demand. Secondly there are few studies in the construction industry that applied the linear regression model.

Also most studies focus on overall BOQ items without specifying the items to be assessed. Some studies also lack thorough validation of their models and the generalizability of outcomes to various scenarios is always unclear.

2.8 Summary

This chapter analyses the already existing knowledge and industry views that are relevant to the impact of inflation rate and project duration on BOQ demand in construction companies. Its main focus was on frameworks, empirical evidence and challenges and gaps in existing research, emphasising on the context of Mutare. The next chapter will me explain the methodology of the research.

Chapter 3 Research Methodology

3.1 Introduction

This chapter explains the research design and methodologies used to analyze the impact of inflation rate and project duration on BOQ demand. Identifying the sophistication of economic data, this chapter thoroughly explains a systematic approach that makes sure both rigor and relevance in the analysis. The chapter will cover data collection, data processing, analyzing of the impact and interpretations.

3.2 Research Paradigm and Research design

3.2.1 Research Paradigm

The suitable paradigm for this research is the positivist research that was developed more by Auguste Comente, who was a French philosopher in the early 19th century. The paradigm focuses on empirical data and observable phenomena, looking more on quantitative analysis and it also depends on statistical techniques to recognize patterns and forecasts based on past data. It is applied in analyzing the impact of inflation rate and project duration on BOQ demand by formulating hypothesis based on my literature review about the connection between inflation rate, project duration and BOQ demand, operationalize variables by defining key variables in measurable terms, by applying quantitative data collection methods, the use of statistical methods to examine the collected data and test my hypothesis and Lastly explaining the outcome in an understandable way by determining if my data is for my H_1 or against.

To conclude the above matches my research because I managed to collect quantitative data from the Archvault contractor's company.

3.2.2 Research Design

The concept's aim is to introduce the framework that leads the whole research process. It states the specific procedures and ways that I will apply to answer the mentioned research questions and to achieve the research objectives. Babbie (2020) says that, the descriptive survey research design regulates the value of my conclusion from my results. The predictive design is a quantitative research technique that uses past data to analyze and predict possible outcomes. It depends on data collection, use of statistical techniques to model the relationships.

3.3 Target and Sampling

According to the research, the target was residential construction projects, stakeholders and economic data; I used relevant economic data sources that provide past data of both inflation rates and project duration. Sampling is the process of choosing a subset of individuals from a larger population to make inferences or conduct analysis. In this research the sample was BOQ demand past data from year 2000 to 2024.

3.4 Data collection and sources

3.4.1Data description

The data consists of three columns which are the date which is from year 2000 to 2024, BOQ demand expressed in units, project duration which is in months and lastly the yearly inflation rate for Zimbabwe which is the external factor. It took me a whole week to collect data from the Archvault contractors' company and a day of finding a reliable source for the inflation rate which came out to be the worlddata.info.

Handling the missing values by, counting the number of elements in the data set that includes the missing values. The second step will be multiplying the mean by the number of elements in the data set and lastly subtract all known values from the product obtained from the second step.

Then we calculated the mean which was equal to the total value for inflation rate, project duration and BOQ demand, median which was equal to the middle value for each data set and lastly the standard deviation (σ) which was equal to the measure of variability in the data sets.

3.4.2 Data collection and sources

It is the process of measuring, gathering and recording data for a purpose. Secondary time data series data of Zimbabwe's inflation rate from 2000 to 2022 was used and was collected from the Worlddata.info which is an online platform. The platform was visited using a phone. The BOQ demand historical data and the project duration were provided by Archvault contractors company. It required knowledge to identify the main data required so as to search using the key points, after the required data was presented I then typed manually in the excel sheet which can be accessed by the R studio. I tried using other data sources such as index Mundi but they failed to provide the required data clearly.

3.4.3 Justification of secondary data:

Secondary data only requires one to have a phone or a laptop and the knowledge of the websites to visit because secondary data is an already collected data. It saves time and it is updated from time to time, making it reliable and no costs are included.

3.4.4 Data Validity

William M. K. Trochim defined validity in three segments which are the construction of validity which makes sure the data truly measures the theoretical construct it claims to measure, Internal validity which evaluates if the outcomes of the study are because of manipulation of the independent variable rather than other factors and the last segment which is the external validity which assess the generalizability of the findings beyond the specific study context. My data set satisfies the above segments; hence it is valid.

3.5 Description of variables

Variables	Indicators	Source
Bill of Quantities (BOQ)	▪ Quantity variance ▪ Cost variance ▪ Project duration ▪ BOQ demand	▪ Archvault construction company records.
Project duration (Pd)	▪ Schedule variance ▪ Duration variance ▪ Estimated duration ▪ Real duration	▪ Archvault construction company records.
Inflation rate(IR)	▪ CPI	▪ Worlddata.info (www.worlddata.info)
Year- independent Variable	▪ Temporal context ▪ Comparative Analysis ▪ Seasonality ▪ Policy impact	From the sources mentioned above.

3.6 Priori expectations based on the characteristics of Monte Carlo simulation and Vector Auto-regression models

The VAR model expects each variable in the system to be a linear function of its own prior values and the prior values of all other variables in the system. It is expected to give the degrees of freedom and accurate predictions. It is also expected to model the forecasts of the future values of multiple time series considering their inter-dependences.

For the best-fitting line, the linear regression model expects a linear relationship between the dependent and independent variables. It should provide unbiased estimators for the regression coefficients due to the use of the ordinary least squares (OLS). The models should be interpretable and the performance metrics are supposed to be comparative.

3.7 Analytical model specification and justification

3.7.1 Vector auto-regression model (VAR)

It is a multivariate time series model that predicts multiple time series simultaneously. To examine if past inflation rates and project durations values determine future BOQ demand levels, there are some equations that are effective. These equations are as follows:

Let **α** be the intercept or constant term, **β** be the coefficients of the lagged variables, **ε** be the error term, **t** be the succeeding time period and **t-1** be the prior time period

BOQ demand equation:

BOQ demand (t) = α1 +β11 × BOQ demand (t-1) + β12 × Project duration (t-1) + β13 × inflation rate(t-1) + ε1t.

Project duration equation:

Project duration (t) = α2 + β21 × BOQ demand (t-1) + β22 × Project duration (t-1) + β23 ×Inflation rate (t-1) + ε2t.

Inflation rate equation:

Inflation rate (t) = α3 + β31 × BOQ demand (t-1) +β32 × Project duration (t-1) + β33 × Inflation rate (t-1) + ε3t

Through the estimation of β of the VAR model, I can determine if past inflation and project duration values have an impact on future BOQ demand levels. For instance, if β32 is not notable or significant, it means that past values do not have a notable effect on the present BOQ demand levels.

When choosing the lag order I will use the Akaike information criterion (AIC) with the formulae, AIC = 2 × In(maximum likelihood) + 2k, where k is the number of parameters. I will use the Breusch-Godfrey LM test to check for serial correlation. It estimates residuals from an Ordinary least square (OLS) regression and running an auxiliary regression of residuals on lagged residuals and other repressors.

3.7.2 Linear Regression model (LRM)

The Linear regression model is a statistical technique that is used to model the relationship between a dependant variable and one or more independent variables by fitting a linear equation to the observed data. When assessing the effect of inflation rate and project durations on BOQ demand, I will use the multiple linear regression model.

It uses the BOQ demand = β_0 + β_1 (inflation rate) + β_2 (project duration) + ε, where BOQ demand is the dependent variable, β_0 is the intercept or constant term, β_1 and β_2 are regression coefficients representing the variation in BOQ demand caused by inflation rate and project durations and ε is the error term.

Its key components include the intercept (the value of BOQ demand when inflation rate and project durations are zeros), the regression coefficients that represents the average variation in BOQ demand for a one-unit variation in inflation rate and project duration accordingly.

The model assumes that there is a linear relationship between the dependent and independent variables. It also assumes that the errors are independent and that there is homoscedasticity, Normality and that there is no multicollinearity between independent variables.

Lastly when interpreting the results, it is important to know that positive coefficients means that there is a direct relationship between the independent variable and BOQ demand, whilst the negative coefficients show an inverse relationship. Lastly the strength of the relationship is determined by the magnitude of the coefficients.

3.8 Model diagnostic tests

When analyzing the impact of inflation rate and project duration on BOQ demand using, it is of significance to perform the following diagnostic tests to ensure both the validity and reliability.

3.8.1 VAR tests for inflation on BOQ demand.

Stationarity: using the Augmented (ADF) tests to check for stationarity before VAR model estimation.

Residual diagnostics: Using the Jerque-Bera test to check for auto-correlation, heteroscedasticity and normality of the residuals.

Granger causality: Testing for granger-causality between variables to understand the direction and influence of the independent variables on the dependent variables

Impulse response functions: Analyzing how a shock to one variable affects the other variables over time.

Variance decomposition: Determining how much each variable's variation is explained by itself and other variables.

3.8.2 Linear regression Diagnostics for project duration

Multicollinearity: to check for high correlation between independent variables using variance inflation factor (IVF).

Outliers: to identify and attend to influential outliers that maybe skewing the results.

Model specification: To check for misspecification of the model using Ramsey RESET.

3.9 Model Performance tests

Mean absolute error (MAE): calculating the average variations between the forecasted and actual values where a lower MAE shows a better model performance and a higher MAE shows otherwise. The formula is MAE = $\frac{1}{n} \times \sum(predicted - actual)$.

Mean squared errors (MSE): calculates the moderate of squared variations between the predicted and the actual values, penalizing bigger errors. It is more heavily than MAE where a lower MSE shows a better fit model performance. The formulae MAE = $\frac{1}{n} \times \sum(predicted\ - actual)^2$.

3.10 Model specification

The study applies two statistical techniques to examine the impact of inflation rate and project duration on BOQ demand which are the Vector auto-regression (VAR) and the multiple linear regression model (MLR).

The VAR model is specified as, $Y_t = c + A_1Y_{t-1} + A_2Y_{t-2} +\ldots +A_pY_{t-p} + \varepsilon_t$, Y_t is an endogenous variables vector (BOQ demand, Inflation rate, project duration).

Whereas the multiple linear regression is specified as, BOQ demand = $\beta_0 + \beta_1$ (inflation rate) + β_2 (project duration) + ε, here BOQ demand is the dependent variable and the independent variables are inflation rate and project duration.

These models consist of some key features which are the capturing of the changing relationships between variables in the VAR model, assessment of linear relationships between the dependant variable and the independent variables. Lastly both the models consider potential interactions and correlations between variables.

3.11 Ethics consideration

- ✓ **Privacy and confidentiality:** I make sure to handle Archvault data with confidentiality and keep it private.

- ✓ **Acknowledgement:** I have provided the websites where I got the yearly Inflation rates of Zimbabwe from.
- ✓ **Compliance with regulations:** Archvault and the Inflation rate data will only be used for MCS and VAR modeling only.

3.12 Conclusion

This chapter clearly assessed the methodology employed to investigate the impact of inflation rate and project duration on BOQ demand, stating the diagnostic tests to be performed in the R software package that will be used to start chapter 4 .

Chapter 4 Data presentation analysis and discussion

4.0 Introduction

To mend the study with effective results, in this chapter some tests were done with the given data using the Vector auto-regression and linear regression models in order to assess the impact of inflation and project duration on BOQ demand. After modelling the relationship, I will then discuss the results, indicating the process that met my research objectives.

4.1 Vector Auto-regression model for inflation on BOQ demand

Model estimations

Figure 1 VAR model estimation

Here the VAR model was used to estimate future BOQ demand levels basing on the given data; this was also done in order to know the MSE of this model that enabled me to compare the two models.

```
VAR Estimation Results:
=========================
Endogenous variables: d_boq, d_duration, d_inflation
Deterministic variables: const
Sample size: 19
Log Likelihood: -248.88
Roots of the characteristic polynomial:
1.103 1.103 1.065 1.065 0.9426 0.9426 0.9073 0.9073 0.9012 0.9012 0.8994 0.89
94 0.869 0.869 0.7348
Call:
VAR(y = diff_data, p = optimal_lag, type = "const")


Estimation results for equation d_boq:
======================================
d_boq = d_boq.l1 + d_duration.l1 + d_inflation.l1 + d_boq.l2 + d_duration.l2
+ d_inflation.l2 + d_boq.l3 + d_duration.l3 + d_inflation.l3 + d_boq.l4 + d_d
uration.l4 + d_inflation.l4 + d_boq.l5 + d_duration.l5 + d_inflation.l5 + con
st

               Estimate Std. Error t value Pr(>|t|)
d_boq.l1         -2.698      6.316  -0.427   0.6981
d_duration.l1   166.040    319.132   0.520   0.6388
d_inflation.l1    1.074      2.843   0.378   0.7307
d_boq.l2          1.655      7.017   0.236   0.8287
d_duration.l2    85.734    471.176   0.182   0.8672
d_inflation.l2   -1.241      3.173  -0.391   0.7218

d_boq.l3          5.455      6.524   0.836   0.4645
d_duration.l3   346.904    482.522   0.719   0.5241
d_inflation.l3   -2.497      2.933  -0.851   0.4571
d_boq.l4        -10.396      9.173  -1.133   0.3394
d_duration.l4   124.570    421.481   0.296   0.7868
d_inflation.l4    4.366      4.102   1.064   0.3652
d_boq.l5         44.427     14.187   3.131   0.0520 .
d_duration.l5   -15.499    289.134  -0.054   0.9606
d_inflation.l5  -19.885      6.321  -3.146   0.0514 .
const           -21.064    197.740  -0.107   0.9219
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1


Residual standard error: 749 on 3 degrees of freedom
Multiple R-Squared: 0.9065,     Adjusted R-squared: 0.4389
F-statistic: 1.939 on 15 and 3 DF,  p-value: 0.3223


Estimation results for equation d_duration:
===========================================
d_duration = d_boq.l1 + d_duration.l1 + d_inflation.l1 + d_boq.l2 + d_duratio
n.l2 + d_inflation.l2 + d_boq.l3 + d_duration.l3 + d_inflation.l3 + d_boq.l4
+ d_duration.l4 + d_inflation.l4 + d_boq.l5 + d_duration.l5 + d_inflation.l5
+ const

                Estimate Std. Error t value Pr(>|t|)
d_boq.l1       -0.010348   0.010508  -0.985    0.397
d_duration.l1  -0.554980   0.530938  -1.045    0.373
d_inflation.l1  0.004853   0.004729   1.026    0.380
d_boq.l2       -0.003141   0.011674  -0.269    0.805
```

```
d_duration.l2  -0.535847   0.783893  -0.684    0.543
d_inflation.l2  0.001220   0.005279   0.231    0.832
d_boq.l3       -0.004677   0.010855  -0.431    0.696
d_duration.l3   0.042385   0.802770   0.053    0.961
d_inflation.l3  0.002105   0.004879   0.431    0.695
d_boq.l4       -0.014191   0.015260  -0.930    0.421
d_duration.l4   0.242806   0.701216   0.346    0.752
d_inflation.l4  0.006247   0.006824   0.916    0.427
d_boq.l5        0.014194   0.023603   0.601    0.590
d_duration.l5   0.266556   0.481031   0.554    0.618
d_inflation.l5 -0.006220   0.010516  -0.591    0.596
const           0.059072   0.328979   0.180    0.869


Residual standard error: 1.246 on 3 degrees of freedom
Multiple R-Squared: 0.8281,     Adjusted R-squared: -0.03122
F-statistic: 0.9637 on 15 and 3 DF,  p-value: 0.5957


Estimation results for equation d_inflation:
============================================
d_inflation = d_boq.l1 + d_duration.l1 + d_inflation.l1 + d_boq.l2 + d_durati
on.l2 + d_inflation.l2 + d_boq.l3 + d_duration.l3 + d_inflation.l3 + d_boq.l4
+ d_duration.l4 + d_inflation.l4 + d_boq.l5 + d_duration.l5 + d_inflation.l5
+ const

               Estimate Std. Error t value Pr(>|t|)
d_boq.l1         -4.605     13.879  -0.332   0.7619
d_duration.l1   308.329    701.229   0.440   0.6899
d_inflation.l1    1.772      6.246   0.284   0.7951
d_boq.l2          4.704     15.419   0.305   0.7802
d_duration.l2    98.195   1035.315   0.095   0.9304
```

4.1.2 Lag length selection

A lag-length selection, I will be determining the best number of historical values to put in my VAR model using the Akaike Information Criterion (AIC). AIC is a calculation of model fit that reduce models with more parameters. The R package vars for modelling and lag-length, where AIC for each model was calculated.

Figure 2 chosen leg length

```
> print(lag_order$selection)
AIC(n)  HQ(n)  SC(n) FPE(n)
     5      5      5      4
```

The selected lag length using the AIC was 5

4.2 Stationarity test

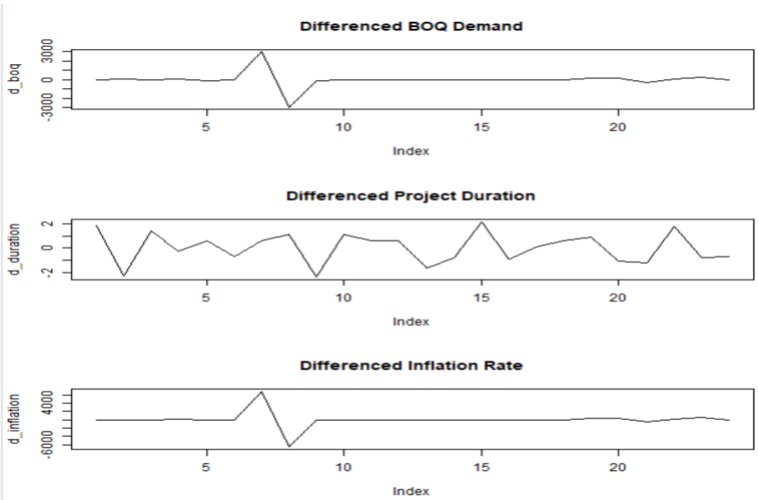
Using the Augmented (ADF) tests to check for stationarity before VAR model estimation, the following results were obtained:

Figure 3: Stationarity results

```
$BOQ

        Augmented Dickey-Fuller Test

data:  boq
Dickey-Fuller = -2.7294, Lag order = 2, p-value = 0.2945
alternative hypothesis: stationary


$Duration

        Augmented Dickey-Fuller Test

data:  duration
Dickey-Fuller = -3.8161, Lag order = 2, p-value = 0.03456
alternative hypothesis: stationary


$Inflation

        Augmented Dickey-Fuller Test

data:  inflation
Dickey-Fuller = -2.8104, Lag order = 2, p-value = 0.2637
alternative hypothesis: stationary
```

The above ADF results show~~s~~ that both BOQ demand and Inflation are not stationary in this form because of the p-values 0.2945 and 0.2637 which are greater than 0.05. Due to this we fail to reject H_0 and conclude that the variables are not stationary, meaning that stationarity is not met hence I applied the differencing method to make the variables stable and obtained the results shown below:

Figure 4: Stationarity results after differencing



```
        Augmented Dickey-Fuller Test

data:  d_inflation
Dickey-Fuller = -3.9858, Lag order = 2, p-value = 0.02375
alternative hypothesis: stationary

>
> # ADF tests after differencing
> adf.test(d_boq)

        Augmented Dickey-Fuller Test

data:  d_boq
Dickey-Fuller = -3.9596, Lag order = 2, p-value = 0.02467
alternative hypothesis: stationary

> adf.test(d_duration)       # Should already be stationary

        Augmented Dickey-Fuller Test

data:  d_duration
Dickey-Fuller = -6.1505, Lag order = 2, p-value = 0.01
alternative hypothesis: stationary
```

The p-values of all my variables are now less than 0.05 0r 0.10 after differencing hence stationarity is now achieved.

4.3 Residual diagnostic test

It is a test that I did to check for auto-correlation, heteroscedasticity and normality of the residuals, using the Jerque-bera test and the results obtained were:

Figure 5: Residual diagnostic test

```
$Normality
$JB

        JB-Test (multivariate)

data:  Residuals of VAR object var_model
Chi-squared = 4.9671, df = 6, p-value = 0.548


$Skewness

        Skewness only (multivariate)

data:  Residuals of VAR object var_model
Chi-squared = 3.9367, df = 3, p-value = 0.2684


$Kurtosis

        Kurtosis only (multivariate)

data:  Residuals of VAR object var_model
Chi-squared = 1.0304, df = 3, p-value = 0.7939
```

```
$Autocorrelation

	Portmanteau Test (asymptotic)

data:  Residuals of VAR object var_model
Chi-squared = 86.166, df = 63, p-value = 0.02794


$Heteroscedasticity

	ARCH (multivariate)

data:  Residuals of VAR object var_model
Chi-squared = 84, df = 180, p-value = 1
```

Looking at normality results, the p-value is greater than 0.05 or 0.10 hence we fail to reject H_0 that the data follows a normal distribution and conclude that it follows the normal distribution, this shows that the normality assumption is met. Secondly the p-value for multivariate is also bigger than 0.05 or 0.10, hence the skewness assumption is also met, the kurtosis assumption is also met due to the 0.7939 p-value. The Portmanteau test above proves that the change in one of the variables might also cause a change in the other variable; this shows that the model did no capture the serial dependence structure of the data. The heteroscedasticity test gave a p-value (1), which is greater than 0.05 proves that the residuals have constant variance which is good for modelling contexts that assume homoscedasticity.

4.4 Granger Causality test

To assess if one of my variables granger-causes another, that is, showing whether past values of one variable provide predictive information about the other, vars, an R package was used. This package contains functions for VAR modelling and Granger causality test.

Figure 6: Granger causality test

```
	Granger causality H0: d_inflation do not Granger-cause d_boq
	d_duration

data:  VAR object var_model
F-Test = 1.3358, df1 = 10, df2 = 9, p-value = 0.337
```

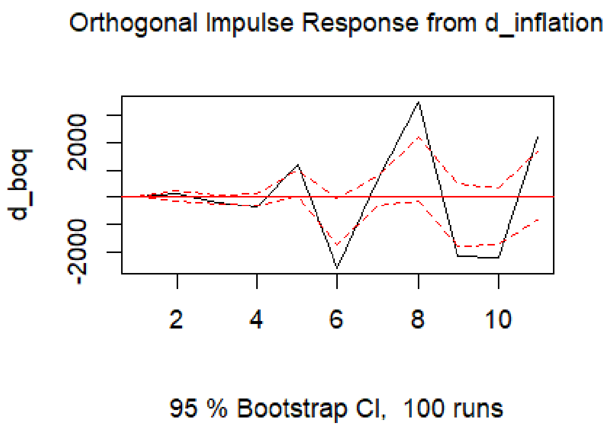
Granger causality test: the p-value is greater than the bench mark 0.05 or 0.10 so we fail to reject H_0. Failing to reject H_0 proposes that historical inflation rates do not predict BOQ demand and project duration in a Granger-causal point of view.

Instantaneous causality test: the p-value is less than 0.01; hence we reject the instantaneous H_0 at conventional significance levels. This proposes that inflation rate has an instant causality relationship with BOQ demand and project duration

4.5 Impulse responsive function

This involves analyzing how a shock to one variable affects the other variables over time. The figure 7 below illustrates how a shock in inflation, variously changes BOQ demand over a 10-period horizon, using orthogonalized shocks with 95% bootstrap confidence interval.

Figure 7: illustration of how a shock in inflation variously changes BOQ demand

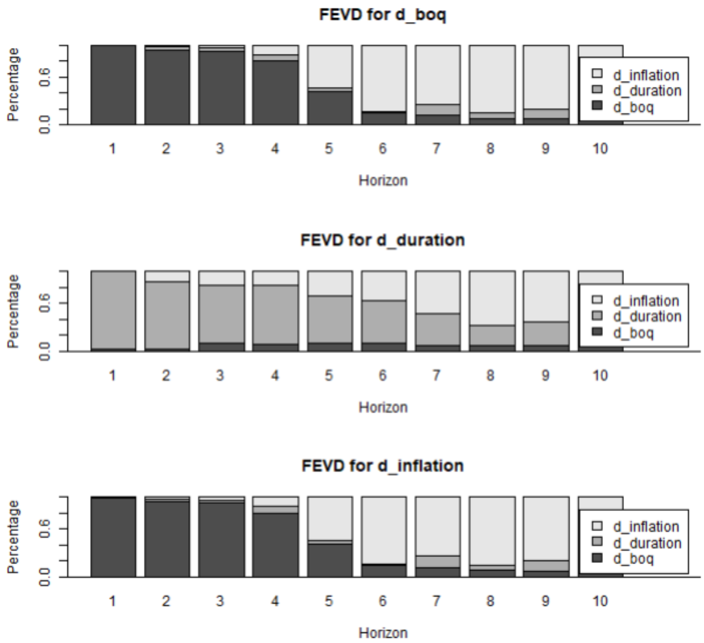


The graph above is showing that a shock in inflation causes the BOQ to increase showing a short-term positive effect. The response curve is varying across the time horizon, crossing from positive to negative. This proposes non-linear or lagged effects, where inflation forces may increase demand in some periods but reduce it later. The wide intervals at some horizons propose upward spiking uncertainty over time. This graph may be proposing that the relationship between inflation and BOQ demand is not static but time sensitive and reverse direction.

4.6 Variance decomposition

This involves ~~D~~determining how much each variable's variation is explained by itself and other variables.

Figure 8: Variation explanation for each variable



The forecast error variance decomposition (FEVD) value for d_boq shows that BOQ demand explains most of its own changes in the short-term and the d_inflation and d_duration starts to influence BOQ demand forecasts more at longer horizons. Then the FEVD for d_duration shows that project duration is stable internally, but longer durations can be partly explained by costs and or demand shocks. Then the FEVD for d_inflation is showing that initial changes are self-driven, but as time goes on project duration and BOQ demand may influence inflation changes and expectations.

4.7.0 Linear regression Diagnostics for project duration

4.7.1 Linear regression model

Figure 9: Linear model

```
Call:
lm(formula = `Project Duration` ~ `BOQ demand` + `Inflation rate in %`,
    data = data)

Residuals:
     Min       1Q   Median       3Q      Max
-1.52763 -0.53798 -0.03909  0.63988  1.43988

Coefficients:
                        Estimate Std. Error t value Pr(>|t|)
(Intercept)             6.082167   0.617229   9.854 1.58e-09 ***
`BOQ demand`            0.001649   0.004639   0.355    0.726
`Inflation rate in %`  -0.000709   0.002090  -0.339    0.738
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.8647 on 22 degrees of freedom
Multiple R-squared:  0.0084,	Adjusted R-squared:  -0.08175
F-statistic: 0.09318 on 2 and 22 DF,  p-value: 0.9114
```

From the linear results above, the coefficients of BOQ demand and inflation rate are both small and it indicates no a weak linear impact on project duration. High p-values indicate that they are not statistically significant, meaning we cannot confidently say that inflation and BOQ demand influence project duration.

4.8 Multicollinearity

This was done to check for high correlation between independent variables using variance inflation factor (IVF).

Figure 10: Variance inflation results

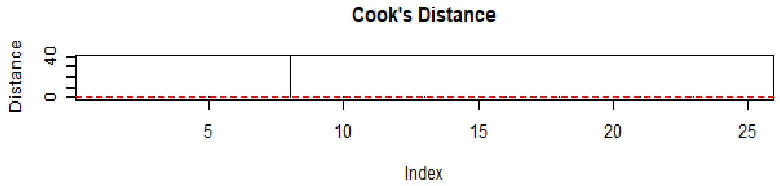
```
`BOQ demand` `Inflation rate in %`
    251.7002              251.7002
```

IVF of one shows no correlation with other variables, the results above of 251.7002 between BOQ demand and inflation rate shows that there is a higher linear correlation between the variables. This may affect the estimated or predicted values for multicollinearity inflates the standard errors of the coefficient estimates.

4.9 Outliers test

This test is to identify using the cook’s distance method and attend to an influential outlier that maybe skewing the results.

Figure 4.9: Cook’s distance results



In the figure above the points are falling below the red dashed line, which indicates the limit. This shows that no observation exerts undue influence over the fitted model's parameters.

4.10 Model specification

To check for misspecification of the model using Ramsey RESET.

Figure 11: Ramsey RESET results

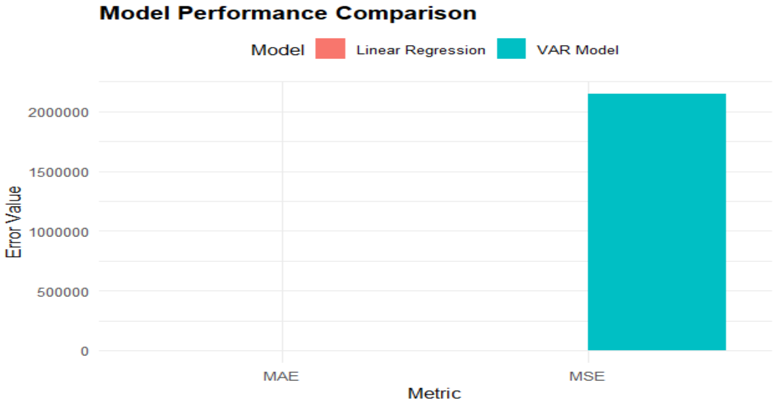
```
        RESET test

data:  lm_model
RESET = 0.057487, df1 = 2, df2 = 20, p-value = 0.9443
```

With a high p-value we fail to reject H_0 that says that the model is correctly specified. The test is also showing no proof of misspecification, meaning that no important variable was left out.

4.10.1 Model validation

Testing how well the two models will assess the impact of inflation rates and project durations on BOQ demand.

Figure 12: Model comparative graph



The graph above shows a high MSE of the VAR model represented by the blue bar which is going above 2000000.

4.11 Results from VAR and LRM models that met the study's objectives

Below are the important results that were selected from the above diagnostic tests that met the research goals and provided significant insights to the problem statement.

Figure 13: The direction and strength of inflation rate and project duration on BOQ demand

```
Call:
lm(formula = boq ~ duration + inflation)

Residuals:
   Min     1Q Median     3Q    Max
-36.02 -26.62 -14.75  20.18 116.50

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 1.055e+02  6.185e+01   1.706    0.102
duration    3.462e+00  9.743e+00   0.355    0.726
inflation   4.496e-01  6.046e-03  74.359   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 39.63 on 22 degrees of freedom
Multiple R-squared:  0.996,     Adjusted R-squared:  0.9957
F-statistic:  2774 on 2 and 22 DF,  p-value: < 2.2e-16
```

Correlation matrix showing the strength between inflation rate and project duration on BOQ

	BOQ demand	Project Duration	Inflation rate in %
BOQ demand	1.000	0.057	0.998
Project Duration	0.057	1.000	0.052
Inflation rate in %	0.998	0.052	1.000

Figure 14: model performance results

mae_lm	30.1274491832511
mae_var	935.577830782669
mse_lm	1381.95318852231
mse_var	2148565.30137218

Figure 15: identification of the causal relationship between variables (inflation rate and project duration on BOQ demand

```
        Granger causality H0: d_inflation do not Granger-cause d_boq
        d_duration

data:  VAR object var_model
F-Test = 1.3358, df1 = 10, df2 = 9, p-value = 0.337

> causality(var_model, cause = "d_duration")$Granger

        Granger causality H0: d_duration do not Granger-cause d_boq
        d_inflation

data:  VAR object var_model
F-Test = 0.42698, df1 = 10, df2 = 9, p-value = 0.8994
```

4.12 Discussion of results

After performing some diagnostic tests for both models, some of the assumptions were achieved. The achievement of the assumptions was confirmed by p-values that at the stationarity diagnostic some adjustments were made using the differencing method, a widely used method to achieve stationarity, which was formally applied by George Box and Gwilyn Jenkins. The application of the method achieved stationarity in both the inflation rate and BOQ demand variable.

In figure 4.10, the inflation rate estimate, t-value and p-value are 0.4496, 74,359 and 2e−16 respectively, this shows that a one unit increase in inflation rate will lead to a 0.45 increase in BOQ demand. Whilst the project duration results in the same linear model for the estimation, t-value and p-value are 3.462, 0.355 and 0.726 respectively, showing that the relationship of project duration and BOQ demand is not statistically significant, proposing no reliable effect of project duration on BOQ demand. To sum it up, the results have proven that inflation rate has a strong and statistically positive effect on BOQ demand while project duration's impact is barely visible in this model. The correlation matrix also supported that the impact of inflation on BOQ demand is strong with a correlation of 0.998 and that of project duration on BOQ demand is weak with a correlation of 0.057.

Figure 4.10.2 shows that linear regression model performed better when it comes to prediction because of its lower MAE and MSE values (30.13 and 1381.95 respectively),The VAR model had a high volatility and poor predict precision, this was proven by its high MAE and MSE (935.58 and 2148565.30 respectively).

Lastly figure 4.10.3 where the inflation granger-cause BOQ demand results are F-statistic (1.336), p-value (0.337) we fail to reject that there is no statistical evidence that past values of inflation help forecast BOQ demand or project duration. Project duration results supported the fact with an F-statistic (0.427) and a p-value (0.889) and again we fail to reject that project duration does not granger-cause BOQ demand or inflation either. The results proved that past values do not determine the future BOQ demand.

In conclusion, the results suggested that the understanding of the dynamic effect of inflation rate and project duration on BOQ demand is important for project managers to so as to estimate the cost of the materials and labour (BOQ) accurately and execute a smart and effective plan. It is also important for stock managers to understand the same effect so as to know the right levels of stock to order or maintain in different inflation scenarios, so as to avoid over or under stocking risks. For instance, if the AC company understand that when inflation is high, BOQ demand rises for a short period of time, for contractors will be locking in prices with the fear that inflation rate will further expand,

4.13 Summary

In this chapter model diagnostic tests were done to meet the first, and the models were estimated and compared to meet the other objectives. The conclusion was highlighting the important effect of inflation rate and project duration on BOQ demand, explaining how accurate estimation of cost and labour is important to project managers and also how estimation of the accurate quantity of material to order that is effective in the current inflation era, is of help to the AC Company. In the next and final chapter I will be further explaining my key findings.

Chapter 5 Findings, Conclusions and Recommendations

5.0 Introduction

This chapter is the final chapter of the research. In this chapter key findings will be outlined~~,~~ , backing them with some existing researches which utilised the same models. Also~~.~~ areas of further research will also be identified in this chapter, showing industries where the models are being used also and are producing effective results. This study seeks to find reliable statistical models to predict accurate or close to accurate BOQ demand levels.

5.1 Summary of key findings

This study sought to determine if past inflation rates and project duration can determine future BOQ demand levels using the Vector auto-regression andlinear regression models.

Key findings:

For Normality, the Jerque-Bera test returned a p-value that was greater than 0.05 showing that the residuals were normally distributed and this supported the validity of statistical inference based on the model. The Breusch-Pagan test provided a p-value that was greater than 0.05 for homoscedasticity proving that the variance of the residuals was constant across observations and this showed that the model was free from heteroscedasticity and the coefficient's standard errors are reliable. Then the portmanteau test returned a p-value that was less than 0.05 for auto correlation test, this proved the presence of positive auto-correlation in the residuals that violates the assumption of independent errors and might lead to undervalued standard errors and increase t-statics. Auto-correlation causes might be time series nature of data or the persistence of the inflationary trends and policy shifts in Zimbabwe that might create momentum effects that progress into the construction demand trend. The problem could have been solved the application of generalised least squares method that changes the model to account for the error structure.

The Linear regression model (LRM) performed better than the Vector auto-regression (VAR) model in forecasting the BOQ demand. This was proved by its lower Mean absolute errors (MAE) and Mean squared errors (MSE) and it proposed that the LRM captured the underlying relationships effectively, due to the relatively stable and direct nature of the estimators involved.

Inflation was discovered to have a positive impact on BOQ demand and this matched the outcomes by BOQ 2022 economic report, that highlighted that rising inflation motivated by strong demand and supply restrictions, is prone to increase construction costs and by extension the value of BOQs. Nyarota et al.(2016) also observed that inflation changes (especially those influenced by external factors) can influence domestic pricing structures, including those in the construction sector.

Project duration showed a weak impact that was less consistent on BOQ demand. Even if longer project duration may lead to cost variability because of the scheduling of resources and exposure to inflation, the statistical proof in this study proposes that duration plays the supporting role compared to inflation. Maruthi et al. (2015) also pointed out that while project durations affect resource allocation, their direct impact on BOQ demand is mostly reduced through optimisations scheduling and contingency planning.

The granger causality showed that inflation granger-causes BOQ demand supporting the forecasting strength of inflation as a leading indicator. However, project duration reflected a weaker causal influence, proposing its role is more reactive than predictive.

The Impact of past inflation rates and project duration on present BOQ demand levels

The Granger causality test proved that the past inflation rate and project durations, has no notable effect on the present BOQ demand levels. The H_0 stated that there are no instant causality between inflation rates and BOQ demand project duration. The p-value (0.159) that is greater than 0.05 and 0.10 gave me a reason to fail to reject H_0.

5.2 Conclusions

The joint observations of this study propose that inflation is the main macroeconomic factor shaping BOQ demand, while project duration plays a milder role. The superior performance of linear regression model (LRM) despite some autocorrelation shows that BOQ demand response more noticeable and effectively to inflationary trends than to temporal factors, particularly in environments characterised by economic changes. This conclusion also matches with broader research pointing out the inflation sensitivity of construction inputs. Anireddy(2023) drew out attention to how inflation induced material prices changes undervalue cost estimation accuracy, highlighting the need for changing pricing models in construction. Pandey and Khan (2023) argued that inflation applies an increasing effect on project costs, often outweighing the influence of weakness scheduling.

Relating to Zimbabwe's economy, where inflation is both persistent and un-forecasted, the results underscore the significance of incorporating inflation predicts into BOQ planning and estimation. The weaker impact of project duration might be showing the sector's adaptation to time-related risks through contingency planning and procurement strategies, as highlighted by Diugwu et al. (2017)

5.3 Recommendations

Combining inflation prediction into BOQ planning and estimation, due to the strong positive relationship between inflation rate and BOQ demand shown in the study, both the construction companies and quantity surveyors should incorporate inflation predicts into cost estimation models. Inflation-indexed pricing or escalation clauses in contracts might help reduce cost overruns, as supported by Anireddy (2023) above.

The superior performance of the LRM proposes that, in data-restricted or changing environments such as Zimbabwe, more simple models may offer more reliable predictions than complex alternatives. This again matched with Diugwu et al.(2017).

To improve model performance, future studies should think of incorporating lagged variables or using Cochrane- orcutt corrections to attend to autocorrelation. These adjustments can help the model to capture the temporal dependencies important in economic and construction data.

To expand the variables, future study should consider adding more variables such as exchange rate, interest rate, policy shifts or material prices to improve model effectiveness and minimise omitted variable bias. This specifically applies to the Zimbabwean economy where inflation and construction costs are often influenced by such factors.

Collaboration between government agencies, construction companies and learning institutions can lead to shared different ideas and predicting techniques developed to Zimbabwe's unique economic landscape This would improve the whole sector resistance to inflation shocks.

The construction sector should invest in more consistent and detailed data gathering, particularly regarding project durations and cost breakdowns. Enhanced data quality would lead to more accurate modelling and improved decision-making.

With the unpredictability of inflation rate at hand, project managers should start the scenario-based planning methods, for it allows for flexible budgeting and procurement ways that can suit various economic conditions, recommended by CRB group's inflation reduction ways.

5.4 Summary

Finally this study adds on to the expanding body of proof that macroeconomic variables especially inflation rate must be central to construction demand modelling, particularly in developing economies with unstable financial environments. It also indicated the practical importance of more simple, interpretable models when data quality or structural stability is restricted.

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APPENDICIES

APPENDIX A: R studio codes for Vector auto-regression model

ADF test for stationarity

```
 library(readxl)
 BOQdata2 <- read_excel("BOQdata2.xlsx")
 View(BOQdata2)
 library(readxl)
 library(tseries)

 # Load data
 data <- read_excel("BOQdata2.xlsx")
boq<- data$`BOQ demand`
 duration <- data$`Project Duration`
 inflation <- data$`Inflation rate in %`

 # ADF Tests
adf_boq<- adf.test(boq)
adf_duration<- adf.test(duration)
adf_inflation<- adf.test(inflation)

 # View results
 list(BOQ = adf_boq, Duration = adf_duration, Inflation = adf_inflation)
```

ADFs after differencing

```
 # First differences
d_boq<- diff(boq)
d_duration<- diff(duration)  # Optional: already stationary
d_inflation<- diff(inflation)

 # Plot differenced series
 par(mfrow = c(3, 1))
 plot(d_boq, type = "l", main = "Differenced BOQ Demand")
 plot(d_duration, type = "l", main = "Differenced Project Duration")
 plot(d_inflation, type = "l", main = "Differenced Inflation Rate")

 # ADF tests after differencing
adf.test(d_boq)
```

VAR model estimation

```
library(vars)

# Differencing (assumes non-stationarity from ADF test)
diff_data<- data.frame(
+     d_boq = diff(boq),
+     d_duration = diff(duration),
+     d_inflation = diff(inflation)
+ )

# Select lag length
lag_selection<- VARselect(diff_data, lag.max = 10, type = "const")
optimal_lag<- lag_selection$selection["AIC(n)"]

# Fit VAR model
var_model<- VAR(diff_data, p = optimal_lag, type = "const")
summary(var_model)
```

Residual diagnostic tests (Normality, Heteroscedasticity and Autocorrelation)

```
# Jarque-Bera Test for Normality
normality_test<- normality.test(var_model)

# Portmanteau Test for Autocorrelation
serial_test<- serial.test(var_model, lags.pt = 12, type = "PT.asymptotic")

# ARCH Test for Heteroscedasticity
arch_test<- arch.test(var_model, lags.multi = 5)

list(Normality = normality_test, Autocorrelation = serial_test,
Heteroscedasticity = arch_test)
```

Granger codes

```
granger_test<- causality(var_model, cause = "d_inflation")
print(granger_test$Granger)
```

Impulse response functions (IRFs) codes

```
Calculate IRFs with 95% confidence intervals
irf_result<- irf(var_model, impulse = "d_inflation", response = "d_boq",
n.ahead = 10, boot = TRUE)

Plot the IRF
plot(irf_result)
```

Forecast error variance decomposition (FEVD)

```
fevd_result<- fevd(var_model, n.ahead = 10)
plot(fevd_result)
```

For VAR MAE and MSE

```
 # First difference for stationarity
diff_data<- data.frame(
+     d_boq = diff(boq),
+     d_duration = diff(duration),
+     d_inflation = diff(inflation)
+ )

 # Select lag and fit VAR
lag_selection<- VARselect(diff_data, lag.max = 10, type = "const")
var_model<-  VAR(diff_data,  p  =  lag_selection$selection["AIC(n)"],  type  =
"const")

 # One-step ahead in-sample predictions
fitted_values<- fitted(var_model)
predicted_var<- fitted_values[, "d_boq"]
actual_var<- diff_data$d_boq

 # Calculate MAE and MSE
mae_var<- mae(actual_var, predicted_var)
mse_var<- mse(actual_var, predicted_var)

 cat("VAR Model MAE:", round(mae_var, 4), "\n")
 cat("VAR Model MSE:", round(mse_var, 4), "\n")
```

VAR validation codes

```
 library(readxl)
 library(vars)
 library(tseries)
 library(lmtest)
 library(urca)

 # Load and prepare the data
 data <- read_excel("BOQdata2.xlsx")
ts_data<- ts(data[, c("BOQ demand", "Project Duration", "Inflation rate in
%")], start = 2000)
diff_data<- diff(ts_data)

 # Fit VAR
var_model<-  VAR(diff_data,  p  =  3,  type  =  "const")   #  Adjust  lag  as
necessary

 # 1. Serial correlation (Portmanteau test)
serial_test<- serial.test(var_model, lags.pt = 10)
 print(serial_test)
```

APPENDIX B for Linear regression model

Fiting the linear regression codes

```
 library(readxl)

 # Load your data
 data <- read_excel("BOQdata2.xlsx")

 # Fit regression model: Project Duration ~ BOQ Demand + Inflation Rate
lm_model<- lm(`Project Duration` ~ `BOQ demand` + `Inflation rate in %`,
data = data)
 summary(lm_model)
```

Multicollinearity check- IVF codes

```
 library(car)


 # VIF values
vif_values<- vif(lm_model)
 print(vif_values)
```

Outliers test using cook's distance method

```
 # Cook's Distance
cooksd<- cooks.distance(lm_model)

 # Plot to spot influential observations
 plot(cooksd, type = "h", main = "Cook's Distance", ylab = "Distance")
abline(h = 4/(nrow(data)-length(lm_model$coefficients)), col = "red", lty
= 2)

 # Identify potentially influential points
influential_obs<-          which(cooksd>         (4/(nrow(data)          -
length(lm_model$coefficients))))
 print(influential_obs)
```

Model specification Reset test

```
 library(lmtest)

 # RESET test
reset_test<- resettest(lm_model, power = 2:3, type = "fitted")
 print(reset_test)
```

Linear MAE and MSE codes

```
 library(readxl)
 library(vars)
 library(Metrics)

 # Load the data
 data <- read_excel("BOQdata2.xlsx")
```

```
boq<- data$`BOQ demand`
 duration <- data$`Project Duration`
 inflation <- data$`Inflation rate in %`

 # Fit linear model
lm_model<- lm(`BOQ demand` ~ `Project Duration` + `Inflation rate in %`,
data = data)

 # Predicted values
predicted_lm<- predict(lm_model)

 # Actual values
actual_lm<- data$`BOQ demand`

 # Calculate MAE and MSE
mae_lm<- mae(actual_lm, predicted_lm)
mse_lm<- mse(actual_lm, predicted_lm)

 cat("Linear Regression MAE:", round(mae_lm, 2), "\n")

 cat("Linear Regression MSE:", round(mse_lm, 2), "\n")
```

Linear validation code

```
 library(readxl)
 BOQdata2 <- read_excel("BOQdata2.xlsx")
 View(BOQdata2)
 # Fit linear model
lm_model<- lm(`BOQ demand` ~ `Project Duration` + `Inflation rate in %`,
data = data)
 data <- read_excel("BOQdata2.xlsx")
 data <- as.data.frame(data)  # Ensure it's a data frame

lm_model<- lm(`BOQ demand` ~ `Project Duration` + `Inflation rate in %`,
data = data)

 # Fit linear model
lm_model<- lm(`BOQ demand` ~ `Project Duration` + `Inflation rate in %`,
data = data)

 # 1. Residual plot
 plot(lm_model, which = 1)

 # 2. Q-Q plot (normality)
 plot(lm_model, which = 2)

 # 3. Cook's Distance (influence)
 plot(lm_model, which = 4)

 # 4. Breusch-Pagan test for heteroscedasticity
 library(lmtest)
```

Approval letter to use the AC company's data in my dissertation.

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CONTRACTORS (PVT) LTD

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20 May 2025

Miss Etppa S. Ngaribvume
No. 2040 Shashi Township
BINDURA

Dear Miss Ngaribvume

RE: APPROVAL LETTER FOR DATA COLLECTION

I am pleased to inform you that your request for data collection template approval has been granted. The purpose of this approval letter is to acknowledge your proposed data collection template and to provide you with the necessary endorsement to proceede with its implementation.

Yours faithfully

P. Chinowaita (Mr)
For and on behalf of Archvault Contractors (Pvt) Ltd

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