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Exploring Key Drivers of Sales Revenues Forecasting: Empirical Evidence from the Aluminium Industry

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ABSTRACT: In the fast-paced and fiercely competitive banking industry and increasing demand for high forecasting accuracy for effective lending decision making, mastering the art of sales revenue forecasting is crucial for banking professionals who are concerned with efficient credit assessment and investment evaluation. This study delves deep into the main independent variables that impact sales revenue forecasting, moving beyond the widely used historical sales lagging approach. Through a comprehensive qualitative analysis utilizing semi-structured in-depth interviews technique with industry experts whereby study model is developed and subsequently validated using Multiple Linear Regression (MLR) analysis. Spanning a period from 2013 to 2022, this empirical research leverages secondary data from sample of 12 selected companies who manufacture primary aluminium from different economics, accordingly with related macro and micro economic figures on quarterly basis. The findings revealed that interviews claimed six independent variables have significant impact on sales revenues forecasting including (Historical Trading metal price at the metal exchange, company strategy) while only four variables were (quantities sold, historical market selling prices, and historical producer price index and historical foreign exchange rates) have significant impact on sales revenue forecasting, empowering banking credit and investment teams with the critical knowledge necessary to make informed lending and investment decisions

KEYWORDS: Banking, Sales forecasting, Budgeting, Time series model, Aluminium industry, MLR

I. INTRODUCTION

No doubt the effective sales revenue forecasting of corporates borrowers is crucial for banks and financial institutions as it directly influence their ability to make informed credit assessments and assess creditworthiness of borrowers that influence the financial stability and growth, simultaneously, forecasting accuracy plays a vital role for management at various enterprises who are concerned with tracking business performance in order to support decision making processes. Unlikely, most of credit teams in banking sector rely mainly on lagging historical figures of sales revenues, often ignoring other macro and microeconomic variables that significantly affect the forecasting accuracy. Moreover, this meticulous method may potentially increase risk associated with the lending process. On other hand, accurate cash flow forecasting since it is the main source of repayment allows banks to anticipate valid client needs.

Benjamin Brewster in 1882 articulated the theory of forecasting whereby, he underscored a fundamental base regarding the relationships between theoretical frameworks and practical application, stating that " there is no difference between theory and practice in theory, however in practice, there is" , On other hand, the uncertainties and complexities of real business environments can lead to significant deviations from theoretical predictions. Therefore, the effective forecasting models require not only a solid understanding of theoretical principles but also the ability to refine and adapt these models in response to practical realities (Petropoulos et al , 2022)

Practically, revenues refer in a business context to the income triggered from selling goods or services during specific period of time. It considered as main indicator of the inflow of the organizational assets, agnist occurred expenses, as the outflow of operating assets. Both credit teams at banks and management closely monitor sales revenues to ensure there is adequate rationale for possible decision related to borrowing or capital investments. Furthermore, sales revenues forecasting indicates that the projection of sales quantities and market price of all products during specific time

Despite of existing researches extensively discussed forecasting theory, much of them focuses on historical sales order recognition, leaving the complexities of revenue forecasting underexplored (Whitfield & Duffy, 2013). Given its significance and complexity, banks should consider the operating environment that affect the revenue recognition. This study acknowledges the obvious gap regarding comprehensive forecasting systems that effectively integrate these different variables impact the sales forecasting in manufacturing contexts.

This research aims to cover the theoretical and practical gap in forecasting process of sales revenue since most of widely used approaches relied on lagging historical sales revenues values, neglecting other factors that might influence their future results (Zhang et al., 2022). Moreover, the principle of forecasting is grounded on techniques that should be understandable and easy to implement in decision –making processes that may be rely on unknown or unproven foundations (Alfons&Batlajery, 2018). By conducting semi-structured in-depth interviews technique with industry experts from aluminum industry and banking sector. This study will contribute to the existing body of knowledge by presenting mix of historical financial variables, accordingly with various macro and micro economic, specifically in the primary aluminum manufacturing from different economics.

II. LITERATURE REVIEW

Generally, financial forecasting is a sophisticated process by which the top level management or decision maker can position the future figures of the company through considering the related various economic factors, technical, competitive and social environment variables that can be used to formulate scenarios for different intervals short, intermediate and long-term vison (Vijendra, 2014).

Brewster's insights into the theory of forecasting enrich the foundation for understanding the complexities of forecasting in various contexts. The theory emphasizes the difference between theoretical base and their application in real-world scenarios. This dichotomy is particularly relevant in the subject of financial forecasting, where the accuracy of predictions often depends on several factors, including data quality inherent unpredictability of human behavior and the environmental variability (Petropoulos et al , 2022)

The process of planning the operating cost and the related investment or capital required should start with forecasting the sales revenues figures. The forecasting methods and techniques for sales are subject to the industry either services sector that the company belongs to. On the other hand, the study showed that the financial dimension of forecasted sales growth and growth has a linear relationship; meanwhile, the time series techniques that rely mainly on historical data might have a limited ability to avoid the expected market shocks. Therefore, there should be advanced techniques to merge among quantitative and qualitative forecasting approaches in order to minimize the variation between actual and projected sales revenues figures (Stancu et al., 2015).

Theoretically, numerous forecasting approaches have explored various models to predict financial figures. These models are structured based on the concept of time or period under forecasting, which plays a crucial role in capturing changes in patterns during past observations. These changes can be systematically analyzed always through regression or correlation models. Another method is the causal model, that indicates the forecasting rely on the historical occurrence of multiple events or characteristics mixing aspect of the previously mentioned models (Alfons&Batlajery, 2018)

In fact, financial forecasting can encompass a variety of situations, a survey conducted by Smith et al. (1996) showed that 92% of the 175 companies that considered forecasting to be essential for their success. Although, some mangers claimed that that the nature of their business renders projection impractical. However, Wallace & Stahl (2008), claimed that all kinds of business can engage in forecasting phase; whereby, the difference here lies in the varying levels of forecast accuracy achievable along various business environments (as cited in Whitfield &Duffy , 2013).

To elaborate more, the primary objective of time series forecasting technique is to capture the pattern in the data representing metrics that fluctuate over time intervals as base to formulate reliable forecasting model across various business contexts. The good model aims to fit the data with high accuracy with least error, ensuring that the integrity of the observed relationships. Time series data can be presented as a set of vectors X(t), where t=0,1,2,…,n. Moreover, the time series can be classified as univariate when the series involves a single parameter that changes over time. Meanwhile, it is defined as multivariate time series data, if there are multiple parameters that subject to temporal variation (Yatish&Swamy,2020).

Based on organizations' sales revenues recognition approach, which is related to the progress of sales order whereby revenues is recognized on the completion of either: start, end and final project completion report. Therefore, a range of forecasting techniques are divided into two groups: quantitative and qualitative approaches. Some of these techniques can be seen more applicable depending on the nature of the data or the industry itself including business, economics and public policy (Whitfield &Duffy , 2013).

2.1. Quantitative Forecasting approaches

Generally, this approach relies on historical numerical data and statistical techniques. However, for non-specialist, a good start should be from demonstrating time series analysis as commonly used method for examining past pattern over time taking into consideration reasons behind variation in the trend in order to use the analysis to predict the future figures, whereby this method could be explained mainly through Linear Regression (LR) or Multiple Linear Regression (MLR) (Alfons&Batlajery, 2018)

Practically, many variables lead to determine which forecasting approach and model to be used, factors such as cost, time span of historical data, availability of data, the purpose for required forecasting results and the required forecasting length either short or medium or long term. Mahmoud and Pegls (1990) claimed that the for short term forecasting, some simple technique can be useful such as LR , Single Exponential Smoothed Forecast.

On other hand, MLR and time series forecasting approaches are the most useful approaches for mid-term and long term forecasting. Those approaches considered as the base for various advanced statistical models for trend or seasonal forecasting, hence time series forecast plays a crucial role to estimate accurately the future demand. Another, industrial application of time series forecasting is electricity load forecasting which is very important parameter to estimate the electrical needs whereby it helps to allocate the load and mitigate problems. Financially, using the historical stock market data can be used for predicting financial time series to calculate the future gains that can be leverage through Machine Learning (ML). Finally, long term approaches are important for commodity and oil forecasting (Yatish&Swamy,2020).

2.2. Qualitative Forecasting approaches

On other word, the complimentary or alternative approach would be the qualitative modeling that based on experts' judgment, intuition and subjective assessment in order to forecast revenues. Hence, this approach is useful when data is scare or forecasting in nascent market which include focus groups, Delphi method and expert panel Whitfield &Duffy , 2013).

Makridakis et.al. (1998) warned agnist excessive reliance on qualitative methods to forecast sales revenues, since these can introduce biases into the final forecasting results. Furthermore, pervious empirical research conducted in this regard indicated that forecasts from sales personals for their region were prone to inaccuracies. Additionally, the judgmental biases can easily undermine the effectiveness of ongoing process and the integrity. Researchers argued that all subjective approaches should be supported or involved with quantitative approaches (Makridakis et.al.,1998)

2.3. Commodity Forecasting

Commodity market was financialized in 2002 such as gold, aluminum, coppers ..etc , whereby market capitalization of commodities has experienced substantial growth. This rise can be attributed to different factors that have grabbed the attention of policymakers, bankers, investors and hedgers alike. Since the commodity market have experienced significant volatility driven by different economic factors which should be considered during forecasting process (Ben ameur et al., 2023)

Generally, forecasting the commodity prices topic has been discussed in different literatures, which shows the importance of prices prediction with the commodity exchange context. The first wave of literature considered main variables for forecasting process depending on macroeconomic factors including inflation, economic uncertainty, accordingly with related financial drivers such as interest rate. Gergano and Timmerman. (2014) reached that the commodity prices have high predictive power at short forecast horizons (monthly and quarterly), while economic growth in industrial production and the investment- capital ratio have predictive power at longer forecast horizons (yearly) They used a large set of historical observation during 1947 till 2010 include macroeconomic and financial variables to reach out the predictability the commodity prices(Gergano and Timmerman ,2014)

The second wave highlighted the importance of use traditional and conventional time series models to forecast the prices. However, it spotted the light on lagging-forward price modeling in order to forecast future lead and zinc prices whereby, showing the effectiveness of Autoregressive Integrated Moving Average (ARIMA). On other hand, Recent studies have challenged the reliability of prediction based only on historical observations and advocated for the use of stochastic models, which are characterized by clearly established and well-defined constraints for forecasting. More recent studies showed that the superiority of artificial intelligence (AI), machine learning (ML), and deep learning (DL) systems, which encompassed advanced computerized tools that mimic human cognitive functions (Ben ameur et al., 2023).

III. METHODOLOGY

This research employs a mixed qualitative and quantitative approach in order to reach the research objective: 1) exploratory research conducted with the concerned parties from the aluminum industry and banking fields in order to develop the study hypothesis, which suggest the main independent variables affecting the sales revenues forecast; 2) subsequently, a comprehensive empirical study executed to test the research hypothesis and validating the proposed study model

3.1.Exploratory Research Procedures

To the best of the researcher's knowledge, the existing literatures lack clear identification of the main independent variables that influence sales revenue forecasting, particularly in the manufacturing sector. Since, most forecasting approaches have relied on lagging the historical revenues data, neglecting other related variables (Zhang et al., 2022). From this angle, exploratory research was conducted to identify independent variables influencing sales revenue and to develop a comprehensive study model, whereby the exploratory research is viewed to be a discovery of the grounded theory, it provides clarity and direction by gathering primary Secondary data (Stebbins, 2001; Mack et al., 2005). data from industry expertise that may determine the feasibility of a larger study and evaluate the accessibility to relevant

3.1.2)Data Collection and Measurement Instrument: The researcher used "semi-structured in-depth interview" in order to collect data through a list of interview questions (see appendix A); since, it is considered as the most valid tools used in an exploratory research (Saunders et al., 2019). Furthermore, Sekaran and Bougie (2009) claimed that this technique has more advantages than other tools, since it would facilitate the collection of different responses that would present the comprehensive exploration of various aspects of the related topic. Furthermore, this approach leaves room for interviewees to enrich the discussion through two ways conversion, which is combining between structured and unstructured interviews (Mack et al., 2005).

3.1.3) Population:

Experts in the banking sector or other financial institutions who prepare financial projections for lending purpose or valuation, on another hand, professionals who are concerned with budgeting in the primary aluminum industry.

3.1.4) Sampling:

Sampling Technique. A non-probability sampling technique was employed due to the inability to define the population's frame. Consequently, judgmental sampling was utilized, since the researcher looked for professionals who are exposed to the area of financial forecasting. (Saunders et al., 2009).

Sampling Unit. Individuals (Employees and professional)

Sampling Size. Carminati (2018) claimed that generalizability is not the big issue with regard to the sample size in qualitative research. In this case, the study focuses mainly on reaching an in-depth interpretation for the required outcomes rather than generalizability. Moreover, data saturation and required information redundancy are difficult to be identified and have no clear base to justify the minimum number of respondents, especially when additional respondents provide the same response to previous ones. Accordingly, with the claim above, the sample size includes four respondents who are professionals and expert in the financial industry and primary aluminum manufacture Company.

3.1.5) Results of the Exploratory Research:

Qualitative Research with the Concerned Parties Reaching new findings is important for gathering insights into this study's topic, forming the core of exploratory research. Thus, an analytical review of relevant literature provided a solid background for understanding sales revenue forecasting in metal commodity industry such as primary aluminum market, alongside the semi-structured in-depth interviews, which helped to discover the independent variables affecting the sales revenue forecast. Interviews were held individually with four key participants: two from the financial sector. Other two from primary aluminum manufacturing Co. The length of each interview lasted approximately 20 to 35 minutes via telephone. and focused on the independent variables influencing sales revenue forecasts. General information regarding each interview is presented in Table 3.1.

Table 0.1: Statistics of the In-depth Interviews

Respondent No.	Organization	Position	Years in Business
Case 1	Financial Advisory	CEO	28 years
Case 2	Financial Institution	Credit Risk Manager	13 years
Case 3	Primary Aluminum manufacturing Co.	Head of Budgeting and Planning sector	22 years
Case 4	Primary Aluminum manufacturing Co.	Head of Exportation and Sales sector	25 years

The In-depth Interview Conclusion and Analysis. Following the completion of the interviews with concerned parties in order to reach the aim of the study, findings from the semi- structured interviews is summarized in the table3.2. Furthermore, this table presents independent variables supported by related literatures to provide a comprehensive overview of the identified variables affect sales revenues forecasting.

Table 0.2: Findings of the In-depth Interviews

Variables Suggested by Respondents	Relevant Literatures	Expected Correlation
Historical Quantities Sold	(Zhang et al., 2020; Cheriyan et al., 2018;Tanaka, 2010).	Positive
Historical Market Selling Price Sold	(Singh & Mohanty, 2015; Schaidnagel et al., 2013; Medeiros et al., 2011).	Positive
Historical Trading Metal Price at the Metal Exchange	(He et al., 2015; Xiarchos & Fletcher, 2009 ;Dooley & Lenihan,2005).	Positive

Historical Foreign Currency Exchange Rate	(Rees,2023;Yusoff et al., 2023; Brown & Hardy ,2019).	Negative
Historical Inflation	(Tiwari et al., 2023; Wang, Yao, & Jiang, 2022; Zou, 2019).	Positive
Company Strategy	(Pavlenkov & Reimov, 2019; Whitfield & Duffy ,2013).	Positive

Therefore, the previous results presented the proposed impact of independent variables on the sales revenues forecasting. Furthermore, the following hypotheses were developed to be tested and validated empirically: -

- H1: There is a significant positive impact of historical quantities sold on the sales revenues forecasting.
- H2: There is a significant positive impact of historical market selling price on the sales revenues forecasting.
- H3: There is a significant positive impact of historical metal price at the metal exchange on the sales revenues forecasting.
- H4: There is a significant negative impact of historical foreign currency exchange rate on the sales revenues forecasting.
- H5: There is a significant positive impact of historical inflation producer price index on the sales revenues forecasting.
- H6: There is a significant positive impact of company strategy on the sales revenues forecasting.

Based on the proposed research hypotheses, the study model is presented in order to validate and analyze the relationships between each independent variable and sales revenues forecasting in the next section.

$$SR = \alpha + \beta 1\ Qs + \beta 2\ SP + \beta 3\ MP - \beta 4\ FX + \beta 5\ PPI + \beta 6\ CS + \mathcal{E}$$

Where,

SR is sales revenues forecast

QS is quantities sold

SP is market selling price

MP is metal prices at the London Metal Exchange (LME)

FX is foreign exchange

PPI is producer price index

CS is company strategy

3.2 Quantitative Research Procedures

Based on exploratory research findings, whereas this section focus shifts to examining and validating the study model that will effectively fulfill the research's objective. The research uses the descriptive analytical approach though employing statistical models using R packages.

3.2.1) Study Population and Sample:

For the sake of conducting the tests considering the study limitations, study includes primary aluminum manufacturing companies worldwide; this population reached approximately 72 companies (Pawlek, n.d.). Subsequently, the final sample for this study reached 12 companies from different economies are summarized in table 3.3 which met the following research criteria: -

1.Audited financial statements and quarterly reports should be available during the period of study.

2.The quantities sold should be available during the period of study.

Table 0.3: Overview of Sample Companies

Company Name	**Country**	**Establishment Year**
ALUMINIUM BAHRAIN B.S.C.(ALBA)	Bahrain	1968
Aluminum Corporation of China Limited (Chalco)	China	2001
China Zhongwang	China	1993
JiaoZuo WanFang Aluminum Manufacturing Co Ltd	China	1966
Hongqiao Aluminum	China	1994
Tianshan Aluminum	China	1997
EgyptAlum	Egypt	1969
Hindalco	India	1958
Norsk Hydro Aluminum	Norway	1915
ALRO S.A.	Romania	1961

Rusal	Russia	2006
Century Aluminum	United Stats of America	1995

3.2.1) Data Source:

In order to approach the required data, the list of primary aluminum manufacturing companies was sources from a prominent website associated with the London Metal Exchange (LME: www.lightmetalage.com). However, the secondary data covering the period from the years 2013 to 2022, including quarterly financial figures of the selected sample was gathered from each country's stock exchange or company's website. Additional related macroeconomic data was compiled from data base of the World Bank, the Fred Louise LME and the Central Bank of Egypt (CBE) .

Table 0.4: Analyzing Descriptive Statistics of Research Variables

Variables	N	Min.	Max.	Median	Mean	S.D	Skewness	Kurtosis
SR	480	33.09	21374.61	531.85	1558.92	2623	3.72	19.18
QS	480	27.12	6295.90	242.85	894.11	1400.47	2.27	4.57
SP	480	0.19	4999.19	2.07	12.58	228.09	21.77	472.97
MP	480	1.49	3.25	1.86	1.98	0.39	1.41	1.81
FX	480	1	103.68	6.61	15.92	22.52	1.87	1.85
PPI	480	-0.05	0.04	0.001	0.002	0.02	-0.35	1.21
CS	480	0	1	0	0.39	0.49	0.45	-1.8

According to table (3.4) , it obvious that the number of observations were 480 for all variables . Consequently, there is no missing values in the collected data. Furthermore, interpretation for each variable will be covered in the following lines

The sales revenues variable exhibits a wide range of values, with a maximum value of 21374.61. There may be potential outliers on the higher end of the distribution. The skewness value of 3.72 indicates a right-skewed distribution, suggesting a longer right tail. These findings, along with the standard deviation (SD) of 2623, which reflects significant variability in sales revenues, that emphasize the importance of conducting diagnostic statistics and data formulation to appropriately identify and handle outliers.

The quantities sold variable shows a skewness of 2.27, indicating a right-skewed distribution and a longer right tail. Potential outliers may exist, given the maximum value of 6295.90. On other hand SD of 1400.47 reflects notable variability in quantities sold, to be addressed through data formulation at next step.

The market selling price variable indicates a highly right-skewed distribution with a skewness of 21.77, indicating a substantial concentration of lower selling prices and a longer right tail. There may be potential outliers on the higher end, as shown by the maximum value of 4999.19, where SD of 228.09 suggests considerable variability in selling prices, thus should be overcame through data formulation at the diagnostic statistics part

The metal prices variable shows a moderately right-skewed distribution with a skewness of 1.41, indicating a slightly longer right tail. No outliers are evident based on the provided statistics. Furthermore, the SD of 0.39 suggests relatively low variability in metal prices. Which indicated the absence of outliers indicates a relatively stable distribution for metal prices.

The foreign exchange variable has a moderately right-skewed distribution with a skewness of 1.87, suggesting a slightly longer right tail. No outliers are evident based on the provided statistics. The SD of 22.52 reflects notable variability in exchange rates. The absence of outliers suggests a relatively stable distribution for foreign exchange rates.

The producer price index variable exhibits a slightly negative skewness of -0.35. No outliers are evident based on the provided statistics. The SD of 0.02 indicates relatively low variability in the PPI values. With no outliers, the PPI distribution appears relatively stable.

The company strategy variable is a dummy variable with values of either zero or one. It represents the presence or absence of a specific company strategy. The variable has a skewness of 0.45, indicating a slightly right-skewed distribution and a slightly longer right tail. There are no outliers evident based on the provided statistics.

3.2.2) Diagnostic Statistics Results:

For the sake of meeting the assumption MLR in order to validate the proposed study model, multi-collinearity test between independent variables, stationarity test and Granger causality test have conducted, wherby SR, QS and FX data sets are smoothed through approaching the log and first difference of data sets in order to ensure the overall validity of the model. Thus, the formulated study model can be presented as follows:-

$\Delta SR = \boldsymbol{\alpha} + \Delta\ QS + SP + MP + \Delta\ FX + PPI + CS + \boldsymbol{\varepsilon}$

3.2.3) *Multiple Linear Regression (MLR)*

Based on diagnostic statistics results , the hypotheses were ready to be tested through investigating the proposed relationship between dependent variable and multiple independent variables using MLR. Table (3.5) illustrate the MLR test results as follows:-

0.5*:* Multiple Linear Regression Model Results

Residuals:				
Min	**1Q**	**Median**	**3Q**	**Max**
-1.03608	-0.03900	0.00155	0.04516	0.58292

Coefficients:				
	Estimate	**Std. Error**	**t value**	**Pr(>|t|)**
(Intercept)	-0.034823	0.028376	-1.227	0.220354
Panel_Data10_06$`QS_1st Diff`	1.057333	0.032713	32.322	< 2e-16 ***
Panel_Data10_06$SP	0.025397	0.005039	5.040	6.62e-07 ***
Panel_Data10_06$MP	-0.010601	0.014834	-0.715	0.475184
Panel_Data10_06$`FX_1st Diff`	-0.235251	0.051306	-4.585	5.81e-06 ***
Panel_Data10_06$PPI	1.062578	0.315449	3.368	0.000818 ***
Panel_Data10_06$CS	0.001523	0.011263	0.135	0.892503
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1				
Residual standard error: 0.1165 on 473 degrees of freedom				
Multiple R-squared: 0.712, **Adjusted R-squared:** 0.7083				
F-statistic: 194.9 on 6 and 473 DF, p-value: < 2.2e-16				

In conclusion, the MLR results shows an overall good fitness of model, where the R-squared is high at a value of 0.712 and the F-statistic is 194.9. This exhibits that a significant portion of the variance in the dependent variable is predictable from the independent variables. However, the outcomes indicate that the independent variables QS, SP, FX, and PPI have a significant impact on SR. However, MP and CS suggest an absence of statistical impacts on SR. These results support the validation of the proposed study model.

Based on the pervious results, the Durbin-Watson (DW) test was conducted to assess the autocorrelation in the context of final MLR model that can be a major influence in the reliability of the MLR model’s predictions

Table 3.6: Durbin-Watson (DW) Test Results

Durbin-Watson test	
data:	model_0101
DW	= 2.3266, p-value = 0.9997
alternative hypothesis: true autocorrelation is greater than 0	

The outcomes of the DW test (Table 3.6) exhibit a statistic of 2.3266 with a p-value of 0.997. This indicates that there is no significant evidence for autocorrelation in the residuals of the MLR model at a significance level of 0.05, which supports the independence principle among residuals, indicating that the model has overall fitness Therefore, the final MLR model is presented in the following equation:

$\Delta SR = -0.034823 + 1.057333\ \Delta\ QS + 0.025397SP - 0.010601MP - 0.235251\ \Delta\ FX + 1.062578\ PPI + 0.001523CS.$

3.2.4) Analysis of Variance (ANOVA) Test

Therefore, ANOVA test was conducted to provide deeper insights into the overall significance of MLR model , since pervious results indicated that all proposed independent variables have a statistical impact on SR. On other hand, the important role of ANOVA test supports the variable selection in the high-dimensional data, which aims to enhance the performance of the MLR model, especially in the context of the time series data analysis.

Table 3.7: Analysis of Variance (ANOVA) Results

Analysis of Variance Table					
Response: Panel_Data10_06$`SR_1st Diff`					
	Df	**Sum Sq**	**MeanSq**	**F value**	**Pr(>F)**
Panel_Data10_06$`QS_1st Diff`	1	15.0716	15.0716	1110.0242	< 2.2e-16 ***
Panel_Data10_06$SP	1	0.3636	0.3636	26.7802	3.375e-07 ***
Panel_Data10_06$MP	1	0.0005	0.0005	0.0356	0.8504907
Panel_Data10_06$`FX_1st Diff`	1	0.2857	0.2857	21.0393	5.770e-06 ***
Panel_Data10_06$CS	1	0.0007	0.0007	0.0540	0.8163789
Panel_Data10_06$PPI	1	0.1541	0.1541	11.3465	0.0008177 ***
Residuals	473	6.4223	0.0136		

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

The ANOVA test results in Table (3.7) show that the F-statistic and p-values for QS, SP, FX, and PPI were low, less than the significance level 0.05 which suggesting their strong impact on SR. However, MP and CS have higher values above 0.05 indicating lower significance in terms of explaining the variation in SR. Thus, the ANOVA results complement outcomes of MLR, providing strong support to accept hypotheses H1, H2, H4, H5 while rejecting H3 and H6.

IV. CONCLUSION AND RECOMMENDATIONS

This research exhibits significant findings to address the theoretical and practical gap in the exploration of main independent variables that influence sales revenues forecasting which is crucial for developing more accurate predictive models. The research passed through two stages, the qualitative approach revealed that quantities sold, historical market selling prices, the historical foreign exchange rates, historical producer price index and company strategy may have significant impact on sales revenues forecasting. Later, the compass of the research shifted in order to validating the study model and testing the main research hypotheses. A full empirical research was conducted covering a period of 10 years between 2013 and 2022, where the secondary data was collected from a sample of 12 selected companies who manufacture primary aluminum from different economies. Therefore, the collected data underwent statistical tests to examine the significance of independent variable. This comprehensive analysis was carried out using MLR which indicated that only historical quantity sold, historical average market selling prices, historical foreign exchange local currency against the USD (which is the currency used for trade in LME), and global PPI while average metal prices at LME and the company strategy have no significant impact.

In light of these outcomes, several financial recommendations. To enhance the quality of financial forecasting, increasing the accuracy of the credit assessment within banks and budgeting within corporates, this would help to reduce the loan default rate (NPL) since it will support the determination of sufficient financial needs for borrowers.

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Appendix A : List of Exploratory Research Interview Questions

1. What are the different ways used to forecast the sales revenues?
2. What are the main financial variables directly used to forecast sales revenues?
3. What are the other macroeconomic variables to be considered while forecasting sales revenues?
4. How often do you review or update variables used in the forecast model?
5. How are you using these variables to forecast sales revenues?
6. What is the minimum period length of historical data required to forecast sales revenues figures?
7. How far ahead should sales values should be forecasted?
8. What are your recommendations to avoid common mistakes while creating sales forecasting?