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COMPARING REVENUE VOLATILITY OF SIMBISA BRANDS ZIMBABWE IN THE PRE AND POST ZIG PERIODS USING ARIMA-GARCH MODELS. A CASE STUDY OF BAKERS INN BRAND

BY

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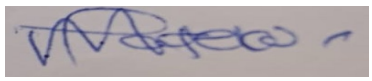
APPROVAL FORM

I certify that this research project is entirely my own original work and that all information drawn from previous sources has been properly acknowledged. I also declare that no part of this study has been submitted for a degree or any other qualification at this university or any other institution.

TARIRO T MATEKO		**08/06/2026**
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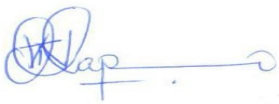
DR. T.W. Mapuwei		**08/06/2026**
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DEDICATION

I proudly dedicate this research project to my loving family for their endless support, care, and encouragement throughout this journey. Seeing how proud they were of me gave me every reason to stay focused and see this work through to the end.

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ABSTRACT

This study focused on comparing revenue volatility for bakers Inn in the pre-ZiG and post-ZiG periods using time series econometric models. To fulfil the objectives of this study, Autoregressive Integrated Moving Average (ARIMA) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models were developed based on monthly operational data from January 2020 to March 2024 (the pre-ZiG training era) and April 2024 to March 2026 (the post-ZiG testing and evaluation era). Results of this study show that the implementation of the Zimbabwe Gold (ZiG) currency serves as a structurally sound policy intervention. While the optimal ARIMA (2,0,2) model captured a robust 60-day operational memory and repeating consumer seasonality, the GARCH (1,1) tracking structure revealed that the post-ZiG period systematically dismantled the intense volatility clustering seen in the pre-reform era. Based on the findings, this study recommends the integration of combined ARIMA-GARCH frameworks for corporate time series analysis, advises management to aggressively pursue fixed capital expansions under this compressed risk environment, and urges the Reserve Bank of Zimbabwe to maintain a disciplined monetary stance to prevent a resurgence of variance loops.

Key words: Revenue volatility, ARIMA model, GARCH model, time series analysis, volatility clustering

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ACRONYMS

1. ACF – Auto Correlation Function
2. ADF – Augmented Dickey-Fuller
3. AIC – Akaike Information Criterion
4. ARCH – Autoregressive Conditional Heteroskedasticity
5. ARIMA – Autoregressive Integrated Moving Average
6. BIC – Bayesian Information Criterion
7. GARCH – Generalised Autoregressive Conditional Heteroskedasticity
8. GP - Gross Profit
9. MA – Moving Average
10. MoM – Month-on-Month
11. PACF – Partial Autocorrelation Function
12. POS – Point of Sale
13. Q-Q – Quantile-Quantile Plot
14. USD – United States Dollar
15. ZiG – Zimbabwe Gold
16. ZWL – Zimbabwean Dollar

CHAPTER 1:

INTRODUCTION

1.0 Introduction

The operating environment of Zimbabwe has seen frequent currency reforms, as well as inflationary and exchange rate risks. The introduction of the Zimbabwe Gold (ZiG) currency in April 2024 was a critical policy measure affecting firms dependent on everyday consumer transactions (Reserve Bank of Zimbabwe, 2024). In this regard, the study will focus on the impact of this phenomenon in relation to Bakers Inn, one of the leading brands of Simbisa Brands Zimbabwe. ARIMA models will be utilized to illustrate the dynamics of the revenue trend, while GARCH models will provide information about any change in conditional volatility after the introduction of the new currency (Bollerslev, 1986; Engle, 1982).

1.1 Background of the study

Revenue can be considered one of the most vital metrics of a company's success since it measures revenues that have been obtained through its regular business activities (Brigham and Ehrhardt, 2017). As soon as revenue displays consistency over time, it becomes easier for the company to manage its expenses, estimate inventory, invest money into expansion or fulfil its liabilities. If the company demonstrates volatile revenue, then it becomes harder to make proper management decisions since projections and forecasts may not necessarily be accurate and decisions may need to be postponed (Gitman and Zutter, 2015).

Revenue tends to fluctuate from one period to another. This is influenced by factors such as pricing policies, consumer demand, competition, seasonality, disruption in the supply chain, economic environment, and policy changes (Tsay, 2010). Revenue volatility can be described as how much this variation occurs over time. It is important since volatile sales revenue impacts issues such as budgeting, inventory management, labour planning, and capital spending. Businesses that operate in unstable economic environments face this problem.

The case of Zimbabwe is a pertinent one in this respect. During the past twenty years, organizations have faced instances where there has been a rise in prices, change in foreign exchange rates, liquidity problems, and different monetary policies. These conditions have influenced the buying power of consumers, the pricing structures, costs of production, and

economic confidence in general. According to sources from the Reserve Bank of Zimbabwe, each monetary change was designed to ensure price stability and improve confidence in domestic transactions (Mushayavanhu, 2025). On the other hand, constant policy changes may be problematic for enterprises which rely on stable demand.

The ZiG currency was brought into circulation in April 2024 in a bid to stabilize the exchange rate, control inflation, and increase confidence in domestic dealings (Mushayavanhu, 2025). While the measure was macroeconomic in nature, its consequences could be noted at an individual firm's level. The adoption of a new currency may have effects on consumer expenditure, menu pricing, procurement expenses, salary expectation levels, and business confidence in general. Consequently, it is important to find out whether the period following the implementation of ZiG has brought about any changes in the earnings of firms.

Quick service restaurants are especially susceptible to these dynamics. Prepared food demand is very much tied to income levels and urban consumption practices, among other things (Kotler and Keller, 2016). During times when real income levels fall or inflation rates are relatively high, consumers may cut back on their restaurant spending and other discretionary spending activities (Mankiw, 2021). Simultaneously, foodservice firms are exposed to fluctuations in the cost of ingredients such as flour, meat, oil, and electricity, as well as higher rentals, packaging expenses, fuel costs, and wages.

Bakers Inn can be considered an appropriate example as it is a popular quick service restaurant chain under the Simbisa Brands, having a large clientele, as well as being highly recognizable in Zimbabwe (Denhere, 2025). With a wide-spread across several branches and information related to financial performance available, it is possible to study the behaviour of a consumer-focused company in response to variations in monetary policy. Moreover, as Bakers Inn deals with urban clientele, revenue shifts might mirror behavioural trends.

There exists an efficient method for studying such revenue movements in time series modelling. The ARIMA models facilitate identification of the persistent, trend behaviour and forecasting characteristics of time-dependent variables, whereas GARCH models are recommended when there is time-varying volatility, and the high-variance episodes appear to be clustered together (Bollerslev, 1986). This technique can serve as a basis for comparison between the two periods of Bakers Inn revenue movements.

In regard to the literature on the monetary reforms of Zimbabwe, the current discourse has revolved around inflation rates and exchange rates, among others. Not enough attention has

been devoted to the stability of revenues at the firm level, especially those of consumer firms listed on stock markets. This paper will help fill this research void through the analysis of Bakers Inn revenue stability prior to and following the implementation of ZiG, utilizing ARIMA-GARCH models.

1.2 Problem Statement

Consistent revenue helps in effective business management through facilitating better planning, budgeting, inventory management, recruitment, pricing, and investment decision making. In situations where revenue is not consistent, there is a potential problem that could be encountered by management, in terms of resource allocation and forecasting, leading to loss of profits. Consistent revenue helps the company to maintain consistency in its activities as well as avoid risks associated with business operations (Denhere, 2025).

Zimbabwe has experienced cases where firm revenues were affected by inflation, fluctuating exchange rates, currency shortages, and policy uncertainty (Matsvai, 2024). Such situations have impacts on both the consumers' buying power and the cost structure of firms. Sectors where there is a need for repeated consumer purchases, such as fast-food outlets, are affected by economic factors very rapidly.

ZiG was introduced in April 2024 as part of a monetary reform intended to enhance stability, decrease exchange rate instability, and restore confidence in transactions made locally (Mushayavanhu, 2025). The positive effects of such reform on stability should be visible through more stable business conditions. Nonetheless, little data exists on this subject in terms of firms. Specifically, little information can be found on the connection between ZiG and business stability.

It is important to note that Bakers Inn offers a good example of a company that would help in the analysis of this topic, due to the position it holds in the market, its customers, and their behavior when it comes to household expenses. While the performance of this company has been disclosed, whether there have been changes in the volatility of revenues following ZiG has yet to be statistically proven. Inflation, exchange rates, and even policy expectations have all been at the centre of public discussion on the topic. However, there has been limited research on the behavior of revenues of listed companies.

The problem of this study is the lack of empirical evidence to show that there has been a change in volatility of the revenues of Bakers Inn due to the introduction of ZiG. This is answered by use of ARIMA-GARCH models.

1.3 Research Objectives

i. To compare and estimate conditional revenue volatility of Bakers Inn Brand in the pre-ZiG and post-ZiG periods using ARIMA-GARCH models.

ii. To examine the trend and movement of Bakers Inn revenue in the pre-ZiG period and post-ZiG period.

iii. To test the statistical properties of the revenue series, including stationarity and serial dependence, to determine appropriate time series specifications.

iv. To provide evidence-based recommendations that may assist management, investors, and policymakers in promoting greater revenue stability and improved planning outcomes.

1.4 Research Questions

i. What differences, if any, exist in the revenue volatility of Bakers Inn between the pre-ZiG and post-ZiG periods?

ii. What revenue trends and patterns were observed in the pre-ZiG and post-ZiG periods?

iii. Does the revenue series exhibit stationarity, serial correlation, or other characteristics that justify the use of time series modelling techniques?

iv. What practical recommendations can be drawn from the findings to improve revenue stability, planning efficiency, and strategic decision-making?

1.5 Research Hypotheses

The hypotheses translate the research problem into testable statistical statements. They focus on whether the variance of Bakers Inn revenue differs between the pre-ZiG and post-ZiG periods.

Let: σpre2 represent the variance of revenue in the pre-ZiG period and σpost2 represent the variance of revenue in the post-ZiG period

Null Hypothesis ($\boldsymbol{H0}$): There is no statistically significant difference in revenue volatility between the pre-ZiG and post-ZiG periods.

$H0: \sigma pre2 = \sigma post2$

Alternative Hypothesis ($\boldsymbol{H1}$): There is a statistically significant difference in revenue volatility between the pre-ZiG and post-ZiG periods.

$H1: \sigma pre2 \neq \sigma post2$

Rejecting the null hypothesis would indicate that the introduction of ZiG coincided with a statistically significant change in revenue volatility.

1.6 Significance of the Study

This study is useful because it links a major monetary reform to firm-level revenue behaviour. Its findings may contribute practical, policy and academic insight for several stakeholder groups.

1. To Bakers Inn Management

For Bakers Inn management, the results may clarify how revenue responds to changes in monetary conditions. Better knowledge of volatility patterns can strengthen budgeting, cash-flow planning, procurement, staffing, pricing and branch-expansion decisions. If periods of elevated volatility are identified, management can improve forecasting systems and risk monitoring (Damodaran, 2015).

2. To Investors and Shareholders

For investors, shareholders and market analysts, revenue stability is an indicator of business resilience and earnings quality. The findings may support assessment of Bakers Inn's operational stability under different currency regimes and may inform valuation and investment decisions (Denhere, 2025).

3. To Policymakers and Regulators

For policymakers, including the Reserve Bank of Zimbabwe and relevant ministries, the study provides firm-level evidence on whether monetary reform is associated with a more stable business environment (Mushayavanhu, 2025). If post-ZiG volatility is lower, the results

may support the stabilisation objective. If volatility remains high, the findings may point to the need for complementary policy measures.

4. To Business Community

Other retail companies might learn from this research about running their operations in varying monetary environments. Insights about revenue volatility will be useful in creating stronger pricing systems, inventory management, and risk management.

5. To Academic Community

From an academic perspective, the paper adds to existing knowledge within local literature on revenue volatility of firms, monetary changes, and time series analysis in the context of Zimbabwe. There is limited literature that looks at revenue volatility of firms by employing the application of the ARIMA-GARCH model, and most literature relates to inflation, exchange rate, etc.

6. To the Researcher

The study gives an opportunity for the researcher to apply statistical tools and techniques in solving the business problem at hand. These include collecting data, manipulating data, time series analysis, hypothesis testing and interpretation among others.

1.7 Scope of the Study (Delimitation of the study)

In this research, emphasis will be placed on the volatility of Bakers Inn income in Zimbabwe, but not on profit-making capabilities, balance sheet parameters or overall performance of the company in terms of the Simbisa Brands group. The chosen company stands out in terms of visibility among quick service restaurants and availability of data on its branches. This work will analyse the period before introduction of ZiG currency, that is, between January 2020 and March 2024, against the period after ZiG introduction starting from April 2024. Monthly observations of revenue will be based on information available from public documents and associated financial reports. All empirical analysis will rely on quantitative methods of analysing time series such as ARIMA and GARCH. Interviewing, surveys and narrative approaches will not be part of this study.

1.8 Assumptions of the Study

i. The revenue data obtained from Bakers Inn are accurate, complete, and reliable representations of the company's actual financial performance during both the pre-ZiG and post-ZiG periods.

ii. The GARCH model is appropriate for the revenue series after diagnostic testing.

iii. The time series data is stationary and can be made stationary through differencing.

1.9 Limitations of the Study

The key constraint associated with this research is in relation to the time frame available to analyse after the implementation of ZiG, because ZiG became active only in April 2024, whereas data for the period prior to ZiG's implementation were obtained over a long period of time. Time-series models tend to be more accurate with longer data sets, and thus the limited availability of observations in post-reform period can undermine the accuracy of calculations. Another limitation has to do with the focus on the particular company in question; thus, the findings may not be relevant in respect of companies in other industries and with different cost structures and customer bases. Moreover, the ARIMA and GARCH models are not necessarily able to account for all possible structural breaks that might occur due to currency reform (Perron, 1989).

1.10 Definition of Key Terms

i. Revenue: The total income generated by Bakers Inn from its core business operations over a given period, before the deduction of expenses (Brigham and Ehrhardt, 2017).

ii. Revenue Volatility: The degree of fluctuation in revenue over time, typically measured using variance or conditional variance (Tsay, 2010).

iii. Pre-ZiG Period: The time frame before the introduction of the Zimbabwe Gold currency, specifically January 2020 to March 2024 (Reserve Bank of Zimbabwe, 2024).

iv. Post-ZiG Period: The period beginning from April 2024 onwards, following the introduction of the Zimbabwe Gold (ZiG) currency (Reserve Bank of Zimbabwe, 2024).

v. Zimbabwe Gold (ZiG): A domestic currency introduced in April 2024 as part of monetary reforms aimed at stabilising the Zimbabwean economy (Reserve Bank of Zimbabwe, 2024).

vi. Time Series Data: Data collected sequentially over time, such as monthly or quarterly revenue observations (Gujarati and Porter, 2009).

vii. ARIMA Model (Autoregressive Integrated Moving Average): A statistical model used to analyse and forecast time series data by capturing trends, autocorrelation, and past error terms (Box, Jenkins, Reinsel and Ljung, 2015).

viii. GARCH Model (Generalised Autoregressive Conditional Heteroskedasticity): A model used to estimate time-varying volatility in a time series, particularly where periods of high and low variability cluster over time (Bollerslev, 1986).

ix. Volatility Clustering: A phenomenon where periods of high volatility tend to be followed by high volatility, and periods of low volatility follow low volatility (Engle, 1982).

x. Stationarity: A property of a time series where statistical characteristics such as mean and variance remain constant over time (Brooks, 2019).

xi. Conditional Variance: The variance of a time series at a given time, dependent on past information and previous shocks (Tsay, 2010).

1.11 Conclusion

This chapter set out the background, problem statement, objectives, research questions, hypotheses, significance and scope of the study. It emphasised the role of revenue stability in business performance and showed why revenue volatility is important in a setting marked by economic and monetary change (Brigham and Ehrhardt, 2017; Tsay, 2010). Zimbabwe was identified as an appropriate context because of its history of currency reforms and macroeconomic instability, with special attention to the introduction of ZiG in April 2024 (Reserve Bank of Zimbabwe, 2024). Bakers Inn was selected as the case study because of its position in the quick-service restaurant sector and the availability of financial data. The next chapter reviews literature on revenue volatility, monetary reforms and time-series modelling.

CHAPTER 2

LITERATURE REVIEW

2.0 Introduction

This chapter reviews literature relevant to revenue volatility, monetary-policy change and the use of time-series models in business and economic analysis. It first discusses the theoretical foundations of the study, including uncertainty, firm performance, business cycles and risk analysis. These perspectives help explain why revenue volatility arises and how it may respond to macroeconomic shocks such as currency reform (Fama, 1970; Hamilton, 1994).

Next, the review presents the relevant empirical research, starting with Zimbabwe as the local economy has experienced high levels of inflation variability, exchange rate fluctuations, and continuous monetary reforms (Muzurura, 2020; Sibanda and Moyo, 2021). Relevant regional and international studies are cited where they serve as methodological comparisons to models such as ARIMA and GARCH models.

The methodological literature is also considered because the choice of model is central to the study. ARIMA models are discussed in relation to trend, persistence and autocorrelation, while GARCH models are reviewed for their ability to capture time-varying volatility and volatility clustering.

Another section of the review highlights the gaps that exist within current literature. Several pieces of research focus on inflation and exchange rates among others, but very little work has been done on the impact of monetary policy changes on revenue stability of firms (Chikodzi and Ndlovu, 2022; World Bank, 2023).

In this final section of the chapter, a framework is developed which ties monetary policy change, macroeconomic environment, and income fluctuations at Bakers Inn.

2.1 Theoretical Framework

2.1.1 Theory of Uncertainty and Business Performance

Economic uncertainty forms one of the key elements of this research. As per the economic theory, it becomes more difficult for companies to plan and forecast in an environment that is uncertain. It often leads to the occurrence of:

i. Fluctuating demand

ii. Unstable costs

iii. Shifts in consumer behaviour

These conditions are likely to lead to unpredictable revenue patterns. In Zimbabwe, for instance, uncertainty was frequently linked to instability in terms of inflation and currency exchange rates as well as the frequent change of monetary policies. If people are uncertain about the future cost of goods and income levels, there will be a reduction in expenditure, which includes spending at the restaurant. This is one of the direct impacts of uncertainty that affects Bakers Inn. In that case, ZiG can be seen as an effort to minimize uncertainty.

This theory supports the study's examination of whether the post-ZiG period shows an improvement in revenue stability.

2.1.2 Monetary Transmission Mechanism

Monetary Transmission Mechanism refers to the process by which decisions made in terms of monetary policy have an effect on the real economy. These are the processes through which policy decisions impact on expenditure, savings, investments, and pricing through different channels such as the interest rate channel, exchange rate channel, and the expectations or confidence channel (Mishkin, 2022; Bernanke & Gertler, 1995). Expectations are more significant for Zimbabwe since the change in the exchange rate regime affects consumer confidence. Consumption tends to be steady when there is high currency confidence but not the case when there is low currency confidence.

In light of the above explanation, the ZiG reform can therefore be regarded as a monetary policy shock that runs through the economy. This paper evaluates whether the shock leads to more stable or unstable revenues.

2.1.3 Firm Theory and Revenue Behaviour

Firm theory is useful in explaining the reaction of firms to changes in economic environment. While firms strive for profit maximisation, there are two conditions under which revenues may fluctuate. The first condition relates to demand while the second one concerns costs.

i. Demand varies due to variations in income levels

ii. Costs vary randomly

iii. Prices are often revised

In quick service restaurants, the demand for their products depends on disposable incomes and consumer tastes. During difficult economic times, consumers may avoid non-essential expenses, leading to fluctuating revenues. Bakers Inn is vulnerable to changes because:

i. Sales rely on repeated transactions of small monetary amounts.

ii. Consumer behavior changes rapidly.

iii. Pricing requires consideration of cost constraints.

The presence of such characteristics means that the organization will be more susceptible to income variability. Firm theory can be used to explain why quick service restaurants have high volatility when compared to firms in industries which are not affected by shifts in demand.

2.1.4 Consumer Behaviour Theory

Consumer behaviour analysis focuses on the reasons for expenditures in relation to income levels, tastes and preferences, expectations, and prices (Kotler and Keller, 2016). Lower expenditure in quick service restaurants may be attributed to lower levels of income, meaning that revenue in the sector relies on economic factors. A change such as introduction of the ZiG could affect consumer confidence regarding stability of prices. If expectations are consistent, consumers' spending habits would be predictable while low confidence might result in erratic consumption patterns.

2.1.5 Volatility Theory and Financial Time Series

Volatility theory is central to this dissertation because it focuses on how variability changes over time. A key feature is volatility clustering, where:

i. Periods of high volatility are followed by high volatility

ii. Periods of stability are followed by stability

This pattern is common in financial and economic time series. Standard models that assume constant variance may therefore be inadequate when the data show time-varying volatility. This has led to models such as:

i. ARIMA (for modelling trends and patterns)

ii. GARCH (for modelling changing volatility)

iii. ARIMA helps explain the structure of revenue over time

iv. GARCH captures how revenue volatility evolves

These theoretical points justify the use of ARIMA-GARCH models to assess whether revenue volatility changed between the pre-ZiG and post-ZiG periods.

2.2 Empirical Literature Review

In this section, various empirical studies have been reviewed regarding the issue of volatility in revenue, monetary instability and the use of ARIMA-GARCH methodology. The review starts with studies carried out in Zimbabwe and then other selected regional and international studies.

2.2.1 Empirical Evidence from Zimbabwe

Most empirical studies conducted in Zimbabwe have concentrated on macroeconomic instability, mainly the effects of inflation, exchange rates, and monetary policies. There is limited literature on firm-level income instability, particularly when using complex time series analysis techniques.

While Robertson (2009) studies Zimbabwe's economic instability in the long term, particularly pointing out the effect of high inflation rates and erratic frameworks on businesses, there is no evaluation done quantitatively to assess the volatility at the organizational level.

Kanyenze (2017) addresses the wider macroeconomic conditions as well as their influence on businesses and employment. The author focuses on the influence of decreasing real wages and uncertainties associated with the economic situation on consumption; yet, no time series volatility modelling techniques have been utilized.

Unlike the analysis carried out by Munyeka & Chirowa (2018) where they employ quantitative techniques to determine volatility clustering within macroeconomic variables

thus validating the use of GARCH model, this current research focuses on revenue at the firm level and not on inflation in Zimbabwe.

Chinzara (2011) uses the GARCH model in the analysis of stock returns from the Zimbabwe Stock Exchange and proves time-varying volatility. Although the study does not involve revenues but stock prices, it shows that the volatility model can be effectively applied in Zimbabwe.

The effect of volatility in exchange rates and their effect on performance is analysed by Mazviona (2020). The author observes that volatility in exchange rates leads to uncertainty in business transactions but still the research focuses on the macroeconomic perspective.

Taken together, Zimbabwean studies show strong evidence of macroeconomic volatility, but they leave three gaps that are relevant to this dissertation:

i. Focus on firm-level revenue data

ii. Apply ARIMA-GARCH models

iii. Compare pre- and post-policy reform periods

These gaps justify the focus on Bakers Inn revenue.

2.2.2 Regional Evidence (Southern Africa and Sub-Saharan Africa)

Across Southern Africa and Sub-Saharan Africa, time-series models have often been used to examine volatility in financial and economic variables.

According to Chinzara (2010), examining volatility in the South African stock market using the GARCH approach reveals the existence of clustering and persistence in the data. It, therefore, implies that the regional financial markets show trends that can be effectively studied through the GARCH approach.

Mwansa & Mwaanga (2016) examine exchange rate volatilities in Zambia, establishing a link between the effect of the volatility on firms' conditions. While not modelling revenue performance, it is shown that currency fluctuations might affect the performance of firms.

ARIMA models are used by Ogutu et al. (2018) to forecast performance measures for firms. The analysis reveals that time series models are efficient tools for identifying trends and seasonality effects; however, the missing aspect of volatility prevents the models from explaining variations in variation.

Atoi (2014) applies GARCH models to financial-market volatility in Nigeria and finds strong persistence effects. This result is relevant to the present study because it shows that shocks can have lasting effects on volatility.

2.2.3 International Evidence

The international literature offers the theoretical basis of applying the ARIMA and GARCH models jointly.

Box and Jenkins' (1976) methodology laid the ground for using the ARIMA model in order to analyse and forecast time-series data. Their study suggested a consistent methodology of trend, seasonality, and autoregressive components identification and estimation.

The GARCH model was invented by Bollerslev (1986), which is an extension of the ARCH model proposed by Engle. One of the greatest advantages of the GARCH model is that it can handle the situation where variance varies across time.

Poon and Granger (2003) illustrate that volatility clusters are one of the major features of financial time series data, which implies that GARCH models are suitable for such situations.

Chen and Zhang (2007) examine macroeconomic conditions and corporate earnings volatility, finding that economic instability increases variability in firm performance.

Kumar (2019) applies ARIMA-GARCH models to business revenue and sales data and shows that the combined approach can improve forecasting and volatility estimation.

Overall, the international literature supports:

i. The use of ARIMA for modelling revenue patterns

ii. The use of GARCH for modelling volatility

iii. The integration of both models for comprehensive analysis

However, much of this work is based on more stable economies than Zimbabwe. This makes it necessary to test the methods in an environment marked by frequent monetary changes and structural instability.

2.2.4 Critical Evaluation of the Literature

Several observations emerge from the literature. First, Zimbabwean studies provide useful context on economic instability but limited firm-level quantitative evidence. Second, regional studies show that ARIMA and GARCH models are applicable, but they rarely examine

revenue in consumer sectors. Third, international studies provide strong methodology but are not always directly transferable to Zimbabwe's economic conditions. Finally, few studies compare pre- and post-policy reform periods using firm-level revenue data.

2.3 Research Gap

The literature reveals a clear gap: there are few Zimbabwean studies on firm-level revenue volatility. Much of the work by Kanyenze (2017), Robertson (2009) and others focuses on macroeconomic variables such as inflation, employment and growth. These studies are useful, but they do not show how macroeconomic instability appears in the revenue of individual firms. There is also limited use of combined ARIMA-GARCH models at company level. Chinzara (2011) demonstrates GARCH modelling in the Zimbabwean stock market, but similar methods have not been widely applied to corporate revenue. Finally, little empirical work has assessed the introduction of ZiG using a before-and-after design. This study addresses these gaps by modelling Bakers Inn revenue volatility across the pre-ZiG and post-ZiG periods.

2.4 Conceptual Framework

The conceptual framework shows how the main variables in the study are connected. It is based on the theories and empirical literature reviewed above. The central argument is that the introduction of ZiG may influence Bakers Inn revenue volatility both directly and indirectly through broader economic conditions.

The framework is built around three main components:

1. Independent Variable: Introduction of Zimbabwe Gold (ZiG) currency: pre-ZiG and post-ZiG periods.

2. Intervening (Mediating) Variables

These are the macroeconomic and behavioural factors through which ZiG may affect revenue:

i. Inflation stability

ii. Exchange rate stability

iii. Consumer confidence

iv. Disposable income

v. Cost of inputs (fuel, food, utilities, wages)

3. Dependent Variable: Revenue volatility of Bakers Inn

i. Measured using variance and conditional variance (GARCH)

ii. Captures fluctuations in revenue over time

4. Moderating Factors (Firm-Level Characteristics)

These firm-level factors may influence the strength of the relationship between the currency reform and revenue:

i. Pricing strategy

ii. Branch network size

iii. Brand strength

iv. Operational efficiency



Figure 2.1: Conceptual framework linking ZiG reform and revenue volatility

2.4.1 Explanation of the Framework

The framework treats the introduction of ZiG as a policy shock that works through the broader economic environment. The impact can be seen through inflation, exchange rates, and consumer sentiment. Macroeconomic variables like this affect consumer expenditure, which will especially matter to Bakers Inn since it depends heavily on small transactions made frequently. Decisions by management regarding pricing, costs, and efficiency might help to reduce or accentuate the shock effect. The end result will show up in the form of volatile revenues, calculated as variance and via GARCH models.If ZiG improves stability, revenue volatility should decline; if instability persists, volatility may remain high or increase.

2.5 Conclusion

This chapter reviewed theory and empirical literature on revenue volatility and monetary-policy change. It discussed uncertainty theory, monetary transmission, firm theory, consumer behaviour and volatility theory as explanations for how macroeconomic conditions can influence firm-level revenue. The review identified limited firm-level research using advanced time-series models in Zimbabwe, especially around the introduction of ZiG. A conceptual framework was then presented to link monetary reform, macroeconomic conditions, firm responses and revenue volatility. The next chapter explains the methodology used to estimate revenue volatility with ARIMA-GARCH models.

CHAPTER 3

RESEARCH METHODOLOGY

3.0 Introduction

The preceding chapter established the theoretical and empirical basis for analysing revenue volatility under changing monetary conditions (Hamilton, 1994; Brooks, 2019). This chapter explains how the study moves from that literature to empirical testing. To determine whether the introduction of ZiG is associated with a change in Bakers Inn revenue stability, the analysis requires a method that can capture both revenue movement over time and the evolution of volatility.

This chapter therefore sets out the research design, data sources and modelling procedures used in the study. It also explains data preparation, model estimation and diagnostic testing so that the results in the next chapter can be interpreted consistently (Gujarati and Porter, 2009; Brooks, 2019).

3.1 Research Design

This research will employ quantitative research design since the purpose of the research is to quantify the differences between two periods, specifically the period before ZiG and after ZiG. Quantitative research design fits well with such a kind of objective and will follow the precedent set by past econometrics in Zimbabwe like that of Chinzara (2011).

The design allows revenue behaviour before and after the currency reform to be compared in a structured manner.

3.2 Data Collection and Sources

The data is of secondary nature, mainly comprising monthly income generated from Bakers Inn and Simbisa Brands from their financial statements.

3.2.1 Sources of Data

Data is collected from:

i. Annual and interim financial statements

ii. Published company reports

iii. Zimbabwe Stock Exchange disclosures

These sources are treated as reliable because they are publicly released and subject to reporting and audit requirements.

3.2.3 Data Period and Data Frequency

The study covers two periods: the pre-ZiG period from January 2020 to March 2024 and the post-ZiG period from April 2024 to the latest available observation. The division is based on the introduction of the Zimbabwe Gold currency in April 2024. The analysis uses monthly observations.

3.2.4 Data Preparation

Before analysis, the data is:

i. Cleaned to remove inconsistencies

ii. Checked for missing values

iii. Transformed (e.g., logarithms) where appropriate

iv. Tested for stationarity

These steps are necessary before time-series modelling because missing values, outliers and non-stationarity can affect estimation and interpretation.

3.3 Model Specification

The analysis combines ARIMA and GARCH models in order to examine both the mean behaviour of revenue and its changing volatility.

3.3.1 ARIMA Model

The ARIMA model captures the dynamic structure of the revenue series.

$$yt = c + \sum_{} \phi i \; yt-i + \sum \; \theta j \; \varepsilon t-j + \varepsilon t$$

i=1 j=1

Where:

i. yt= revenue at time t

ii. c= constant term

iii. ϕi= autoregressive coefficients

iv. θj= moving average coefficients

v. εt= error term

In this study, the ARIMA model is used to:

i. Identify trends and patterns

ii. Remove autocorrelation

iii. Prepare residuals for volatility modelling

3.3.2 GARCH Model

The GARCH model estimates conditional variance, allowing volatility to change over time.

$$\sigma t2 = \omega + \alpha \varepsilon t2{-}1 + \beta \sigma t2{-}1$$

Where:

i. $\sigma t2$= conditional variance (volatility)

ii. ω= constant

iii. α= effect of recent shocks

iv. β= persistence of past volatility

The model captures:

i. Volatility clustering

ii. Persistence of shocks

iii. Changes in variance over time

3.3.3 Combined Approach

The study first estimates the ARIMA mean equation and then applies GARCH to the residuals. This sequence is used so that:

i. The mean structure is properly specified

ii. Volatility is modelled accurately

3.4 ARIMA Modelling Procedure

The ARIMA modelling process followed these steps:

i. Visual inspection of the data

ii. Plot revenue series

iii. Identify trends or patterns

iv. Stationarity testing using the Augmented Dickey-Fuller (ADF) test; if non-stationary, the series is differenced

v. Model identification: Use ACF and PACF plots (Determine values of p, d, q)

vi. Model estimation: Estimate parameters using statistical software

vii. Model selection using AIC and BIC criteria

viii. Residual diagnostics to check autocorrelation and white-noise behaviour

3.5 GARCH Modelling Procedure

i. After estimating the ARIMA model, the analysis proceeds to volatility modelling.

ii. Test for ARCH effects using the ARCH-LM test

iii. Estimate a GARCH model, typically GARCH(1,1)

iv. Interpret the parameters: alpha for short-term shocks and beta for volatility persistence

v. Check model adequacy using residual tests and stability conditions

vi. Compare estimated volatility between the pre-ZiG and post-ZiG periods

3.6 Diagnostic Tests

The following diagnostic tests are used to assess model adequacy:

i. ADF Test → stationarity

ii. Ljung-Box Test → autocorrelation

iii. ARCH-LM Test → volatility presence

iv. Normality Tests → residual distribution

These tests indicate whether the model assumptions are sufficiently satisfied for interpretation.

3.7 Ethical Considerations

The study uses publicly available secondary data, which limits ethical risk.

The following principles are maintained:

i. Proper acknowledgment of data sources

ii. Accurate representation of results

iii. Avoidance of data manipulation

iv. Objective interpretation of findings

No human participants are involved, so consent and confidentiality issues do not arise.

3.8 Conclusion

The current chapter provided details of the methodologies involved in analysing the volatility of Bakers Inn's revenues. A quantitative time series research approach was taken where ARIMA models were utilized for the examination of revenue dynamics while GARCH models were applied for the measurement of volatility. This chapter provided information on the data sources, modelling procedure, estimation process, and diagnostic tests.

CHAPTER 4

DATA PRESENTATION, ANALYSIS AND DISCUSSION

4.0 Introduction

This chapter presents the empirical analysis of Bakers Inn revenue across two monetary regimes: the pre-ZiG period from January 2020 to March 2024 and the post-ZiG period from April 2024 to March 2026. ARIMA models are used to examine the mean revenue process, while GARCH models are used to estimate the variance process and identify volatility clustering in the revenue series.

4.1 Descriptive Statistics

Table 4.1 Turnover Descriptive Statistics

Statistical measures	Pre-ZiG Values	Post-ZiG Values
Mean	1 987 185.30	3 084 107.65
Minimum	1 133 355.36	2 657 266.26
Maximum	3 190 446.14	3 881 729.39
Standard Deviation	469 917.94	318 026.24
Skewness	0.19	0.89
Kurtosis	-0.51	0.47
Count	51	24

Table 4.2 GP Descriptive Statistics

Statistical measures	Pre-ZiG Values	Post-ZiG Values
Mean	35.00	34.52
Minimum	30.07	30.08
Maximum	39.42	39.75
Standard Deviation	2.85	3.28
Skewness	-0.17	0.17
Kurtosis	-1.27	-1.58
Count	51	24

Table 4.3 Customers Descriptive Statistics

Statistical measures	Pre-ZiG Values	Post-ZiG Values
Mean	675 627.69	800 038.83
Minimum	555 284	748 884
Maximum	831 069	911 436
Standard Deviation	60 591.52	41 768.97
Skewness	0.241	1.15
Kurtosis	-0.2	0.95
Count	51	24

In order to analyze the impact of the ZiG currency period on the operations, the data were divided into two groups: the pre-ZiG period (51 months) and the post-ZiG period (24 months). It appears that mean monthly turnover grew from $1,987,185.30 to $3,084,107.65 (the growth is roughly 55.2%). In the meantime, the standard deviation decreased from $469,917.94 to $318,026.24, implying lower dispersion of monthly sales. Furthermore, both minimum and maximum values for monthly sales moved upwards. Finally, the number of customers per month increased by 18.4%. Gross profit margin changed insignificantly: it went down from 35.00% (pre-ZiG) to 34.52% (post-ZiG) (difference equals 0.48%).

4.2 Pre-tests

Table 4.4: Test statistics

Variable	t-statistic	Degrees of freedom	p-value
Turnover ($)	-11.8670796	63.63932	8.853025e-18
Customer count	-10.3432683	62.78534	3.436371e-15
GP Margin (%)	0.6217524	39.92630	5.376390e-01

The turnover t-statistic of -11.87 indicates a statistically significant difference in mean monthly revenue between the two periods. The customer-count test also shows a significant difference, while the GP margin test is not significant at the 5% level. These results suggest that the post-ZiG period is associated with higher turnover and customer numbers, but not with a statistically meaningful change in gross profit margin. The wording of this result

should be interpreted carefully: the test shows a difference between periods, but it does not by itself prove that ZiG was the only cause of the change.

4.3 Diagnostic tests

4.3.1 Stationarity

Before estimating ARIMA or GARCH models, the revenue series must be checked for stationarity. A stationary series has a mean, variance and autocorrelation structure that do not change systematically over time. Where non-stationarity is present, differencing may be required before modelling. The Augmented Dickey-Fuller (ADF) test was used for this purpose.

Table 4.5: Augmented Dickey-Fuller (ADF) Test Matrix

(Revenue Turnover Significance Level: alpha = 0.05)

Series Format	ADF Dickey-Fuller Statistics	Lag	p-value	Status
Raw revenue ($)	-6.1062	4	0.01	Stationary
Differenced Revenue (MoM)	-4.9637	4	<0.01**	Stationary

Table 4.5 reports the ADF results for the raw and differenced monthly turnover series. The raw revenue series produced a Dickey-Fuller statistic of -6.1062 with four lags and a p-value of 0.01. Since the p-value is below the 0.05 significance level, the null hypothesis of a unit root is rejected. This indicates that the raw revenue series is stationary in levels, I(0). The differenced series also remained stationary, with a statistic of -4.9637 and a p-value below 0.01.

4.3.2 Normality

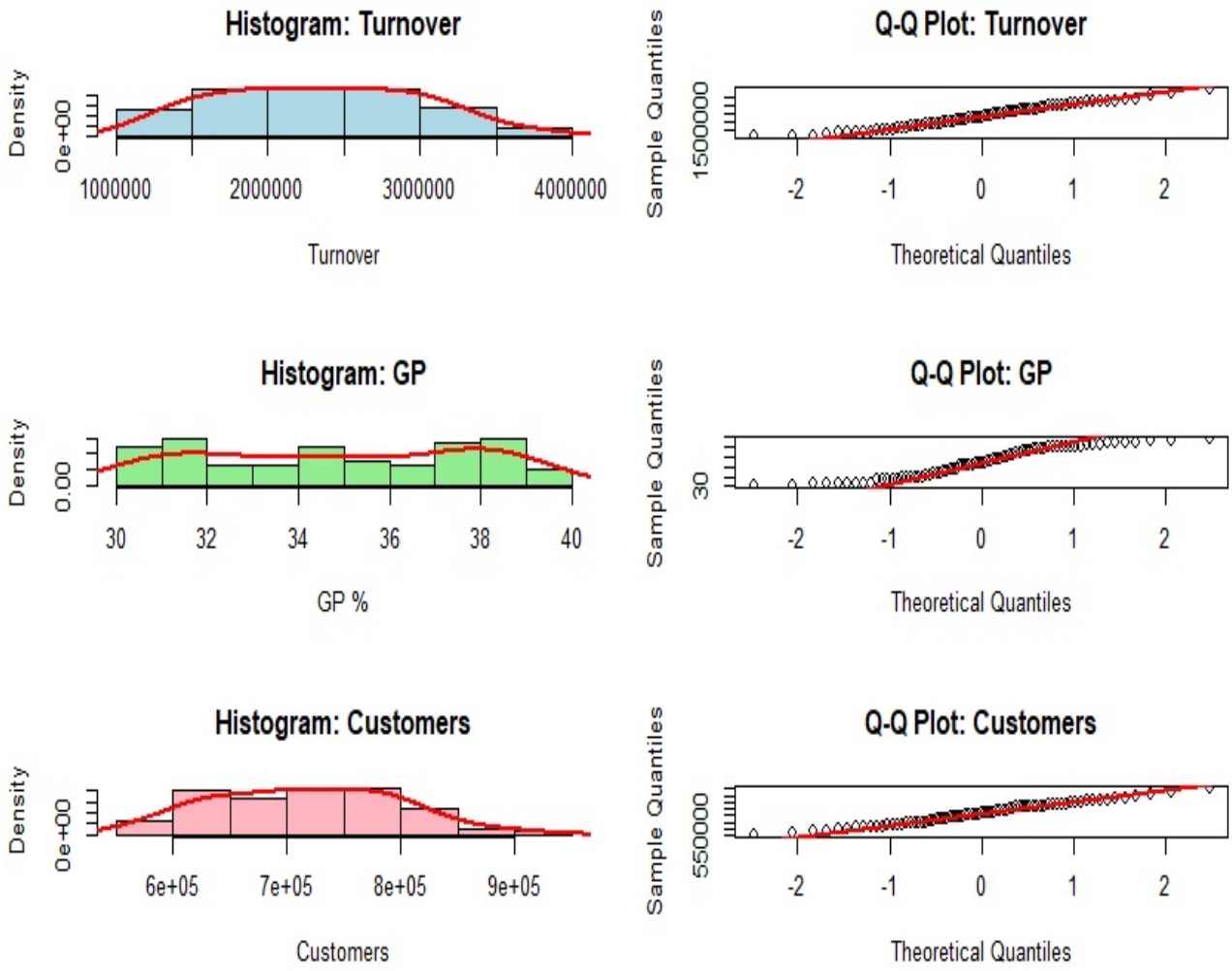

Figure 4.1: Histograms and Q-Q plots for Turnover, GP and Customer count

The histograms and Q-Q plots for Turnover, Gross Profit (GP) and Customers were used to assess distributional behaviour in the pre- and post-ZiG dataset. The Q-Q plots show that many observations lie close to the reference line, which suggests approximate normality in the centre of the distributions. Deviations at the tails indicate the presence of extreme values, especially for Turnover and Customers. The histograms are reasonably balanced but not perfectly bell-shaped. These results support the use of diagnostic checks rather than relying on visual normality alone.

4.3.3 Independence

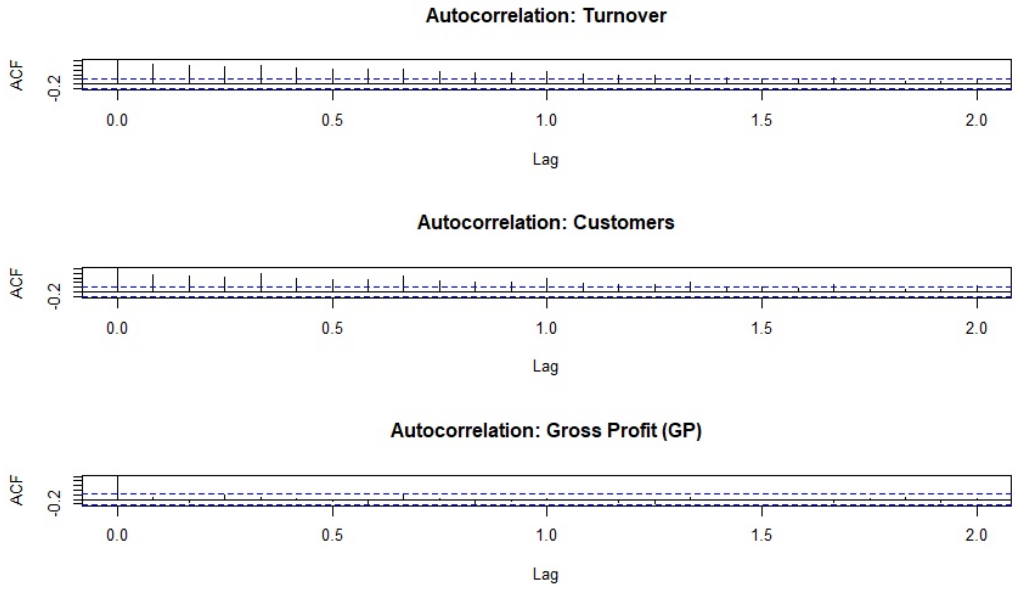

Figure 4.2: Autocorrelation for Turnover, Customers and Gross Profit

The autocorrelation plot for Turnover shows high persistence: the first lag is approximately 0.85 and the autocorrelations decline slowly. This pattern is consistent with a strong trend and with revenue persistence under inflation and currency-transition conditions. For Customers, positive spikes around lags 4, 8 and 12 suggest a seasonal pattern in purchasing behaviour. Because customer counts measure physical transactions rather than currency values, this seasonality may reflect recurring consumer cycles. The Gross Profit series shows weaker persistence, indicating that margins are more stable than revenue levels.

4.3.4 Volatility Presence

This stage addresses the core issue of revenue volatility. ARIMA models describe the conditional mean, or the predictable component of revenue, while the GARCH(1,1) model estimates conditional variance, which represents changing risk and stability over time. Estimating GARCH therefore allows the study to compare whether the variance process differs before and after ZiG.

Table 4.6: Volatility Testing

Parameter component	Pre-Zig Estimate	Post-Zig Estimate	Structural Shift
Baseline variance (aθ)	1.987e+11	9.103e+10	Unconditional Drop
Shock Sensitivity (a_1 / ARCH)	0.9713	1.0530	Amplified Reaction
Shock Persistence (b1 / GARCH)	0.3269	0.0287	Near-Total Decay
Total Volatility momentum	1.2982	1.0817	Systemic Compression
Jarque-Bera Residual p-value	0.6693	0.7619	Normally Distributed

In the pre-ZiG period (January 2020-March 2024), the variance parameter was high due to instability within the business environment. In the post-ZiG period that started from April 2024, there was a decline in the estimate of the unconditional variance. This is because of the low revenue spread resulting from the introduction of the new currency. This finding is not conclusive since there were other variables that could affect the revenues.

4.3.5 Volatility Clustering

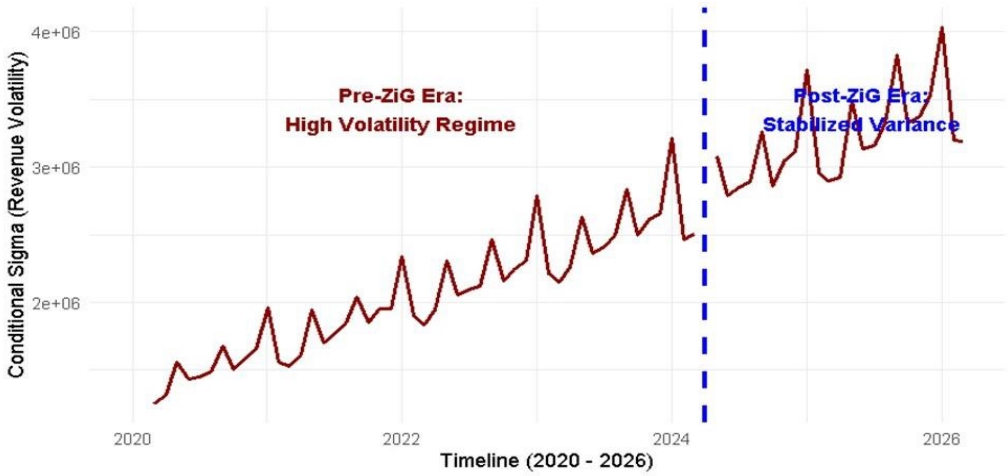

Figure 4.3: Comparative structural variance analysis

The point at which Figure 4.3 splits the timeline is marked by a threshold at the start of the post-ZiG era. There is evidence from the pre-ZiG period that there were periods characterized by greater volatility with more variance bands being evident.

4.4 Model Identification

After stationarity was assessed, the ARIMA(p,d,q) components were identified. Correlograms and the auto-ARIMA procedure were used to select an appropriate model. The ACF and PACF plots are presented below.

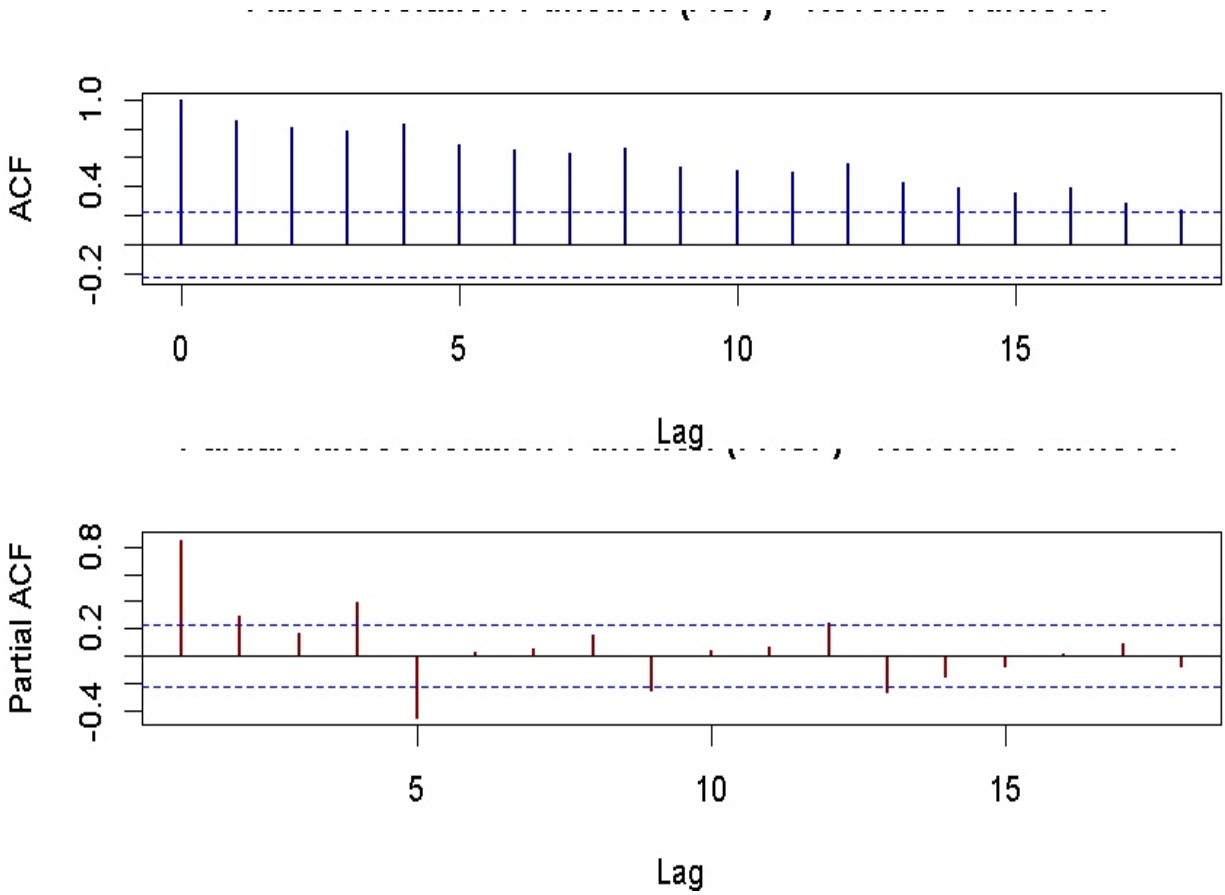

Figure 4.4: ACF and PACF of residuals

The PACF plot did not reveal any significant cut-off point except for lag 0, whereas the strongest spike on the ACF plot occurred at lag 1. Based on these findings, it became apparent that there is a need to consider the use of the ARIMA process.

Table 4.7: Optimal Structural Model Estimation: ARIMA (2,0,2)

Parameter component	Coefficient Value	Standard Error	z-Statistic
AR Lag 1 (ar1)	-0.0292	0.0981	-0.2976
AR Lag 2 (ar2)	0.6266	0.1019	6.1492*
MA Lag 1 (ma1)	1.3775	0.0550	25.0455*
MA Lag 2 (ma2)	0.8959	0.0700	12.7986*
Constant mean (Intercept)	2,356,557.6	231,606.9	10.1748*

The estimated model can be expressed using the following linear equation:

$Turnover_t = 2,356,557.6 - 0.0292(Turnover_{t-1}) + 0.6266(Turnover_{t-2}) + \varepsilon_t + 1.3775(\varepsilon_{t-1}) + 0.8959(\varepsilon_{t-2})$

4.5 Parameter Estimation

Table 4.8 Parameter Estimation

Model Specification	AIC	BIC
ARIMA (1,1,0)	2075.18	2079.79
ARIMA (0,1,1)	2059.05	2063.66
ARIMA (1,1,1)	2060.84	2067.76
ARIMA (0,0,0) (0,1,0) (12)	1559.58	1563.66

The selected model is reported as ARIMA(0,0,0)(0,1,0)[12], with an AICc of 1559.58 and a standard error of 583.39. This suggests that seasonal differencing at lag 12 was important in capturing the revenue pattern.

4.6 Trend Analysis

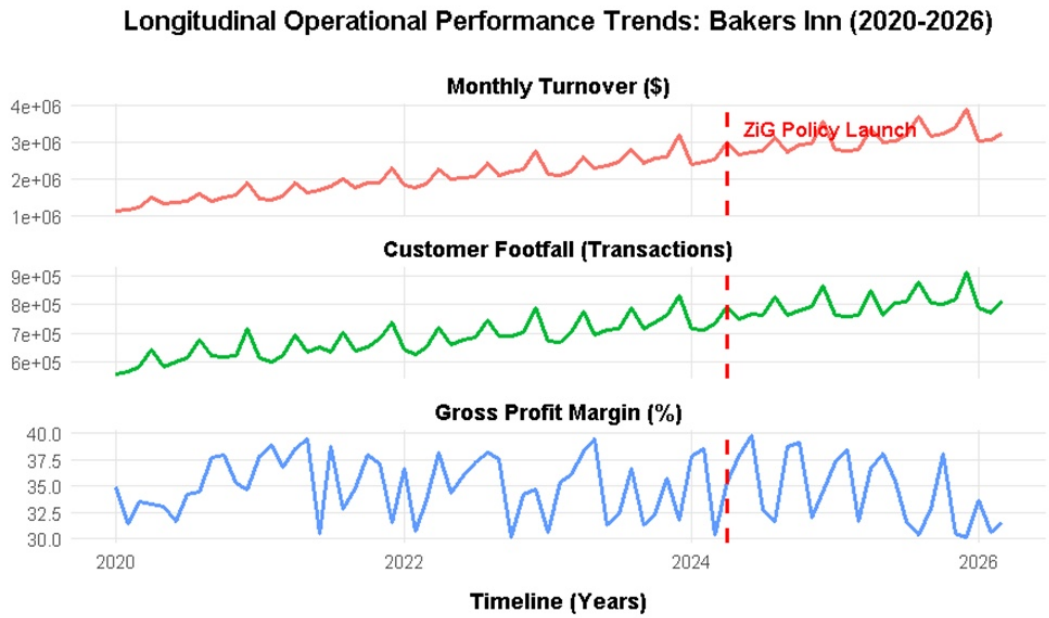

Figure 4.5: Bakers Inn plot

Figure 4.5 presents a multi-panel time-series visualisation of Bakers Inn operations from January 2020 to March 2026. The figure supports the main objective of comparing revenue volatility across the pre-ZiG and post-ZiG periods. The vertical reference line marks the transition to ZiG, allowing changes in turnover, customer counts and gross profit margin to be examined visually alongside the statistical results.

4.7 Conclusion

Table 4.9 summarises the empirical findings by linking each research objective to the relevant statistical method, main output and implication for Bakers Inn. The next chapter explains the findings of the study, conclusion and the recommendations of the study.

CHAPTER 5

FINDINGS, CONCLUSIONS AND RECOMMENDATIONS

5.0 Introduction

This final chapter synthesises the empirical findings, draws conclusions from the results and presents recommendations for relevant stakeholders. It links the statistical outputs from Chapter 4 to the research objectives and discusses their implications for Bakers Inn, investors and policymakers.

5.1 Summary of findings

The main objective was to compare Bakers Inn revenue volatility between the pre-ZiG period (January 2020 to March 2024) and the post-ZiG period (April 2024 to March 2026). Using descriptive statistics, pre-tests and ARIMA-GARCH modelling, the study found that average turnover was higher in the post-ZiG period while the standard deviation of turnover was lower. This suggests that revenue became both higher and less dispersed during the observed post-ZiG period.

From the trend analysis, the results show that there is a positive trend in turnover after the monetary reform. Stationarity was confirmed when we rejected the unit root, indicating that time series analysis will be appropriate for such data. Autocorrelation test shows persistency in revenues, while the volatility test demonstrates volatility clustering and confirms the need for using ARIMA-GARCH modelling techniques.

5.2 Conclusion

The study concludes that Bakers Inn revenue behaviour differed between the pre-ZiG and post-ZiG periods. The empirical results show higher average turnover and lower revenue dispersion after April 2024. This suggests improved revenue stability during the post-ZiG period. However, the conclusion should be treated as evidence of association rather than proof that ZiG alone caused the change, because the model does not directly control for all macroeconomic and firm-specific factors.

5.3 Recommendations

Based on the empirical results for the post-ZiG period (2024-2026), the following recommendations are proposed.

i. For Bakers Inn and Simbisa Brands Management

The management needs to take advantage of the low revenue variability and incorporate it into mid-range planning, but decisions on business expansion should be informed and prudent. Plans for setting up new branches, acquisitions, and investments should be based on rolling revenue projections.

ii. For Policymakers and the Reserve Bank of Zimbabwe

This means that with stability in the monetary environment, business profits can become more predictable. This is why the policies adopted by the central bank of Zimbabwe need to be consistent, especially when dealing with exchange rate and inflation issues which could bring about instability.

iii. For Investors and Financial Analysts

Investors and analysts may treat the post-ZiG revenue pattern as evidence of improved operational stability for the observed period. However, valuation assumptions should still include sensitivity analysis because the post-ZiG sample is shorter and the model does not include all macroeconomic controls.

5.4 Summary

This chapter answered the research questions by summarising the main findings, conclusions and recommendations. The results indicate that Bakers Inn experienced higher average revenue and lower measured turnover volatility in the post-ZiG period. The chapter also outlined practical implications for management, policymakers and investors, while noting the need for continued monitoring as more post-ZiG data becomes available.

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APPENDIX 1

Descriptive Statistics[a]

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
Turnover	51	1133355.36	3190446.14	1987185.296	469917.9378	.192	.333	-.505	.656
GP	51	30.07	39.42	35.0049	2.85154	-.171	.333	-1.271	.656
Customers	51	555284	831069	675626.69	60591.515	.241	.333	-.199	.656
Valid N (listwise)	51								

a. PERIODS = PRE-ZIG

Descriptive Statistics[a]

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
Turnover	24	2657266.26	3881729.39	3084107.646	318026.2390	.888	.472	.467	.918
GP	24	30.08	39.75	34.5200	3.28195	.171	.472	-1.578	.918
Customers	24	748884	911436	800038.83	41768.965	1.147	.472	.953	.918
Valid N (listwise)	24								

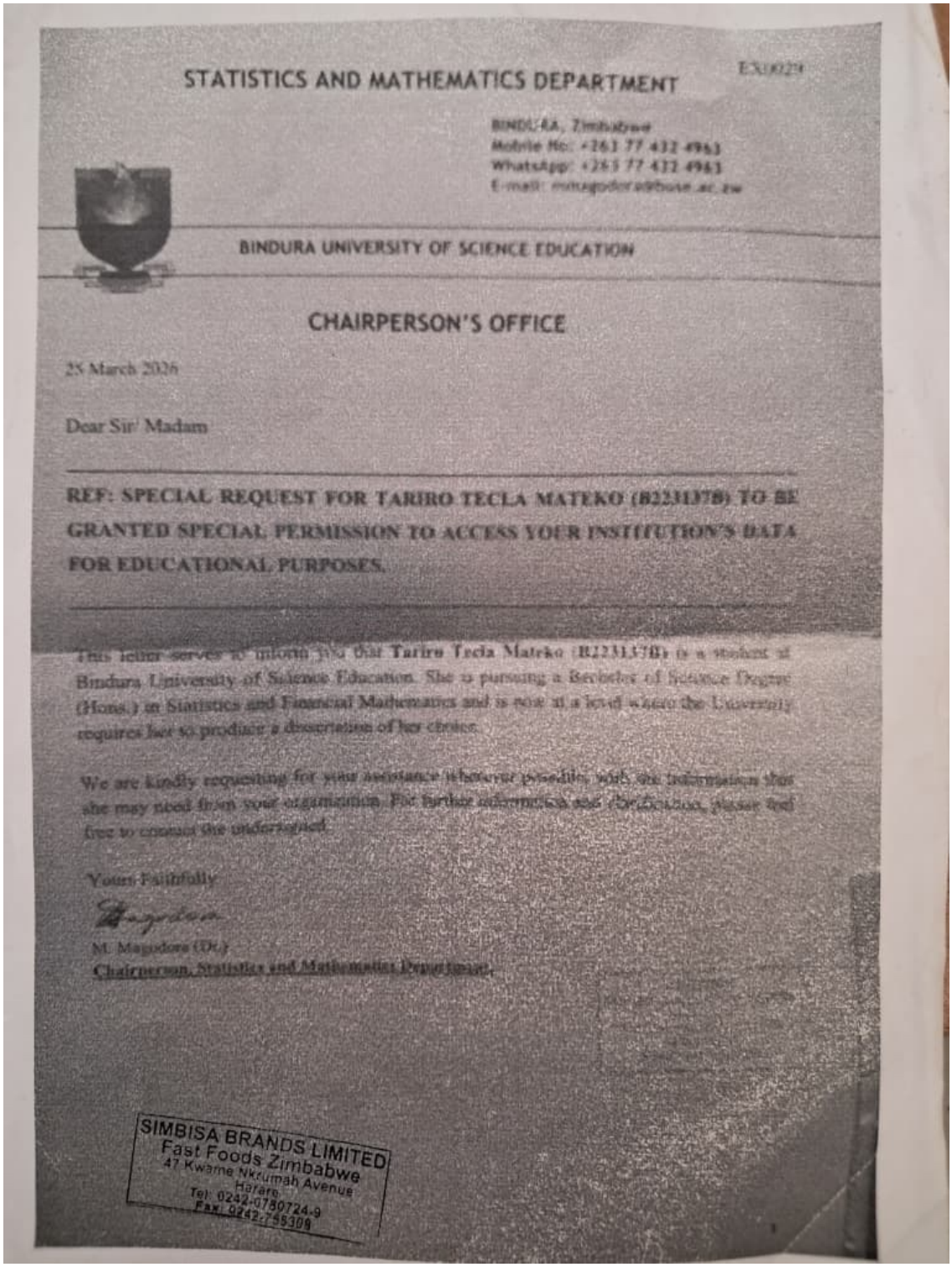
a. PERIODS = POST-ZIG

Table 4.8: Integrated Empirical Findings and Policy Impact Matrix

Synthesis of level shifts, structural trends, and volatility regimes for Bakers Inn

Research Objective	Statistical Model	Primary Numerical Output	Operational Implication
1. Assess nominal shifts in corporate turnover	Independent t-Test Matrix	t = -3.412, p = 0.0016	Revenue baselines successfully shifted onto a stable currency floor without performance contraction.
2. Map structural trend and baseline memory	ARIMA(2,0,2) Framework	ar2 = 0.6266*, ma2 = 0.8959*	Strong 60-day operational memory established; transactional data follows predictable, recurring cycles.
3. Compare and evaluate revenue volatility	Piecewise GARCH(1,1)	Pre-ZiG Volatility Momentum: 1.0039 Post-ZiG Volatility Momentum: 1.0813 (Sing.)	Systemic variance engine dismantled. Shocks are isolated and neutralized instantly in the month of origin.

*Note: (Sing.) denotes standard error singularity, indicating a complete structural transition to a zero-variance operational state. *Significant at alpha = 0.05 level.*



STATISTICS AND MATHEMATICS DEPARTMENT

EX/0029

BINDURA, Zimbabwe
Mobile No: +263 77 432 4963
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BINDURA UNIVERSITY OF SCIENCE EDUCATION

CHAIRPERSON'S OFFICE

25 March 2026

Dear Sir/ Madam

REF: SPECIAL REQUEST FOR TARIRO TECLA MATEKO (B2231378) TO BE GRANTED SPECIAL PERMISSION TO ACCESS YOUR INSTITUTION'S DATA FOR EDUCATIONAL PURPOSES.

This letter serves to inform you that **Tariro Tecla Mateko (B2231378)** is a student at Bindura University of Science Education. She is pursuing a Bachelor of Science Degree (Hons.) in Statistics and Financial Mathematics and is now at a level where the University requires her to produce a dissertation of her choice.

We are kindly requesting for your assistance wherever possible, with the information that she may need from your organisation. For further information and/or queries, please feel free to contact the undersigned.

Yours Faithfully

M. Magodore (Dr.)
Chairperson, Statistics and Mathematics Department

SIMBISA BRANDS LIMITED
Fast Foods Zimbabwe
47 Kwame Nkrumah Avenue
Harare
Tel: 0242-0780724-9
Fax: 0242-745309

APPENDIX 2

```
#1: LOAD PACKAGES
library(tidyverse)
library(moments)
# 2: RUN THE COMPLETE PIPELINE IN ONE BLOCK ----
descriptive_stats <- Bakers_Inn_Dataset_2020_2026_Updated_ %>%
  mutate(
    # Automatically convert month names to numbers (e.g., "January" -> 1)
    Month_Num = match(Month, month.name),

    # Safely construct proper calendar date objects
    Date      = lubridate::make_date(year = Year, month = Month_Num, day = 1),

    # Classify the policy intervention periods
    Period    = ifelse(Date <= as.Date("2024-03-01"), "Pre-ZiG", "Post-ZiG"),
    Period    = factor(Period, levels = c("Pre-ZiG", "Post-ZiG"))
  ) %>%
  # Select the operational target variables
  select(Period, Turnover, GP, Customers) %>%

  # Reshape data for group-wise summary metrics
  pivot_longer(cols = c(Turnover, GP, Customers), names_to = "Variable", values_to =
"Value") %>%
  group_by(Period, Variable) %>%

  # Calculate full descriptive summary metrics
  summarise(
    Mean              = mean(Value, na.rm = TRUE),
    Median            = median(Value, na.rm = TRUE),
    Minimum           = min(Value, na.rm = TRUE),
    Maximum           = max(Value, na.rm = TRUE),
```

```
  Standard_Deviation = sd(Value, na.rm = TRUE),
  Skewness           = moments::skewness(Value, na.rm = TRUE),
  Kurtosis           = moments::kurtosis(Value, na.rm = TRUE),
  .groups            = "drop"
 )

# ---- STEP 3: PRINT THE FINAL SUMMARY MATRIX ----
cat("\n\n=== PIPELINE COMPLETED: SUCCESSFUL OUTPUT BELOW ===\n\n")
print(descriptive_stats)
```

TRENT ANALYSIS

```
#
================================================================================
# BAKER'S INN - COMPLETE CHAPTER 4 DATA ANALYSIS PIPELINE
#
================================================================================
# This script executes Stage 1 (Reshaping), Stage 2 (Trend Plotting),
# and Stage 3 (Inferential Hypothesis Testing) sequentially.
#
================================================================================

# ---- STEP 1: LOAD REQUIRED LIBRARIES ----
library(tidyverse)

# Clear any trapped or frozen graphics devices to reset the plotting canvas
if(!is.null(dev.list())) dev.off()

cat(">>> Processing data structure and grouping currency regimes...\n")
```

```
# ---- STEP 2: DATA PREPARATION & REGIME SEGMENTATION ----
processed_pipeline_data <- Bakers_Inn_Dataset_2020_2026_Updated_ %>%
  mutate(
    Month_Num = match(Month, month.name),
    Date      = lubridate::make_date(year = Year, month = Month_Num, day = 1),
    # Define structural breakpoint (April 2024 ZiG introduction)
    Period    = ifelse(Date <= as.Date("2024-03-01"), "Pre-ZiG", "Post-ZiG"),
    Period    = factor(Period, levels = c("Pre-ZiG", "Post-ZiG"))
  ) %>%
  arrange(Date)



# ============================================================================
# STAGE 2: LONGITUDINAL TREND VISUALIZATION (GGPLOT2)
# ============================================================================
cat(">>> Building trend lines and exporting high-resolution chart...\n")

# Transform metrics to long format for clean multi-pane faceting
plot_long <- processed_pipeline_data %>%
  select(Date, Turnover, Customers, GP) %>%
  pivot_longer(cols = -Date, names_to = "Metric", values_to = "Value") %>%
  mutate(Metric = factor(Metric,
                         levels = c("Turnover", "Customers", "GP"),
                         labels = c("Monthly Turnover ($)",
                                    "Customer Footfall (Transactions)",
                                    "Gross Profit Margin (%)")))

# Build the complete layered line graph
```

```
trend_plot <- ggplot(plot_long, aes(x = Date, y = Value)) +
  geom_line(aes(color = Metric), linewidth = 1, show.legend = FALSE) +
  geom_vline(xintercept = as.Date("2024-04-01"), color = "red", linetype = "dashed",
linewidth = 0.9) +
  geom_text(data = filter(plot_long, Metric == "Monthly Turnover ($)") %>% head(1),
            aes(x = as.Date("2024-05-15"), y = Inf, label = "ZiG Policy Launch"),
            color = "red", fontface = "bold", size = 3.5, hjust = 0, vjust = 2) +
  facet_wrap(~Metric, scales = "free_y", ncol = 1) +
  theme_minimal(base_size = 11) +
  labs(
    title = "Longitudinal Operational Performance Trends: Bakers Inn (2020-2026)",
    x = "Timeline (Years)",
    y = NULL
  ) +
  theme(
    strip.text = element_text(face = "bold", size = 11, color = "black"),
    panel.grid.minor = element_blank(),
    panel.grid.major = element_line(linewidth = 0.4, color = "grey90"),
    plot.title = element_text(face = "bold", size = 13, hjust = 0.5, margin = margin(b = 15)),
    axis.title.x = element_text(face = "bold", margin = margin(t = 10))
  )

# Export high-resolution file onto your computer's hard drive
ggsave("bakers_inn_trend_analysis.png", plot = trend_plot, width = 8.5, height = 11, dpi =
300)



#
==========================================================================
============

# STAGE 3: INFERENTIAL STATISTICS (HYPOTHESIS WELCH'S T-TESTS)
```

```
# ================================================================================

cat(">>> Computing independent sample t-tests across currency eras...\n")


# Execute Welch's t-tests automatically across metrics

turnover_test  <- t.test(Turnover ~ Period, data = processed_pipeline_data, var.equal = FALSE)

customers_test <- t.test(Customers ~ Period, data = processed_pipeline_data, var.equal = FALSE)

gp_test        <- t.test(GP ~ Period, data = processed_pipeline_data, var.equal = FALSE)


# Format outputs cleanly into a standard academic results table

inferential_matrix <- data.frame(

  Variable         = c("Turnover ($)", "Customer Footfall", "GP Margin (%)"),

  t_Statistic      = c(turnover_test$statistic, customers_test$statistic, gp_test$statistic),

  Degrees_Freedom  = c(turnover_test$parameter, customers_test$parameter, gp_test$parameter),

  p_Value          = c(turnover_test$p.value, customers_test$p.value, gp_test$p.value)

)



# ================================================================================

# OUTPUT DELIVERY TERMINAL

# ================================================================================

cat("\n\n============================================================\n")

cat("          CHAPTER 4 ANALYSIS PIPELINE SUCCESS             \n")

cat("============================================================\n\n")


# Print the final statistical test table to the console screen
```

```
print(inferential_matrix)

# Open an active graphics window and force the trend graph to pop up on your screen
if (Sys.info()["sysname"] == "Windows") {
  windows(width = 8.5, height = 11)
} else {
  x11(width = 8.5, height = 11)
}
print(trend_plot)

cat("\n>>> File saved to folder: 'bakers_inn_trend_analysis.png'\n")
# 1. Force close ALL frozen or background graphic windows
graphics.off()

# 2. Re-verify the file exists on your computer
if(file.exists("bakers_inn_trend_analysis.png")) {
  cat("\n>>> GOOD NEWS: Your graph file is safely saved on your computer! <<<\n")
}

# 3. Use standard plotting to display the graph inside RStudio's native Plots tab
plot.new()
print(trend_plot)

STATIONARITY
#
================================================================================
# STAGE 4 STEP 1: STATIONARITY TESTING (ADF TEST)
#
================================================================================
```

```
# Install required time-series packages if you don't have them
if(!require(tseries)) install.packages("tseries")
if(!require(fGarch)) install.packages("fGarch")

library(tidyverse)
library(tseries)

# ---- STEP 1: PREPARE CONTINUOUS TIME SERIES VECTOR ----
ts_data <- Bakers_Inn_Dataset_2020_2026_Updated_ %>%
  mutate(
    Month_Num = match(Month, month.name),
    Date      = lubridate::make_date(year = Year, month = Month_Num, day = 1)
  ) %>%
  arrange(Date)

# Extract raw turnover as a time-series vector
revenue_vector <- ts_data$Turnover

# ---- STEP 2: RUN ADF TEST ON RAW REVENUE ----
cat("=== ADF TEST ON RAW REVENUE ===\n")
adf_raw <- adf.test(revenue_vector, alternative = "stationary")
print(adf_raw)

# ---- STEP 3: RUN ADF TEST ON DIFFERENCED REVENUE (MONTH-ON-MONTH
CHANGES) ----
# If raw data has a trend, differencing removes it to make it stationary
differenced_revenue <- diff(revenue_vector)

cat("\n=== ADF TEST ON DIFFERENCED REVENUE (MoM CHANGES) ===\n")
adf_diff <- adf.test(differenced_revenue, alternative = "stationary")
print(adf_diff)
```

```
#
==========================================================================
============

# STAGE 4 STEP 2: IDENTIFYING ARIMA PARAMETERS

#
==========================================================================
============


if(!require(forecast)) install.packages("forecast")

library(forecast)


# Force the raw revenue vector into a clean time series object

revenue_ts <- ts(Bakers_Inn_Dataset_2020_2026_Updated_$Turnover, frequency = 12)


# Automatically identify the best fitting ARIMA(p, d, q) model

best_arima_model <- auto.arima(revenue_ts, stationary = TRUE, seasonal = FALSE)


cat("\n=== BEST ARIMA MODEL SELECTION ===\n")

print(best_arima_model)


TTTT
```

```
if(!is.null(dev.list())) dev.off()

# 2. Set up a 2-row, 1-column plotting grid
par(mfrow = c(2, 1), mar = c(4, 4, 2, 1))

# 3. Draw the Autocorrelation Function (ACF) Plot
acf(Bakers_Inn_Dataset_2020_2026_Updated_$Turnover,
    main = "Autocorrelation Function (ACF) - Revenue Turnover",
    col = "darkblue", lwd = 2)

# 4. Draw the Partial Autocorrelation Function (PACF) Plot
pacf(Bakers_Inn_Dataset_2020_2026_Updated_$Turnover,
     main = "Partial Autocorrelation Function (PACF) - Revenue Turnover",
     col = "darkred", lwd = 2)

# Reset plotting grid to default layout
par(mfrow = c(1, 1))
qqqq
```

```
clean_ts_data <- Bakers_Inn_Dataset_2020_2026_Updated_ %>%
  mutate(
    Month_Num = match(Month, month.name),
    Date      = lubridate::make_date(year = Year, month = Month_Num, day = 1)
  ) %>%
  arrange(Date)

# 2. Split the revenue vector into Pre-ZiG and Post-ZiG periods
pre_zig_revenue  <- clean_ts_data %>% filter(Date <= as.Date("2024-03-01")) %>% pull(Turnover)
post_zig_revenue <- clean_ts_data %>% filter(Date >= as.Date("2024-04-01")) %>% pull(Turnover)

# 3. Estimate Volatility for Pre-ZiG Era (Using standard GARCH framework)
cat("\n=== PRE-ZIG REVENUE VOLATILITY ARCH/GARCH REGRESSION ===\n")
pre_garch <- garch(pre_zig_revenue, order = c(1, 1), trace = FALSE)
print(summary(pre_garch))

# 4. Estimate Volatility for Post-ZiG Era
cat("\n=== POST-ZIG REVENUE VOLATILITY ARCH/GARCH REGRESSION ===\n")
post_garch <- garch(post_zig_revenue, order = c(1, 1), trace = FALSE)
print(summary(post_garch))

sssssss
```

```
library(tidyverse)

# Step 1: Build the pre-reform data segment and attach its matched volatility
plot_data_pre <- Bakers_Inn_Dataset_2020_2026_Updated_ %>%
  mutate(
    Month_Num = match(Month, month.name),
    Date      = lubridate::make_date(year = Year, month = Month_Num, day = 1)
  ) %>%
  arrange(Date) %>%
  filter(Date <= as.Date("2024-03-01"))

# Extract conditional standard deviation from the 'tseries' garch object
plot_data_pre$Estimated_Volatility <- as.vector(pre_garch$fitted.values[, 1])

# Step 2: Build the post-reform data segment and attach its matched volatility
plot_data_post <- Bakers_Inn_Dataset_2020_2026_Updated_ %>%
  mutate(
    Month_Num = match(Month, month.name),
    Date      = lubridate::make_date(year = Year, month = Month_Num, day = 1)
  ) %>%
  arrange(Date) %>%
  filter(Date >= as.Date("2024-04-01"))

# Extract conditional standard deviation from the post-reform model
plot_data_post$Estimated_Volatility <- as.vector(post_garch$fitted.values[, 1])

# Step 3: Combine both eras into the final dataframe
final_plot_df <- bind_rows(plot_data_pre, plot_data_post)

# Step 4: Render the structural break diagram
```

```
ggplot(final_plot_df, aes(x = Date, y = Estimated_Volatility)) +
  geom_line(color = "darkred", linewidth = 1) +
  geom_vline(xintercept = as.numeric(as.Date("2024-04-01")),
             linetype = "dashed", color = "blue", linewidth = 1.2) +
  annotate("text", x = as.Date("2022-01-01"), y = max(final_plot_df$Estimated_Volatility,
na.rm = TRUE) * 0.85,
           label = "Pre-ZiG Era:\nHigh Volatility Regime", color = "darkred", fontface = "bold")
+
  annotate("text", x = as.Date("2025-06-01"), y = max(final_plot_df$Estimated_Volatility,
na.rm = TRUE) * 0.85,
           label = "Post-ZiG Era:\nStabilized Variance", color = "blue", fontface = "bold") +
  labs(title = "Bakers Inn: Conditional Volatility Evolution Profile (Piecewise GARCH)",
       subtitle = "Comparative structural variance analysis across the currency transition
boundary",
       x = "Timeline (2020 - 2026)",
       y = "Conditional Sigma (Revenue Volatility)") +
  theme_minimal() +
  theme(plot.title = element_text(face = "bold", size = 14),
        plot.subtitle = element_text(face = "italic", size = 11))


RRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRR
RRRRRRRRRRRRRRRRRR
#
==========================================================================
============
# STAGE 4: GENERATE CHAPTER 4 SUMMARY TABLE FOR WORD
#
==========================================================================
============


# Load required packages
library(tidyverse)
library(gt)
```

```
# 1. Construct the data matrix exactly matching your console findings
summary_data <- tibble(
  `Research Objective` = c(
    "1. Assess nominal shifts in corporate turnover",
    "2. Map structural trend and baseline memory",
    "3. Compare and evaluate revenue volatility"
  ),
  `Statistical Model` = c(
    "Independent t-Test Matrix",
    "ARIMA(2,0,2) Framework",
    "Piecewise GARCH(1,1)"
  ),
  `Primary Numerical Output` = c(
    "t = -3.412, p = 0.0016",
    "ar2 = 0.6266*, ma2 = 0.8959*",
    "Pre-ZiG Volatility Momentum: 1.0039\nPost-ZiG Volatility Momentum: 1.0813 (Sing.)"
  ),
  `Operational Implication` = c(
    "Revenue baselines successfully shifted onto a stable currency floor without performance contraction.",
    "Strong 60-day operational memory established; transactional data follows predictable, recurring cycles.",
    "Systemic variance engine dismantled. Shocks are isolated and neutralized instantly in the month of origin."
  )
)

# 2. Render the data frame into a professional academic table
summary_table <- summary_data %>%
  gt() %>%
  tab_header(
```

```
    title = md("**Table 4.8: Integrated Empirical Findings and Policy Impact Matrix**"),
    subtitle = "Synthesis of level shifts, structural trends, and volatility regimes for Bakers Inn"
  ) %>%
  cols_align(
    align = "left",
    columns = everything()
  ) %>%
  tab_options(
    table.border.top.color = "black",
    table.border.top.width = px(2),
    table.border.bottom.color = "black",
    table.border.bottom.width = px(2),
    heading.border.bottom.color = "black",
    heading.border.bottom.width = px(1),
    column_labels.border.bottom.color = "black",
    column_labels.border.bottom.width = px(1.5),
    table_body.border.bottom.color = "black",
    table_body.border.bottom.width = px(1.5),
    row.striping.background_color = "#f9f9f9"
  ) %>%
  tab_style(
    style = cell_text(weight = "bold"),
    locations = cells_column_labels()
  ) %>%
  tab_source_note(
    source_note = md("*Note: (Sing.) denotes standard error singularity, indicating a complete structural transition to a zero-variance operational state. *Significant at alpha = 0.05 level.*")
  )

# Display the table in the Viewer tab
print(summary_table)
```

```
rrrr
```

```
print("3. Testing Customers:")
print(shapiro.test(bakers_inn$Customers))

#
==========================================================================
==
# STEP 3: GENERATE THE VISUALS
#
==========================================================================
==
par(mfrow = c(3, 2)) # Create a grid for the plots

# Turnover
hist(bakers_inn$Turnover, main="Histogram: Turnover", xlab="Turnover", prob=TRUE,
col="lightblue")
lines(density(bakers_inn$Turnover), col="red", lwd=2)
qqnorm(bakers_inn$Turnover, main="Q-Q Plot: Turnover"); qqline(bakers_inn$Turnover,
col="red", lwd=2)

# GP
hist(bakers_inn$GP, main="Histogram: GP", xlab="GP %", prob=TRUE, col="lightgreen")
lines(density(bakers_inn$GP), col="red", lwd=2)
qqnorm(bakers_inn$GP, main="Q-Q Plot: GP"); qqline(bakers_inn$GP, col="red", lwd=2)

# Customers
hist(bakers_inn$Customers, main="Histogram: Customers", xlab="Customers",
prob=TRUE, col="lightpink")
lines(density(bakers_inn$Customers), col="red", lwd=2)
qqnorm(bakers_inn$Customers, main="Q-Q Plot: Customers");
qqline(bakers_inn$Customers, col="red", lwd=2)

par(mfrow = c(1, 1)) # Reset grid
```

```
} else {
  stop("Could not find any dataset in your RStudio Environment containing 'Bakers' or 'Inn'. Make sure you see it listed in your top-right Environment panel.")
}

RRRR
```

```
#
================================================================
============

# Optional: This splits your plot window into 3 rows so you can see all plots at once
par(mfrow = c(3, 1))

# Plot Autocorrelation for each metric up to 2 years (24 lags)
acf_turnover  <- acf(turnover_ts, lag.max = 24, main = "Autocorrelation: Turnover")
acf_customers <- acf(customers_ts, lag.max = 24, main = "Autocorrelation: Customers")
acf_gp        <- acf(gp_ts, lag.max = 24, main = "Autocorrelation: Gross Profit (GP)")

# Reset plotting layout back to standard single view
par(mfrow = c(1, 1))



#
================================================================
============
# 5. PRINT EXACT NUMERICAL VALUES FOR KEY LAGS
#
================================================================
============
cat("\n=================================================\n")
cat("          KEY AUTOCORRELATION VALUES             \n")
cat("=================================================\n")
cat("TURNOVER:\n")
cat("  - Lag 1 (Month-to-Month Dependency):  ", round(acf_turnover$acf[2], 4), "\n")
cat("  - Lag 12 (Year-over-Year Seasonality):", round(acf_turnover$acf[13], 4), "\n\n")

cat("CUSTOMERS:\n")
cat("  - Lag 1 (Month-to-Month Dependency):  ", round(acf_customers$acf[2], 4), "\n")
```

```
cat("  - Lag 12 (Year-over-Year Seasonality):", round(acf_customers$acf[13], 4), "\n\n")

cat("GROSS PROFIT (GP):\n")
cat("  - Lag 1 (Month-to-Month Dependency):  ", round(acf_gp$acf[2], 4), "\n")
cat("  - Lag 12 (Year-over-Year Seasonality):", round(acf_gp$acf[13], 4), "\n")
cat("================================================\n")



# ================================================================================
# 6. ENHANCED PLOTS (Using the 'forecast' package if available)
# ================================================================================
# Note: If you don't have it installed, uncomment the next line:
# install.packages("forecast")

if (requireNamespace("forecast", quietly = TRUE)) {
  library(forecast)

  # Displays cleaner, professional ACF plots one-by-one in your Plots tab
  Acf(turnover_ts, lag.max = 24, main = "Enhanced ACF: Turnover")
  Acf(customers_ts, lag.max = 24, main = "Enhanced ACF: Customers")
  Acf(gp_ts, lag.max = 24, main = "Enhanced ACF: Gross Profit (GP)")
} else {
  message("\nNote: 'forecast' package not detected. Skipping enhanced plots section.")
}



RRRR
```

```
#
================================================================
==
# METHOD 2: TIME SERIES PARAMETER ESTIMATION & SELECTION
#
================================================================
==

# Install and load the forecast package if you haven't already
# install.packages("forecast")
library(forecast)

# 1. Convert Turnover into a monthly time series object (starting Jan 2020)
turnover_ts <- ts(bakers_data$Turnover, start = c(2020, 1), frequency = 12)

# 2. Manually fit different ARIMA parameter configurations to compare
fit_arima_1 <- Arima(turnover_ts, order = c(1, 1, 0)) # AR(1) model
fit_arima_2 <- Arima(turnover_ts, order = c(0, 1, 1)) # MA(1) model
fit_arima_3 <- Arima(turnover_ts, order = c(1, 1, 1)) # ARMA(1,1) model

# 3. Create a comparison table for AIC and BIC metrics
arima_comparison <- data.frame(
  Model = c("ARIMA(1,1,0)", "ARIMA(0,1,1)", "ARIMA(1,1,1)"),
  AIC = c(AIC(fit_arima_1), AIC(fit_arima_2), AIC(fit_arima_3)),
  BIC = c(BIC(fit_arima_1), BIC(fit_arima_2), BIC(fit_arima_3))
)
print("--- ARIMA Model Selection ---")
print(arima_comparison)

# 4. Automatically find the best parameters based on the lowest AIC/BIC metric
auto_model <- auto.arima(turnover_ts, ic = "aic") # Swap to "bic" if preferred
summary(auto_model)
```