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THE IMPACT OF FOOD WASTE ON REVENUE POTENTIAL IN RESTAURANTS: A CASE OF ROCOMAMAS' (SIMBISA BRANDS ZIMBABWE)

BY

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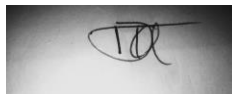
APPROVAL FORM

I, Denzel Gombarago, declare that this submission is my work apart from the references to other people’s work, which has duly been acknowledged. I hereby declare that this work has been presented neither in whole nor in part for any degree at this university or elsewhere.

Denzel Gombarago. T  12-06-2024 ....

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DEDICATION

I dedicate this work to my family.

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I thank the Lord Almighty God the provider of knowledge and wisdom for seeing me through my studies and for enabling me to undertake my research successfully for without His grace I would not have made it. I extend my deepest appreciation to my supervisor Dr. M. Magodora for the guidance and detailed insights he provided during the study that made it possible for me to tackle this report. I am greatly indebted to the staff of Simbisa Brands for their aid and cooperation in the provision of the needed information vital for this research. I wish to express my sincere gratitude to all those who made tremendous contributions to this study. To my family and classmates, I extend my heartfelt thanks for your encouragement and moral support.

ABSTRACT

The major objective of the research is to determine the impact that food waste has on revenue in restaurants as compared to other factors for the period January 2021 to December 2023, using the ADF test, Johansen test, Vector Autoregression model, Granger causality and Pearson correlation coefficient. The findings of the ADF revealed that revenue, food cost and inflation were stationary at level, while food waste and exchange rate were stationary at first differencing. The Johansen test findings indicated that the impact of food waste, food cost, inflation and exchange rate is noted only in the short run, which led to the implication of the VAR model. The results of the VAR indicated that food waste positively influences revenue if reincorporated back as a source of income. Granger causality reaffirmed the notion provided by the VAR as the results revealed that the lagged food waste values are able to explain variation in revenue, while the lagged exchange rate value explains a variation in inflation.

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ADF	Augmented Dickey Fuller
CalRecyle	California Department of Resources Recycling and Recovery
CPI	Consumer Price Index
EPA	United States Environmental Protection Agency
FAO	United Nations Food and Agriculture Organization
FSC	Food Supply Chain
MSC	Management Control System
RBZ	Reserve Bank of Zimbabwe
UK	United Kingdom
USDA	United States Department of Agriculture
VAR	Vector Autoregressive
VIF	Variance Inflation Factor
WMT	Waste Management Theory
WRAP	Waste and Resource Action Programme

CHAPTER 1: INTRODUCTION

1.0 Introduction

The FAO estimates that approximately one-third (1300 tons) of globally produced food is lost or wasted (FAO, 2019). This study focuses on revenue potential in restaurants, examining both internal (food waste) and external factors (food cost, inflation, and exchange rate), with a primary focus on the overall impact of the wasted value of food and this chapter introduces the basics of the study that the researcher looked into.

1.1 Background of the study

Food waste has emerged as a critical issue in the global food system, with significant implications for environmental sustainability, economic efficiency, and social equity. The restaurant industry, a key player in the food supply chain, contributes substantially to this problem. While the economic and environmental impacts of food waste have been extensively studied, the specific influence of food waste on restaurant revenue potential remains an under-explored area.

Previous research has primarily focused on the overall economic costs of food waste, highlighting its impact on food security, resource depletion, and greenhouse gas emissions (FAO, 2014). Studies have quantified the financial losses associated with food waste across the entire food supply chain, including production, processing, distribution, and retail (Gustavsson et al., 2011). However, these studies often provide aggregated data without delving into the specific consequences for individual businesses, such as restaurants.

While the restaurant industry has recognized the importance of sustainability and waste reduction, the financial benefits of implementing effective food waste management strategies are not fully understood. Although some studies have explored the cost-saving potential of reducing food waste in restaurants (Lean Path, 2016), there is a scarcity of research that directly links food waste to revenue generation.

To address this gap, this study aims to investigate the specific impact of food waste on restaurant revenue potential. By examining the relationship between food waste levels and financial performance, this research seeks to provide valuable insights for restaurant operators, policymakers, and stakeholders in developing strategies to mitigate food waste and enhance profitability.

1.2 Statement of the problem

Restaurants represent a profitable business venture that typically operates on narrow profit margins. Success in this industry is dependent on efficient stock management and operations to drive profits. As such the management control system compiles a turnover or revenue budget that must be met to realize these desired profits to maintain the day-to-day activities. Most restaurants fail because the actual revenue is usually significantly lower than what is projected in their budgets.

The lack of consistency in failing to achieve goals is often due to external factors such as competitive pricing in the industry, while internal issues that could significantly boost revenue are being overlooked. The phenomena in question is indeed wasted potential in the form of food value. Setting aside the fact that a revenue budget can be achieved or not, the issue of wasted food from restaurants is not thoroughly studied in this particular situation, which hinders the comprehension of what leads to it and its impact, especially in transitioning economies where the number of people eating out is increasing. This research adds to our understanding by examining how restaurants in Zimbabwe handle food waste, a country in Southern Africa that is going through a period of transition and development.

1.3 Objectives of the study

The paramount objectives of this project are:

1. To find the most appropriate definition for food waste within the research framework.
2. To unearth how restaurant waste is tallied and quantified.
3. To examine how much of an impact food waste has on revenue realization in a restaurant as compared to other factors

1.4 Research questions

1. Does the definition of food waste prescribe how it emerges and how it is treated in restaurants?
2. Is it safe to assume that the existing categorisation and quantification means of food waste are the same for all stakeholders in the food industry?
3. How much of an impact does the food waste value have on revenue compared to other factors and is it significant enough to be considered?

1.5 Significance of the study

The researcher's study contributes to a gap in the internal management system of a restaurant's affairs, referred to as wasted potential. As research is only limited to the food waste value, this amount has been theorized as a form of undocumented loss that is unaccounted for in a restaurant's cash flow in Zimbabwe. It is therefore the researcher's goal to unravel this mystery or theory through profound fundamental application of econometric models. Hidden the fact may be, the research contributes more to also prove that internal restaurant budgetary revenue-related constraints can be solved in the short run to never create an unprofitable lag in the long run, which coincides more with the developing economy in question, that is, Zimbabwe.

1.6 Hypothesis of the study

In carrying out this research, the hypothesis is put into effect:

H_0: Food waste has impact on revenue potential compared to other factors

H_1: Food waste has no impact on revenue

1.7 Limitations of the study

Due to a lack of practical studies, it is challenging to accurately establish the complete extent of food waste in the restaurant industry (Fillimonau and de Coteau, 2019). The definition of food waste poses a challenge for managers as there is ambiguity between food loss and food waste, making the term "wasted food" a more suitable way to emphasize human behaviour in creating waste (Neff et al, 2015).

In this case, food waste assessments in restaurants are often based on rough estimates of the actual amount of waste produced. For instance, managers may estimate waste by looking at the number of rubbish bins filled over a certain period. However, this approach fails to account for the true value of the discarded food, making it difficult to accurately analyze the data in the future.

Secondly, gathering primary data on food wastage is a challenge due to the wide variety of restaurants in Zimbabwe. This leads to discrepancies in the information regarding the quality and characteristics of wasted food between establishments, making it difficult to generalize about the entire sector. Furthermore, basing assumptions on one restaurant's food wastage makes it tricky to predict or assess the overall performance of the sector as a whole.

Moreover, the substantial differences in the geographical market for takeaway food present another constraint. This indicates that data on food waste in the restaurant industry of one country cannot be extrapolated to accurately portray the restaurant sector in another country. This limitation highlights the lack of extensive research on food waste in transitioning economies compared to developed nations. Consequently, the criteria for modelling food waste cannot be applied uniformly across all regions.

1.8 Conclusion

The opening chapter of the study carefully outlined the topic and main focus of the research. It discussed the background information that inspired the researcher to conduct the study, as well as the significance and limitations. The chapter emphasized the importance of addressing food waste issues in Zimbabwe. The problem statement clearly defined the challenges that need to be addressed, with research objectives aimed at finding solutions.

CHAPTER 2: LITERATURE REVIEW

2.0. Introduction

Food waste analysis is a topic that has captured the interest of many researchers in the food industry, leading to extensive research in developed countries. Most of this research focuses on identifying the causes and consequences of food waste. However, there is a lack of literature on the risk of food waste in restaurants and models for analyzing the impact of food waste on revenue in emerging economies, particularly in Zimbabwe. This research seeks to fill this void by building on existing research on food waste management. The researcher draws on various authorities to provide insights and choose a suitable model for the study.

2.1 Theoretical literature review

2.1.1 Waste Management Theory (WMT)

The Waste Management Theory (WMT) suggests that the way we define a target determines how we act towards it. This means that the amount of food waste generated is heavily influenced by how we categorize it (Pongracz E., 2002). Therefore, variations in definitions have a significant impact on how research studies are designed and how data is collected, analyzed, and interpreted. There are conflicting opinions on what constitutes waste, especially at the source (Phillips P.S. et al., 2002). This has led to the development of a dual concept that distinguishes between food loss and waste; however, consensus on this issue has not been reached. Generally speaking, there are two primary groups of definitions: one that centres on monitoring food losses and waste across the supply chain, and another that distinguishes between edible and inedible food losses and waste.

2.1.2 Food waste and revenue

The USDA in 2020 described food waste as a subset of food loss that occurs when edible food is not consumed, thus capturing the dollar value discarded or thrown away at the retail or consumer level. The subsequent explanation illustrates the impact of food waste on income.

2.1.2.1 The lean path theory

This theory essentially centres on pinpointing value streams and systematically removing waste during the production process to ensure a continual flow of high-quality value to the end consumer (Lennon, 2020). It proposes that by adopting effective food waste management strategies, such as controlling portions, tracking inventory, and optimizing menus, restaurants can cut down on expenses linked to discarded food and enhance their overall profitability.

2.1.3 Food cost and revenue

As stated by Chibili in 2017, expenses related to food can be seen as a necessary cost to generate income within a fully functioning operation. While the term "cost" typically conveys a negative connotation, suggesting a mere burden, in this context it holds a different significance. It is important to differentiate between standard costs and actual costs. Standard costs indicate the expected cost of a product or service based on a specified sales volume, serving as a reference point for comparing actual costs (Chibili, 2017). Actual costs refer to expenses incurred, as opposed to those budgeted or predicted (Datar & Rajan, 2017).

2.1.3.1 Gross Profit Margin Theory

In adherence to this theory, the gross profit margin is determined by deducting the cost of goods sold (incorporating food expenses) from overall revenue. It further elaborates that a greater gross profit margin suggests that a restaurant can price its menu items higher compared to its production cost, resulting in the possibility of increased revenue (Nariswari & Nugraha, 2020).

2.1.3.2 Menu Engineering Theory

This theory presents a strategic method for designing menus and setting prices to maximize revenue by evaluating the popularity, profitability, and variety of menu items (Kasavana & Smith, 1982). It introduces a four-part menu matrix that categorizes dishes based on their sales volume and contribution margin (revenue minus food cost). Dishes that fall under the category of "stars" are products that not only generate a high sales volume but also have a high contribution margin (Dittmer & Keefe, 2009), while "plough horses" are popular items despite having a lower contribution margin (Chibili, 2017). "Puzzles" are profitable but have low sales volume, and "dogs" are items that are neither popular nor highly profitable (Ojugo, 2010). By examining the contribution margin of each menu item, restaurants can make pricing adjustments or promote specific items to maximize overall revenue and profitability.

2.1.4 Inflation and revenue

Inflation is described as the pace at which prices rise within a specific timeframe, typically within a year. It gauges the extent to which a collection of goods and services has risen in cost over a specific period (Olusola et al., 2022). Here, we explore some of the inflation theories that are pertinent to the research.

2.1.4.1 Cost-push inflation theory

Based on this theory, inflation happens when production costs rise, like raw materials or input expenses, resulting in price increases (Mankiw, 2016). Consequently, restaurants may need to increase their menu prices to sustain their profit margins. This could result in decreased demand for meals if customers are not willing or able to pay more, ultimately affecting a restaurant's revenue potential.

2.1.4.2 Income Effect Theory

Marshall (1890) presented this theory suggesting that a variation in price causes a corresponding adjustment in the quantity demanded, as consumers modify their consumption habits to uphold their standard of living. The purchasing power of consumers can be weakened by inflation, as their incomes fail to increase at the same rate as prices (Blanchard et al., 2017), leading to a potential decrease in revenue for restaurants as consumers may reduce their dining out frequency or choose cheaper options.

2.1.5 Exchange rate and revenue

An exchange rate refers to the value of a single unit of foreign currency to the local currency (Bradley and Moles, 2002). Essentially, it acts as the fundamental connection between the domestic and international markets for different products, services, and financial assets (Okika Christian, Francis, & Greg, 2018). A company's revenues can be impacted by the exchange rate through transactions, translations, and economic exposures. The effect is explained by the trade channel and financial channel theories about how a company performs in an economy with a fluctuating exchange rate. While the financial channel may not directly address this idea, evidence indicates that it indirectly implies the presence of the trade channel.

2.1.5.1 The financial channel

The influence of fluctuations in exchange rates on the financial well-being of a company or a nation becomes evident in its balance sheet when there is a discrepancy in the currencies of its assets and liabilities (Lane & Shambaugh, 2010). Subsequently, Kearns and Patel (2016) developed comparable debt-weighted effective exchange rates and discovered that the effects of exchange rate changes on trade are counterbalanced to some extent by financial implications, especially in emerging market economies.

2.1.5.2 The trade channel

Belghitar and colleagues (2021) suggest that the trade channel concept stems from the elasticities and absorption approach within the balance of payments theory. This theory highlights the impact of exchange rate fluctuations on individual firm performance via changes in relative prices, income distribution, and their influence on suppliers, customers, and competitors.

2.2 Empirical literature

2.2.1 The definition of food waste and how it is treated

In an attempt to define food losses and waste within the food value chain, the FAO initially described food loss as the loss, degradation, or consumption of food products intended for human consumption by pests at any point in the food chain (FAO, 2011). In 2011, the FAO also made a clear demarcation between food losses and waste. Food losses happen during production and processing because of logistical and infrastructural issues, whereas food waste occurs at the end of the food chain during distribution, sale, and consumption, mainly because of behavioural factors (FAO, 2011).

Grolleaud emphasizes that food loss pertains to the reduction in the quality of food, rendering it unsuitable for human consumption (Groulleaud, 2002). However, in 2011, Parfitt et al adopted this explanation and extended food waste, focusing on the later stages of the food supply chain. They suggest that food waste is primarily linked to behavioural issues, while food losses are connected to the need for infrastructural investment. The Agricultural and Rural Commission of the European Parliament later that year provided a comprehensive definition of food waste, describing it as all discarded products within the food supply chain. These products may be edible and intended for human consumption but are eliminated due to aesthetic reasons or proximity to their expiry date.

This leads to negative impacts from an environmental standpoint, as well as financial losses and potential income foregone by businesses (European Parliament, 2011).

The second set of definitions differentiates between food losses and waste that are suitable for consumption and those that are not. For instance, the Environmental Protection Agency (EPA, 2015) in the United States defines food waste as uneaten food and food waste generated during food preparation in households and commercial establishments like grocery stores, bars, and restaurants. The California Department of Resources Recycling and Recovery describes food waste as food scraps, encompassing any leftover food including excess production and unsold items. This definition specifically includes food that can be eaten but is thrown away since it is not consumed by the end user, along with scraps that are not fit for consumption.

2.2.2 The magnitude, categorization, and main factors influencing food wastage

Due to the lack of precise numbers provided by scholars, there have been several industry reports that have emerged to detail the occurrence and somewhat contested categorization of food waste in restaurants (Filimonau et al., 2020). According to an article by the Waste and Resources Action Programme in 2013, food waste in restaurants primarily stems from three key processes: food preparation (45%), customer leftover food on plates (34%), and spoilage during transportation and on-site (21%). In contrast, Winnow (2018) has definitively stated that over 70% of food is discarded before it even makes it to the customer's plate during the serving process, largely due to an excess supply of food and overproduction of meals during food handling.

Winnow's findings in 2018 supported the idea that there is a clear link between food wastage and the way food is stored and managed per WRAP (2013a) guidelines. This link was created by putting into practice operational methods such as forecasting consumer needs and maintaining a consistent turnover of goods. These actions were thought to play a crucial role in decreasing food waste resulting from spoilage. However, despite the apparent simplicity of these operational strategies, they are quite challenging for managers to implement due to the seasonal fluctuations and unpredictable nature of consumer food preferences in restaurants (Papagyropoulou et al., 2016).

Filimonau and colleagues (2019) conducted a study through interviews in Bulgaria to explore how restaurant managers assess and describe food wastage. Despite their efforts, none of the participants provided specific numbers and instead used qualitative terms like "significant", "large" or "manageable". This lack of precise figures was downplayed to focus on other important operational tasks such as revenue management and customer satisfaction. However, research by Sakaguchi and team (2018) in the United States presented a different perspective, showing that restaurant owners in California regularly measure their food waste. This was attributed to the support provided by local government authorities, particularly through training sessions for restaurant managers on how to quantify the main food waste stream in their establishments (Sakaguchi et al., 2018). Leverenz and colleagues' study in 2019 further reinforced Sakaguchi's findings by demonstrating that receiving guidance on reducing food waste significantly reduces the amount of wasted food by over 50%.

In 2016, Visschers et al. highlighted the significant body of literature surrounding people's attitudes toward food waste in the fields of consumer behaviour and environmental psychology. Research into the main causes of food waste in restaurants has shown that customers are often blamed (Filimonau et al., 2019). Despite this, it has been found that customers' plates only contribute to less than half of the food waste in restaurants (Winnow, 2018), leading to suggestions that restaurant managers may try to shift blame onto consumers. Additionally, it is noted that restaurants play a crucial role in influencing consumption habits and can promote more responsible practices by using behavioural economics principles to address food loss and waste (Filimonau, Lemmer, Marshall & Bejjani, 2017). However, despite this potential, many are reluctant to try and change customer behaviour towards food waste due to fears of negative responses from customers and potential loss of loyalty (Filimonau et al., 2019).

2.2.3 More Detailed Literature

Rutten (2013) argued that reducing food waste has its advantages as it can lower production costs and increase incomes for producers through repurposing and selling surplus food. As a result, this could lead to reduced food prices and higher savings for consumers. Chaboud and Daviron (2017) backed the notion of decreasing food wastage, yet highlighted the lack of comprehension regarding the economic compromises encountered by those involved. Lusk and Ellison (2017) contended that numerous assessments of food wastage perceive it as an error rather than an economic event impacted by preferences, rewards, and limitations. This suggests that consumers and producers have limitations in terms of time and resources, making it impractical to rescue every piece of food. Britz et al. (2019) also noted that reducing food waste will have distributional effects as it will lead to a redistribution of wealth and income, particularly affecting those in the food production and service industry. This shows that deciding on whether to retain or discard food is not always a simple decision, as different factors need to be taken into account from the viewpoints of the producer, consumer, and economy.

Cost is seen as the investment or opportunity lost to achieve a specific goal, typically quantified as the amount of money needed to purchase goods or services (Datar & Rajan, 2017). In the realm of management accounting, cost is perceived as an expenditure required to generate income (Chibili, 2017). Dopson and Hayes (2016) explained that the total cost of food sold encompasses all expenses related to food, including purchasing raw materials, whether the food was consumed by guests, stolen, discarded due to errors, or spoiled. Given that the majority of revenue in hospitality businesses goes towards covering expenses (Chibili, 2017), effectively managing costs is crucial for maintaining financial equilibrium and achieving profitability.

Monitored expenses in the food industry in the UK include the costs associated with acquiring packaging and condiments, beverages, and the food cost of a meal (Rigas, 2018). Therefore, to accurately measure these costs, it is important to understand how costs behave, particularly how they change with different levels of activity. As activity levels go up or down, certain costs may also increase or decrease. However, Rigas (2018) also noted that costs for standardized recipes, which are part of the overall food cost, typically remain stable throughout a season unless there is a significant change in market prices or if a specific ingredient is unavailable and a substitute is required. In such cases, recalculations are necessary for accurate cost reporting. It's crucial to understand that the food cost percentage has a significant effect on the overall gross profit percentage. These two factors are closely connected, as an increase in food costs results in a decrease in gross profit.

Inflation is currently one of the most closely watched macroeconomic indicators. High inflation can lead to higher prices for goods and raw materials, which in turn increases production costs and decreases demand for products (from the perspective of producers). This can result in declining sales, reduced business income, and a negative impact on expected returns. In essence, inflation not only impacts stock returns but also affects the profitability of businesses (Sanusi & Wiayanti, 2022). Additionally, as Belanova (2023) points out, inflation's effects, such as rising prices for goods and services, affect both companies and households. If income growth does not keep pace with inflation, these negative effects can become more pronounced. Research conducted by Bhutta and Hasan (2013) has shown a strong correlation between inflation and businesses' profitability, although the significance of this relationship may vary depending on how businesses manage their expenses relative to inflation (Terstena et al., 2023).

The economic literature has long recognized that inflation can impact economic behaviour, with individuals demonstrating different behaviours in high and low inflation scenarios (Basu et al., 2010). Some studies suggest that higher inflation and inflationary expectations can lead to an increase in consumer spending, while others indicate that these factors may have minimal to no effect on consumer spending (Olusola et al., 2022). Consumers may boost their current spending if they believe inflation rates will rise, thanks to a wealth redistribution mechanism (Olusola et al., 2022). Therefore, it is important to have effective management in place to control inflation, ensuring low and stable inflation rates and helping organizations achieve their goals efficiently.

The fluctuating exchange rate increasingly influences the performance of businesses, impacting their domestic pricing, profits, distribution of resources, and choices regarding investments (Okika Christian, Francis, & Greg, 2018). Belghitar et al. (2021) highlight that a devaluation of the currency has the potential to enhance the profitability of exporting companies by increasing the competitiveness of their products in international markets. Nevertheless, their earnings could experience an impact if they bring in intermediate goods, due to the depreciation leading to increased domestic prices and production expenses. This is similar to how food costs in restaurants can increase. Watkins (2014) explains that exchange rate fluctuations directly impact import prices, producer prices, and the consumer price index (CPI), affecting a country's overall price levels through imported consumption and intermediate goods.

However, how these changes affect the consumer price index (CPI) depends on how much of the consumption basket consists of imported goods. This means that if a decrease in currency value leads to increased prices for imported products, there will be a rise in demand for local products that compete with imports. Consequently, as demand goes up, there will be a positive effect on domestic prices and nominal wages (Okika Christian, Francis, & Greg, 2018).

From a broad perspective, it is evident that this can impact customer behaviour, prompting them to seek alternative options or adjust their spending habits, resulting in lower revenue for a business, such as a restaurant, unfortunately, is beyond the control of the business. Nonetheless, many businesses may adopt a strategy known as pricing-to-market, where they maintain their prices but adjust the markup when exchange rates fluctuate. Essentially, businesses may accept temporary losses in revenue to retain their market share against competitors. (Okika Christian, Francis, & Greg, 2018).

2.3 Research gap

It is worth noting that there has been a gradual rise in the number of studies focusing on food waste management in the food service sector (Filimonau and de Coteau 2019), reflecting a growing concern from the public and academics about the significant global issue. Existing research has primarily used quantitative methods such as surveys and analysis of mass flow to measure, categorize, and describe food waste in restaurants (Betz et al. 2015; Christ and Burritt 2017). Additionally, qualitative approaches, including interviews with managers and staff, have been utilized to investigate managerial attitudes toward food waste reduction and to assess the effectiveness of different mitigation strategies in restaurants (Derqui et al. 2016; Goh and Jie 2019; Filimonau et al. 2019a).

This research focuses on how managers in restaurants can reduce food waste, using qualitative research to explore the quantitative side of the issue. Filimonau et al. (2019) briefly mentioned the potential for businesses to grow by reusing wasted food to generate revenue. The European Parliament defined food waste as a missed opportunity for companies to make money in 2011. This study specifically looks at how this concept applies to restaurants in developing countries like Zimbabwe. By filling a gap in the existing literature, this research aims to investigate and address the potential for restaurants to increase their revenue by properly managing food waste.

2.4 Conceptual framework

For this study, the proposed model explains several variables that determine a restaurant's revenue. Figure 2.2 shows a simplified conceptual framework that shows the relationship between revenue and its determinants. The conceptual framework is aimed at enhancing a quick understanding of the proposed determinants of revenue to the reader as inflation and exchange rate influence each other in a way but both affecting food cost directly as well food waste affecting food cost which in turn impacts revenue.

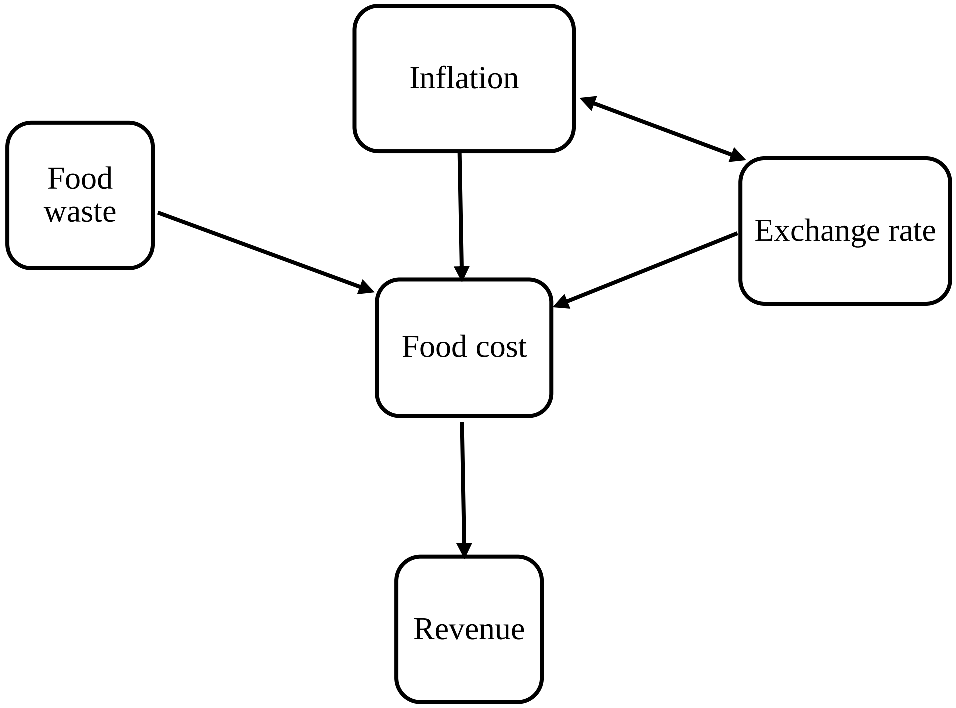

Figure 2.2 Conceptual framework model (source: Researcher's design, 2024)

2.5 Conclusion

This chapter discussed the theories that explain the roots of food waste and food waste management, the behaviours linked to it, and the mitigation approaches that were proposed and mainly disputed over. The theoretical framework of food waste generation was briefly discussed emphasizing key areas and connections in some of the research paradigms' inner details. Empirical proof regarding the extent and key factors influencing food waste was also detailed.

CHAPTER 3: METHODOLOGY

3.0 Introduction

This chapter presents a structure for researching to evaluate the influence of food waste and other elements, such as inflation, exchange rates, and food expenses, on revenue when not addressed in both the short and long term. Additionally, it discusses research methodology, data analysis techniques, and data sources. To accomplish this, techniques such as the vector autoregressive (VAR) model and Johansen cointegration are employed.

3.1 Research design

This investigation utilised a quantitative methodology with an explanatory (causal) approach. This method is used to determine the extent and nature of cause-and-effect relationships, specifically how one variable influences another. While causal research design aids in better understanding the issue at hand, it does not offer definitive proof. This approach is particularly suitable when there is a need to delve deeper into understanding, explaining, predicting, and managing relationships among factors beyond superficial analysis. Casual research can be carried out to evaluate the effects of particular alterations on established standards, different processes, and other aspects (Yin, 2009).

3.2 Population and Sampling

The study focused on the population of the Rocomamas brand, owned by Simbisa Brands in Harare, Zimbabwe. This particular franchise was chosen because it carries out food portioning in-house, leading to food waste that impacts the restaurant's potential revenue. Critical case sampling, a type of purposive sampling was employed in the study. This approach entails choosing a limited number of important cases that are expected to offer valuable insights and make a significant contribution to the expansion of knowledge. This sampling approach was chosen because it allows the researcher to draw meaningful conclusions from the evidence gathered while studying a few specific cases (Patton, 2014).

3.3 Data source

There are various sources of data, with secondary data being one of them. Analysts of social and economic change view secondary data as crucial, as it is not feasible to conduct a new survey that can effectively capture past trends (Saunders et al., 2012). This research utilizes secondary data, specifically monthly time series data spanning 36 months from January 2021 to December 2023 collected from Rocomamas and the Reserve Bank of Zimbabwe (RBZ).

3.4 Data collection

The student wrote a formal letter to Simbisa Brands requesting access to Rocomamas' financial information, such as turnover, food cost percentage, and food waste values. Additional information was gathered from a trustworthy electronic database that the Reserve Bank of Zimbabwe manages. Quantitative research tools, including Microsoft Excel, Microsoft PowerBI, and Eviews 12 Student lite, were utilized to collect, clean, and analyze the data. In addition to these tools, articles, internet sources, and textbooks were consulted to gather foundational information for the study.

3.5 Description of variables

All the factors for the research are outlined in the table provided, with revenue identified as the dependent factor and the others known as explanatory factors.

Table 3.1 Variable Description

Variables	Units	Symbol	Source
Revenue	Amount ($)	RV	Rocomamas
Food waste	Amount ($)	FW	Rocomamas
Inflation	Percentage (%)	INF	RBZ
Exchange rate	ZWL to 1 USD	ER	RBZ
Food cost	Percentage (%)	FC	Rocomamas

3.6 Pre-testing procedures

3.6.1 Correlation Analysis

Correlation is a measure that indicates the degree to which two or more variables fluctuate simultaneously. The relationship between variables is categorized as positive, negative, and no relationship. On that note, correlation does not imply causation because there might be an unknown factor that affects both variables in the same way (Chen & Popovich, 2002).

3.6.2 Multicollinearity

In this research, the investigator employed a correlation matrix alongside Pearson r correlation to investigate the connections between different factors and determine whether there was multicollinearity present among the independent variables. Additionally, tolerance and variance inflation factor (VIF) were used to detect multicollinearity in the data. The following formulae are how we calculate the two respectively:

$$Tol_{\mathrm{i}} = 1 - R_{\mathrm{i}}^2$$

$$VIF_{\mathrm{i}} = \frac{1}{Tol_{\mathrm{i}}}$$

Where R^2 is the coefficient of determination from the model. Furthermore, using the two methods multicollinearity exists when tolerance is less than 0.1 and when the value of VIF is 10 or above (Pituch & Stevens, 2016).

3.6.3 Unit root test

It is recommended to check the stationarity of data before applying any model to analysis. This involves verifying if the averages and standard deviations remain consistent over time and ensuring there is no trending behaviour. The researcher conducted an Augmented Dickey-Fuller (ADF) test, which is a test for unit root, used to determine the stationary nature of the data. This test can be expressed as follows:

$$\Delta y_{\mathrm{t}} = \alpha y_{\mathrm{t-1}} + x'\delta + \beta_1 \Delta y_{\mathrm{t-1}} + \cdots + \beta_{\mathrm{p}} \Delta y_{\mathrm{t-p}} + \nu_{\mathrm{t}}$$

Where, $\Delta y_t = y_t - y_{t-1}$, $\alpha = \rho - 1$, ρ and δ are parameters that need to be estimated while it is assumed that y follows an autoregressive (AR) process of order p. The series is stationary if and only if the null hypothesis $\alpha=0$ is rejected. Generally speaking, a series is considered to be integrated of order d (I(d)) if it needs to be differenced d times in to become a stationary series or a common I(0) if the series is already stationary without differencing (Huhtamaki, 2010).

3.6.4 Determination of lag length

To decide on the correct number of lags in vector autoregression, a series of lag length criteria tests are conducted. Likelihood ratio (LR), Log-likelihood (LogL), Final prediction error (FPE), Aikake information criterion (AIC), and Hartmann-Quinn information criterion (HQ) are among the tests that can be utilized. The AIC test was chosen for the study as it is considered the most suitable for small sample sizes, as the information criterion recommends varying lags in the model (Ivanov & Killian, 2005). Its formula is as follows:

$$AIC = \log\left(\frac{\Sigma {\varepsilon_i}^2}{N}\right) + \frac{2k}{N}$$

Where k represents the parameters, n refers to the data points, and ε signifies the maximum value of the likelihood function for the model. (Huhtamaki, 2010).

3.6.5 Autocorrelation LM test

This test calculates the multivariate LM statistics for residual serial correlation up to a certain level, that is to say, to test the autocorrelation in the errors in a model. A Breusch-Godfrey test statistic is calculated to detect autocorrelation at a specific lag order, h. This is done by performing a supplementary regression analysis using the residuals u_t, the original predictors, and the lagged residual u_{t-h}. In cases where the first h values of u_{t-h} are missing, they are replaced with zeros in the analysis. Assuming there is no serial correlation of order h values under the null hypothesis, the LM statistic will approach a chi-squared distribution with k^2 degrees of freedom in the long run. (Maddala & Lahiri, 2009).

A different version of this examination seeks to identify self-correlation for periods 1 to h. The test alters the LM statistic mentioned earlier by incorporating all of the adjusted lagged residual predictors from s = 1 to s = h. When assuming the default hypothesis, the LM statistic ultimately becomes chi-squared asymptotically with hk^2 degrees of freedom. The test was used in this research because it is more general than the Durbin-Watson statistic and is statistically more powerful (Asteriou & Hall, 2011)

3.6.6 White heteroscedasticity test

In 1980, Halbert White introduced an approach for calculating standard errors that are consistent in the presence of heteroscedasticity, along with the White test. This test is employed to determine if the errors in a model have a constant variance, which is known as homoscedasticity. The test requires conducting a regression analysis in which each combination of the residuals is regressed against the combination of the independent variables before assessing the overall statistical significance of the regression outcomes. There are two options for conducting this test: one with cross terms and one without cross terms. The primary difference between the two options is that the option with cross-terms includes all possible combinations of the original regressors in the regression equation, while the option without cross-terms only includes the original regressors at their base values and squared values. According to Gujarati & Porter (2009), if there is no heteroscedasticity (as per H_0), the regressors that are not consistently present should not show collective significance.

3.7 Vector Autoregression (VAR) model

The multivariate time series model is a development of the univariate autoregression model, which gained popularity following Sims' (1980) seminar paper. In this model, all variables are considered dependent or response variables. Essentially, each variable has its equation as an endogenous variable, and on each equation's right-hand side, there are delayed values for all response variables in the system without any contemporary variables. The model is mathematically represented in a general VAR(p) form as:

$$y_{\mathrm{t}} = a + A_1 y_{\mathrm{t-1}} + A_2 y_{\mathrm{t-2}} + \cdots + A_{\mathrm{p}} y_{\mathrm{t-p}} + u_{\mathrm{t}}$$

Where,

y_t = (n x 1) vector of time series variables

a = (n x 1) vector of intercepts

A_i = (n x n) coefficient matrices

u_t = a vector of white noise

To illustrate the model in matrix form the equation below is used:

$Y_t = a + AY_{t-1} + U_t$, where,

$$Y_t = \begin{bmatrix} y_t \\ y_{t-1} \\ \vdots \\ y_{t-p+1} \end{bmatrix}, A = \begin{bmatrix} A_1 & A_2 & \cdots & A_{p-1} & A_p \\ I_k & 0 & \cdots & 0 & 0 \\ 0 & I_k & \cdots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & I_k & 0 \end{bmatrix}, U_t = \begin{bmatrix} u_t \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

I_k being an identity matrix (k x k) (Huhtamaki, 2010).

VAR models are available in three different types: reduced form, recursive form, and structural form. In a reduced form VAR, each variable is expressed as a linear function of its previous values and other variables, along with an error term that is serially uncorrelated. To estimate the equations in a simplified VAR model, ordinary least squares are used, along with different techniques to determine the correct number of lagged values to incorporate in each equation. When there is a connection between the variables, the error terms in the simplified model will also be interconnected across the equations. (Stock & Watson, 2001).

A recursive VAR is characterized by having error terms in each regression equation purposely constructed to not be correlated with the error in the previous equations, achieved by incorporating certain contemporaneous values as regressors. Using ordinary least squares to estimate each equation results in residuals that do not correlate across equations. This requires making an estimate of the simplified version and subsequently computing the Cholesky factorisation of the simplified form VAR covariance matrix. The sequence of variables in the VAR equations can be altered, which affects coefficients and residuals. There are multiple n! recursive VARs corresponding to different orderings, hence the outcomes are influenced by the arrangement of the variables (Lutkepohl, 2007).

The current connections between variables are determined by utilising structural VAR models, first introduced by Sims in 1980. This type of VAR model relies on making assumptions that enable correlations to be understood in terms of causation. These assumptions cover all aspects of the VAR model to ensure that each causal link is clearly defined. By using this method, we create instrumental variables that enable us to estimate current relationships through instrumental variable regression, as explained by Lutkepohl in 2007.

As well as providing a description of data, structural inference and policy analysis, the VAR model is commonly utilised for forecasting. The equations below show the first step forecast made using the information that was available at time T and the forecast for a future time h steps ahead:

$$Y_{T+1|T} = a + A_1Y_T + A_2Y_{T-1} + \ldots + A_pY_{T-p+1}$$

$$Y_{T+h|T} = a + A_1Y_{T+h-1|T} + A_2Y_{T+h-2|T} + \ldots + A_pY_{T+h-p|T}$$

The predictions produced by VAR models are very flexible because they can be modified according to the expected future trajectories of specific model variables. (Stock & Wilson, 2015).

The actual model for the study is as follows:

$$RV_t = \beta_0 + \sum_{i=1}^{n} B_i RV_{t-i} + \sum_{i=1}^{n} U_i FW_{t-i} + \sum_{i=1}^{n} \Omega_i INF_{t-i} + \sum_{i=1}^{n} \phi_i ER_{t-i} + \sum_{i=1}^{n} \theta_i FC_{t-i} + \varepsilon_{RV} \quad (1)$$

$$FW_t = \beta_0 + \sum_{i=1}^{n} B_i RV_{t-i} + \sum_{i=1}^{n} U_i FW_{t-i} + \sum_{i=1}^{n} \Omega_i INF_{t-i} + \sum_{i=1}^{n} \phi_i ER_{t-i} + \sum_{i=1}^{n} \theta_i FC_{t-i} + \varepsilon_{RW} \quad (2)$$

$$INF_t = \beta_0 + \sum_{i=1}^{n} B_i RV_{t-i} + \sum_{i=1}^{n} U_i FW_{t-i} + \sum_{i=1}^{n} \Omega_i INF_{t-i} + \sum_{i=1}^{n} \phi_i ER_{t-i} + \sum_{i=1}^{n} \theta_i FC_{t-i} + \varepsilon_{INF} \quad (3)$$

$$ER_t = \beta_0 + \sum_{i=1}^{n} B_i RV_{t-i} + \sum_{i=1}^{n} U_i FW_{t-i} + \sum_{i=1}^{n} \Omega_i INF_{t-i} + \sum_{i=1}^{n} \phi_i ER_{t-i} + \sum_{i=1}^{n} \theta_i FC_{t-i} + \varepsilon_{ER} \quad (4)$$

$$FC_t = \beta_0 + \sum_{i=1}^{n} B_i RV_{t-i} + \sum_{i=1}^{n} U_i FW_{t-i} + \sum_{i=1}^{n} \Omega_i INF_{t-i} + \sum_{i=1}^{n} \phi_i ER_{t-i} + \sum_{i=1}^{n} \theta_i FC_{t-i} + \varepsilon_{FC} \quad (5)$$

Where ε_{RV}, ε_{FW}, ε_{INF}, ε_{ER} and ε_{FC} are the error terms of revenue, food waste, inflation, exchange rate and food cost respectively.

3.8 Johansen cointegration test

This test is a method for examining whether multiple time series exhibit cointegration. It was selected for the research because it can identify lasting connections between variables and is widely applicable, enabling multiple cointegrating relationships to be explored. The Johansen test comprises two types: the trace test and the maximum eigenvalue test. The key distinction between the two lies in the null and alternative hypotheses they assess. The trace test assesses whether there are r cointegrating vectors as the null hypothesis, as opposed to the alternative hypothesis of n cointegrating vectors. The maximum eigenvalue test, on the other hand, contrasts the alternative hypothesis of r+1 cointegrating vectors with the null hypothesis of r cointegrating vectors. The equations for trace and maximum eigenvalue are shown below respectively:

$$J_{trace} = -T \sum_{i=r+1}^{n} \ln(1-\lambda_{\mathrm{i}})$$

$$J_{max} = -T \ln(1-\ \lambda_{\mathrm{i+1}})$$

Where T represents the size of the sample and is the highest canonical correlation. If trace statistic and max eigenvalue statistic values exceed their critical values it indicates that there is cointegration in the model (Hjalmarsson & Osterholm, 2007).

3.9 Granger causality test

The examination conducted in this research utilises a test to gain further insights into how variables interact. It assesses if the historical values of one variable can be used to predict another variable. To illustrate, if inflation does not contribute towards predicting revenue, then the coefficients of past inflation values will all be zero in the simplified revenue equation (Asteriou & Hall, 2011). This test has the following hypothesis:

H_0: X_t does not Granger cause Y_t

H_1: X_t Granger causes Y_t

Let X_t, and Y_t be two stationary time series with zero means. The basic causal model is:

$$X_{\mathrm{t}} = \sum_{i=1}^{m} a_{\mathrm{i}} X_{\mathrm{t-i}} + \sum_{i=1}^{m} b_{\mathrm{i}} Y_{\mathrm{t-i}} + \varepsilon_{\mathrm{t}}$$

$$Y_{\mathrm{t}} = \sum_{i=1}^{m} c_{\mathrm{i}} X_{\mathrm{t-i}} + \sum_{i=1}^{m} d_{\mathrm{i}} Y_{\mathrm{t-i}} + u_{\mathrm{t}}$$

Where ε_t and u_t are considered to be two independent white noise series and m is the number of lagged variables. The above equations show that Y_t is causing X_t, given b_i is not zero. Similarly, X_t is causing Y_t provided c_j is not zero. Nevertheless, a broader model involving immediate causation can be expressed as follows:

$$X_{t} + b_0 Y_{t} = \sum_{i=1}^{m} a_{i} X_{t-i} + \sum_{i=1}^{m} b_{i} Y_{t-i} + \varepsilon_{t}$$

$$Y_{t} + c_0 X_{t} = \sum_{i=1}^{m} c_{i} X_{t-i} + \sum_{i=1}^{m} d_{i} Y_{t-i} + u_{t}$$

3.10 Granger causality test

3.11 Summary

This chapter centred on the procedures carried out during the research to generate the outcomes in the subsequent chapter. The primary techniques employed in this study included the Vector autoregression model, the Johansen cointegration test, and the Granger causality test.

CHAPTER 4: DATA PRESENTATION, ANALYSIS AND DISCUSSION

4.0 Introduction

This chapter presents findings about the impact of food waste on revenue as compared to other factors in restaurants in Zimbabwe. Descriptive statistics and the entire tests mentioned in chapter three were performed, presented in tabular form and interpreted. This chapter is vital since conclusions are drawn from it.

4.1 Descriptive statistics

Table 4.1: Descriptive statistics

	Food waste	Exchange rate	Food cost	Inflation	Revenue
Mean	2294.963	1611.465	0.403733	2.463531	122185.1
Median	2249.000	502.9247	0.396000	1.599657	121431.3
Maximum	5144.000	8409.677	0.531300	12.10356	214810.0
Minimum	696.0000	100.0000	0.287000	-3.733408	48438.00
Standard deviation	948.7542	2479.060	0.060116	3.174772	32970.20
Skewness	0.606584	1.603925	0.255797	1.491972	0.500293
Kurtosis	3.527665	3.944449	2.374195	5.765827	4.813706
Jarque-Bera	2.625309	16.77343	0.980042	24.83057	6.436052
Probability	0.269105	0.000228	0.612614	0.000004	0.040034
Sum	82618.67	58012.74	14.53440	88.68712	4398665
Range	4448.000	8309.677	0.244300	15.83697	166372
Count	36	36	36	36	36

Source: Author's computation

Revenue: The Rocomama's brand makes $122185.10 on average per month in revenue. Half of the revenues realized by the restaurant were more than $121431.30, whilst half were less than that amount. Most revenues are not close to the average revenue amount and to each other. The combination of the mean ($122185.10) and skewness (0.500293) shows that revenue is increasing.

Referring to the Jarque-Bera probability, revenue is not normally distributed if the probability is less than 0.05. $4398665.00 is the total revenue generated by the brand from trading for 36 months.

Inflation: In Zimbabwe, 2.463531% was the average monthly inflation from January 2021 to December 2023. Half of the monthly inflation rates recorded in the country were above 1.599657% whilst half were less than that. Most rates were not close to the average inflation rate and to each other. The combination of mean (2.463531) and skewness (1.491972) shows that inflation is increasing. The possible reason for the inflation increase is, that people prefer to spend than to hold cash that is depreciating. Referring to the Jarque-Bera probability, inflation is not normally distributed for the probability is less than 0.05. 88.68712% was the total inflation rate recorded for the country in 36 months.

Food cost: 40.3733% was the average monthly food cost from January 2021 to December 2023. Half of the monthly food cost percentages recorded were above 39.60% whilst half were less than that. Most costs were not close to the average and to each other. The combination of the mean (40.3733) and skewness (0.255797) shows that food costs are increasing. The possible reason for the food cost increase is somewhat linked to the inflationary pressure on the supplier's side thus giving rise to the cost of purchasing the food in the restaurant. Referring to the Jarque-Bera probability, inflation is not normally distributed for the probability is less than 0.05.

Exchange rate: In Zimbabwe, 1611.465 was the average monthly exchange rate from January 2021 to December 2023. Fifty per cent of the monthly exchange rates recorded in the country over the same time interval were above 502.9247 whilst half were less than that. Most rates were not close to the average and to each other. The combination of mean (1611.465) and skewness (1.491972) shows there is an increase. This increase signifies that Zimbabwe's local currency (ZWL) is depreciating as compared to the United States American dollar (USD). Referring to the Jarque-Bera probability, inflation is not normally distributed for the probability is less than 0.05.

Food waste: $2294.963 was the average monthly food waste for 36 months from January 2021 to December 2023. Half of the monthly food waste values recorded at the restaurant were above $2249.00. The combination of the mean ($2294.963) and skewness (0.606584) shows that inflation is increasing. Referring to the Jarque-Bera probability, inflation is normally distributed if the probability is greater than 0.05. $82618.67 was the total amount of food waste value recorded in 36 months.

4.2 Correlation analysis

Table 4.2: Correlation matrix

	Revenue	**Food waste**	**Food cost**	**Inflation**	**Exchange rate**
Revenue	1	0.466785**	-0.208820	0.108146	0.348703
Food waste	0.466785**	1	-0.138016	0.010705	-0.315028
Food cost	-0.208820	-0.138016	1	-0.091440	-0.257428
Inflation	0.108146	0.010705	-0.091440	1	0.187707
Exchange rate	0.348703	-0.315028	-0.257428	0.187707	1

**. Correlation is significant at the 0.01% level (Source: Author's computation)

The relationship among variables is summarized in Table 4.2 in terms of the Pearson correlation coefficient. It is evident from the summary that food waste, inflation and exchange rate have a positive correlation, while food cost has a negative correlation with the dependent variable revenue. Positive as it may be, the correlation of food waste, inflation and exchange rate with revenue is a weak positive one, whilst food cost has a weak negative correlation with revenue. All predictors have relatively weak positive and weak negative correlations amongst each other and there is no multicollinearity because the correlation coefficients are between 0.9 and -0.9 (Dohoo et al, 1997).

Table 4.3: Tolerance and VIF

	Tolerance	**VIF**
Food waste	0.845634	1.182544
Food cost	0.879719	1.136727
Inflation	0.958576	1.043214
Exchange rate	0.781502	1.279588

Source: Author's computation

Tolerance for predictors are all greater than 0.1 and their VIF is less than 10. This, according to Pitch & Stevens in 2016, means that the remaining variables are not highly correlated.

Table 4.4: Eigenvalue and Conditional Index

Dimension	Eigenvalue	Condition index
1	6790970604.79	2.42E-10
2	136372593.57	1.20E-08
3	1802185.65	9.10E-07
4	4.188644	0.392
5	1.640394	1

Source: Author's computation

Predictors are said to be highly correlated when most of the eigenvalues are close to zero and when the conditional indices are greater than 30. In this case, most eigenvalues are not close to zero and all conditional indices are below 30, hence the remaining predictors are not highly correlated (Hair et al, 2013).

4.3 Lag testing

Table 4.5: Variable lag structure

Variables	Lag length
Revenue	2
Food waste	2
Food cost	2
Inflation	2
Exchange rate	2

Source: Author's computation

The lag length is based on the Aikake Information Criterion as shown in Appendix B, and as such the optimal lag length is 2.

4.4 Unit root test

Table 4.6: ADF test results

Variables	Intercept			Trend and intercept		
	Level	**1st diff**	**Stationary**	**Level**	**1st diff**	**Stationary**
Revenue	-3.179**		I(0)	-4.379**		I(0)
Food waste	-2.657	-5.159**	I(1)	-2.443	-5.177***	I(1)
Food cost	-4.785***		I(0)	-5.942***		I(0)
Inflation	-3.767***		I(0)	-3.741**		I(0)
Exchange rate	6.478	-4.988***	I(1)	4.108	-5.568***	I(1)

Key: Significance level, ***=1% level; **=5% level; *=10% level Source: Author's computation

Concerning Table 4.6, it is noted that at $\alpha = 0.05$, all variables do not have a unit root. This means that at a 5% significance level, all variables are stationary, food waste and exchange rate after the first differencing I(1), while revenue, food cost and inflation are at the level I(0), both at intercept and trend and intercept.

4.5 Johansen Cointegration Test

Table 4.7 Johansen cointegration test

		Trace			Maximum Eigenvalue		
Hypothesized no. of CE(s)	**Eigenvalue**	**Trace statistic**	**0.05 Critical value**	**Prob**	**Max-Eigen statistic**	**0.05 Critical value**	**Prob**
None	0.619472	80.27132	88.80380	0.1761	32.85064	38.33101	0.1864
At most 1	0.475567	47.42068	63.87610	0.5330	21.94486	32.11832	0.4976
At most 2	0.284811	25.47581	42.91525	0.7655	11.39708	25.82321	0.9071
At most 3	0.220299	14.07874	25.87211	0.6511	8.460703	19.38704	0.7785
At most 4	0.152307	5.618033	12.51798	0.5103	5.618033	12.51798	0.5103

Source: Author's computation

For None, the trace statistic (80.27132) is less than the critical value (88.80380) and the max-eigen statistic (32.85064) is less than the critical value (38.33101), hence we failed to reject the null hypothesis and conclude that there is no cointegration. Referring to both the trace and maximum eigenvalue tests, there is no cointegration among variables, hence, a short-run relationship exists among the variables at a 5% significance level.

4.6 VAR

Table 4.9: VAR model coefficients

Standard errors in ( ) and t-statistics in [ ]

	RV	**FW**	**FC**	**INF**	**ER**
RV(-1)	-0.691867** (0.24715) [-2.79934]	-0.002633 (0.00676) [-0.38971]	-8.89E-07** (4.3E-0.7) [-2.07117]	1.01E-05 (2.8E-05) [0.36668]	-0.003228 (0.00718) [-0.44975]
RV(-2)	-0.473873* (0.24643) [-1.92296]	-0.001549 (0.00674) [-0.22994]	-9.7E-07** (4.3E-07) [-2.27846]	7.36E-06 (2.7E-05) [0.26819]	0.004834 (0.00716) [0.67549]
FW(-1)	16.10735* (8.48998) [1.89722]	-0.218286 (0.23212) [-0.94039]	1.07E-05 (1.5E-05) [0.72499]	-0.000568 (0.00095) [-0.60122]	0.045335 (0.24654) [0.18389]
FW(-2)	16.54522* (8.72650) [1.89598]	-0.149620 (0.23859) [-0.62711]	2.17E-05 (1.5E-05) [1.43406]	-0.001070 (0.00097) [-1.10107]	-0.174977 (0.25341) [-0.69049]
FC(-1)	60053.13 (95575.3) [0.62833]	2536.026 (2613.09) [0.97051]	-0.662428** (0.16599) [-3.99070]	-14.97582 (10.6399) [-1.40752]	-99.48299 (2775.41) [-0.03584]
FC(-2)	84816.19 (94928.9) [0.89347]	-7523837 (2595.42) [-0.02899]	-0.170099 (0.16487) [-1.03171]	-12.77116 (10.5679) [-1.20849]	114.8605 (2756.64) [0.04167]
INF(-1)	2431.956 (2362.26)	38.74779 (64.5859)	0.010235** (0.00410)	-0.331384 (0.26298)	10.16931 (68.5978)

	[1.02950]	[0.59994]	[2.49464]	[-1.26012]	[0.14825]
INF(-2)	452.1460 (1933.40) [0.23386]	25.17220 (52.8605) [0.47620]	0.006960** (0.00336) [2.07283]	0.142816 (0.21523) [0.66354]	15.72218 (56.1440) [0.28003]
ER(-1)	-5.508767 (9.96837) [-0.55262]	-0.097716 (0.27254) [-0.35854]	-4.52E-05** (1.7E-05) [-2.61208]	-0.001057 (0.00111) [-0.95274]	0.129448 (0.28947) [0.44719]
ER(-2)	10.9392 (9.62683) [1.14201]	0.019151 (0.26320) [0.07276]	2.60E-05 (1.7E-05) [1.55377]	-0.002020* (0.00107) [-1.88468]	-0.285974 (0.27955) [-1.02297]
C	4715.352 (6103.47) [0.77257]	58.36523 (166.873) [0.34976]	0.004556 (0.01060) [0.42976]	0.691490 (0.67946) [1.01770]	275.3554 (177.239) [1.55358]

Key: Significance key; **=5% level; *=10% level (Source: Author's computation)

In the short run, food waste lag 1 and food waste lag 2 have a positive impact on revenue at a 10% significant level, while the rest are considered insignificant as their coefficients' p-values lie outside the required confidence interval. As such, a percentage increase in food waste at lag 1 and lag 2 will result in a $16.11 and $16.55 average increment in revenue respectively.

4.6.1 VAR residual serial correlation lm test

Table 4.10: LM test

Null hypothesis: No serial correlation at lag h						
Lag	LRE*stat	df	Prob	Rao F-stat	df	Prob
1	28.18378	25	0.3013	1.160687	(25, 49.8)	0.3197
2	19.59613	25	0.7677	0.750345	(25, 49.8)	0.7794

Source: Author's computation

At $\alpha = 0.05$, there is no serial correlation both at lag 1 and 2, because the p-values are greater than α.

4.6.2 VAR residual heteroscedasticity tests

Table 4.11: White heteroscedasticity test results

Joint test		
Chi-sq	df	Prob
288.4187	300	0.6743

Source: Author's computation

At $\alpha = 0.05$, p is greater than α, hence, homoscedasticity exists.

4.7 Granger causality test

Table 4.12: Granger causality test results

Null hypothesis	**Probability**	**Conclusion(α=0.05)**	**Conclusion(α=0.10)**
FW does not granger cause RV	0.0611*	No evidence to reject H_0	Do not reject H_0
RV does not granger cause FW	0.8176	No evidence to reject H_0	No evidence to reject H_0
FC does not granger cause RV	0.7067	No evidence to reject H_0	No evidence to reject H_0
RV does not granger cause FC	0.2626	No evidence to reject H_0	No evidence to reject H_0
INF does not granger cause RV	0.6804	No evidence to reject H_0	No evidence to reject H_0
RV does not granger cause INF	0.7770	No evidence to reject H_0	No evidence to reject H_0
ER does not granger cause RV	0.7258	No evidence to reject H_0	No evidence to reject H_0
RV does not granger cause ER	0.5342	No evidence to reject H_0	No evidence to reject H_0
FC does not granger cause FW	0.3416	No evidence to reject H_0	No evidence to reject H_0
FW does not granger cause FC	0.6818	No evidence to reject H_0	No evidence to reject H_0
INF does not granger cause FW	0.7005	No evidence to reject H_0	No evidence to reject H_0
FW does not granger cause INF	0.6993	No evidence to reject H_0	No evidence to reject H_0
ER does not granger cause FW	0.9413	No evidence to reject H_0	No evidence to reject H_0
FW does not granger cause ER	0.7239	No evidence to reject H_0	No evidence to reject H_0
INF does not granger cause FC	0.1390	No evidence to reject H_0	No evidence to reject H_0
FC does not granger cause INF	0.3916	No evidence to reject H_0	No evidence to reject H_0
ER does not granger cause FC	0.3663	No evidence to reject H_0	No evidence to reject H_0
FC does not granger cause ER	0.7898	No evidence to reject H_0	No evidence to reject H_0

ER does not granger cause INF	0.0798*	No evidence to reject H_0	Do not reject H_0
INF does not granger cause ER	0.8893	No evidence to reject H_0	No evidence to reject H_0

Key: Significance key; **=5% level; *=10% level (Source: Author's computation)

At a significance level of 0.05, we were unable to dismiss the null hypothesis in any of the study's scenarios. However, at α=0.10, the food waste granger causes revenue while the exchange rate granger causes inflation. This shows that at a 10% significance level, the lagged food waste values explain the variation in revenue, whilst the exchange rate explains the variation that occurs in inflation.

4.8 Summary

Pre-tests, Johansen test, Granger causality test and VAR mentioned in the prior chapter were all done and interpreted. It has also been instrumental in answering the research objectives and questions.

CHAPTER 5

SUMMARY, CONCLUSION AND RECOMMENDATIONS

5.0 Introduction

In this chapter, the researcher focuses on the summary of chapters, conclusions and recommendations based on the research objectives and questions as well as research findings.

5.1 Summary of findings and conclusions

The major objective of the research was to determine the impact that food waste has on revenue in restaurants as compared to other factors for the period January 2021 to December 2023, using the ADF test for stationarity, Johansen test for long run relationship, Vector Autoregression model, Granger causality and Pearson correlation coefficient for the degree to which variables fluctuate simultaneously.

The findings of the ADF revealed that revenue, food cost and inflation were stationary at level, while food waste and exchange rate were stationary at first differencing. The Johansen test findings indicated that the impact of food waste, food cost, inflation and exchange rate is noted only in the short run, which then resulted in the use of the VAR model. The results of the VAR indicate that food waste positively influences revenue, which means a way to reincorporate it back as a source of turnover is a considerable idea. Granger causality reaffirmed the notion provided by the VAR as the results revealed that the lagged food waste values are able to explain variation in revenue, while the lagged exchange rate value explains a variation in inflation.

5.2 Recommendations

The company should collaborate franchising and intensive distribution so as to improve sales performance that is to say, the brand should employ a customer loyalty program for off menu items solely based on boosting their revenue stream. The idea behind this is the injection of the edible by-products of food production and beverages and ingredients that just passed their best before date but discarded in anticipation of negative consumer behavior.

5.3 Suggestions for further research

Future researchers are advised to conduct a cross regional study of several restaurant brands. This kind of study may produce more comprehensive findings about factors that affect a restaurant's revenue. They may also include other variables like disposal income and demographic variables in the analysis and use other models for analysis. The researcher should also consider using a larger sample of the variables and structured interviews across several brands to actually have a more concrete insight on what really affects the revenue potential in restaurants thus minimizing a researcher's influence.

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Appendix A: Correlation analysis

Correlations

		Revenue	Food waste	Food cost	Inflation	Exchange rate
	Pearson correlation	1				
	Sig. (1-tailed)	-----				
	N	36				
	Pearson correlation	0.466785**	1			
	Sig. (1-tailed)	0.0041	-----			
	N	36	36			
	Pearson correlation	-0.20882	-0.138016	1		
	Sig. (1-tailed)	0.2216	0.4221	-----		
	N	36	36	36		
	Pearson correlation	0.108146	0.010705	-0.091440	1	
	Sig. (1-tailed)	0.5301	0.9506	0.5958	-----	
	N	36	36	36	36	
	Pearson correlation	0.348703	-0.315028	-0.257428	0.187707	1
	Sig. (1-tailed)	0.0371	0.0613	0.1296	0.2730	-----
	N	36	36	36	36	36

**. Correlation is significant at the 0.01 level (1-tailed)

Coefficients

Model	Unstandardized coefficients		Standardized coefficients	t	Sig.	Collinearity statistics	
	B	Std. error	Beta			Tolerance	VIF
Constant	53391.39	36276.28		1.471799	0.1512		
Food waste	22.45375	4.841138	0.646	4.638113	0.0001	0.845634	1.182544
Food cost	13191.98	74908.81	0.0241	0.176107	0.8614	0.879719	1.136727
Inflation	-15.01872	1358.835	0.00145	-0.011053	0.9913	0.958576	1.043214
Exchange rate	7.430628	1.927262	0.559	3.855537	0.0005	0.781502	1.279588

a. Dependent Variable: Revenue

Collinearity Diagnostics

Dimension	Eigenvalue	Condition index	Variance proportions				
			Constant	Food waste	Food cost	Inflation	Exchange rate
1	6.79E+09	2.42E-10	0.914768	0.085845	0.995693	0.001467	0.113401
2	1.36E+08	1.20E-08	0.085232	0.725810	0.004307	0.022799	0.085232
3	1802186.65	9.10E-07	3.60E-07	0.043450	1.50E-08	0.975733	3.60E-07
4	4.188644	0.391629	1.88E-16	0.123118	7.70E-18	3.84E-13	1.88E-16
5	1.640394	1	7.64E-17	0.021776	2.73E-18	4.66E-13	7.64E-17

a. Dependent Variable: Revenue

Appendix B: Lag testing

VAR Lag Order Selection Criteria
Endogenous variables: DRV DFW DFC DINF DER
Exogenous variables: C
Date: 05/01/24 Time: 11:17
Sample: 2021M01 2023M12
Included observations: 32

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-934.0199	NA	2.12e+19*	58.68874	58.91776*	58.76466*
1	-911.1048	37.23701	2.47e+19	58.81905	60.19318	59.27453
2	-882.3835	37.69667*	2.21e+19	58.58647*	61.10570	59.42152
3	-862.5725	19.81107	4.33e+19	58.91078	62.57512	60.12540

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

VAR Lag Order Selection Criteria
Endogenous variables: DFW DFC DINF DER DRV
Exogenous variables: C
Date: 05/01/24 Time: 11:20
Sample: 2021M01 2023M12
Included observations: 32

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-934.0199	NA	2.12e+19*	58.68874	58.91776*	58.76466*
1	-911.1048	37.23701	2.47e+19	58.81905	60.19318	59.27453
2	-882.3835	37.69667*	2.21e+19	58.58647*	61.10570	59.42152
3	-862.5725	19.81107	4.33e+19	58.91078	62.57512	60.12540

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

VAR Lag Order Selection Criteria
Endogenous variables: DFC DINF DER DRV DFW
Exogenous variables: C
Date: 05/01/24 Time: 11:21
Sample: 2021M01 2023M12
Included observations: 32

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-934.0199	NA	2.12e+19*	58.68874	58.91776*	58.76466*
1	-911.1048	37.23701	2.47e+19	58.81905	60.19318	59.27453
2	-882.3835	37.69667*	2.21e+19	58.58647*	61.10570	59.42152
3	-862.5725	19.81107	4.33e+19	58.91078	62.57512	60.12540

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

VAR Lag Order Selection Criteria
Endogenous variables: DINF DER DRV DFW DFC
Exogenous variables: C
Date: 05/01/24 Time: 11:22
Sample: 2021M01 2023M12
Included observations: 32

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-934.0199	NA	2.12e+19*	58.68874	58.91776*	58.76466*
1	-911.1048	37.23701	2.47e+19	58.81905	60.19318	59.27453
2	-882.3835	37.69667*	2.21e+19	58.58647*	61.10570	59.42152
3	-862.5725	19.81107	4.33e+19	58.91078	62.57512	60.12540

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Appendix C: Unit root test

Null Hypothesis: REVENUE has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on AIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.378930	0.0073
Test critical values:	1% level	-4.252879	
	5% level	-3.548490	
	10% level	-3.207094	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(FW) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on AIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.177459	0.0010
Test critical values:	1% level	-4.262735	
	5% level	-3.552973	
	10% level	-3.209642	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: FOODCOST has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on AIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.941590	0.0001
Test critical values:	1% level	-4.243644	
	5% level	-3.544284	
	10% level	-3.204699	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: INFLATION has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on AIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.740962	0.0325
Test critical values:	1% level	-4.243644	
	5% level	-3.544284	
	10% level	-3.204699	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(EXCHANGERATE) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on AIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.567623	0.0004
Test critical values:	1% level	-4.262735	
	5% level	-3.552973	
	10% level	-3.209642	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: REVENUE has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on AIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.178675	0.0299
Test critical values:	1% level	-3.632900	
	5% level	-2.948404	
	10% level	-2.612874	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(FW) has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on AIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.158718	0.0002
Test critical values:	1% level	-3.646342	
	5% level	-2.954021	
	10% level	-2.615817	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: FOODCOST has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on AIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.784506	0.0005
Test critical values:	1% level	-3.632900	
	5% level	-2.948404	
	10% level	-2.612874	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: INFLATION has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on AIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.767358	0.0071
Test critical values:	1% level	-3.632900	
	5% level	-2.948404	
	10% level	-2.612874	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(EXCHANGERATE) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on AIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.977787	0.0003
Test critical values:	1% level	-3.639407	
	5% level	-2.951125	
	10% level	-2.614300	

*MacKinnon (1996) one-sided p-values.

Appendix D: Johansen Cointegration

Date: 04/26/24 Time: 12:49
Sample (adjusted): 2021M03 2023M12
Included observations: 34 after adjustments
Trend assumption: Linear deterministic trend (restricted)
Series: REVENUE FW FOODCOST INFLATION EXCHANGERATE
Lags interval (in first differences): 1 to 1

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None	0.619472	80.27132	88.80380	0.1761
At most 1	0.475567	47.42068	63.87610	0.5330
At most 2	0.284811	25.47581	42.91525	0.7655
At most 3	0.220299	14.07874	25.87211	0.6511
At most 4	0.152307	5.618033	12.51798	0.5103

Trace test indicates no cointegration at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None	0.619472	32.85064	38.33101	0.1864
At most 1	0.475567	21.94486	32.11832	0.4976
At most 2	0.284811	11.39708	25.82321	0.9071
At most 3	0.220299	8.460703	19.38704	0.7785
At most 4	0.152307	5.618033	12.51798	0.5103

Max-eigenvalue test indicates no cointegration at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegrating Coefficients (normalized by b'*S11*b=I):

REVENUE	FW	FOODCOST	INFLATION	EXCHANGER...	@TREND(21M02)
4.78E-05	-0.000698	24.52976	0.121198	-0.000152	0.048899
5.58E-05	-0.000742	-22.19587	-0.187517	-8.37E-05	-0.159866
6.34E-06	-0.001142	-6.339456	0.234526	-0.000309	0.075841
9.53E-07	-0.000803	1.267554	-0.300727	-0.000306	0.067427
-1.53E-05	0.000768	-1.238769	-0.057957	-0.000123	0.119233

Unrestricted Adjustment Coefficients (alpha):

D(REVENUE)	-15866.71	-14858.13	-128.9991	268.3930	-458.1383
D(FW)	-105.9463	-133.3532	100.2226	114.9456	-234.9647
D(FOODCOST)	-0.029317	0.005077	0.022864	-0.007282	0.004009
D(INFLATION)	-0.633075	0.311940	-0.146777	1.272681	0.465155
D(EXCHANG...	154.0674	-108.6830	138.1399	222.3021	185.9279

1 Cointegrating Equation(s):	Log likelihood	-951.7484			

Normalized cointegrating coefficients (standard error in parentheses)

REVENUE	FW	FOODCOST	INFLATION	EXCHANGER...	@TREND(21M02)
1.000000	-14.59719	512887.5	2534.101	-3.180157	1022.424
	(4.68344)	(106484.)	(1419.48)	(3.05751)	(716.943)

Adjustment coefficients (standard error in parentheses)

D(REVENUE)	-0.758854
	(0.22930)
D(FW)	-0.005067
	(0.00652)
D(FOODCOST)	-1.40E-06
	(4.8E-07)
D(INFLATION)	-3.03E-05
	(2.8E-05)
D(EXCHANG...	0.007369
	(0.00687)

Appendix E: Autocorrelation LM test

VAR Residual Serial Correlation LM Tests
Date: 05/01/24   Time: 11:31
Sample: 2021M01 2023M12
Included observations: 33

Null hypothesis: No serial correlation at lag h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	28.14378	25	0.3013	1.160687	(25, 49.8)	0.3197
2	19.59613	25	0.7677	0.750345	(25, 49.8)	0.7794

Null hypothesis: No serial correlation at lags 1 to h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	28.14378	25	0.3013	1.160687	(25, 49.8)	0.3197
2	50.74607	50	0.4440	0.967503	(50, 39.8)	0.5481

*Edgeworth expansion corrected likelihood ratio statistic.

Appendix F: White heteroscedasticity test

VAR Residual Heteroskedasticity Tests (Levels and Squares)
Date: 05/01/24 Time: 11:36
Sample: 2021M01 2023M12
Included observations: 33

Joint test:

Chi-sq	df	Prob.
288.4187	300	0.6743

Individual components:

Dependent	R-squared	F(20,12)	Prob.	Chi-sq(20)	Prob.
res1*res1	0.600100	0.900376	0.5965	19.80331	0.4703
res2*res2	0.627279	1.009785	0.5099	20.70022	0.4150
res3*res3	0.676598	1.255277	0.3500	22.32774	0.3230
res4*res4	0.698270	1.388530	0.2835	23.04290	0.2867
res5*res5	0.549894	0.733020	0.7395	18.14651	0.5778
res2*res1	0.516382	0.640648	0.8171	17.04060	0.6503
res3*res1	0.454937	0.500790	0.9173	15.01292	0.7757
res3*res2	0.584929	0.845537	0.6425	19.30267	0.5022
res4*res1	0.585118	0.846195	0.6420	19.30890	0.5018
res4*res2	0.632934	1.034583	0.4915	20.88682	0.4038
res4*res3	0.514334	0.635418	0.8213	16.97303	0.6547
res5*res1	0.772575	2.038230	0.1033	25.49497	0.1831
res5*res2	0.475446	0.543829	0.8898	15.68972	0.7357
res5*res3	0.495349	0.588939	0.8575	16.34650	0.6949
res5*res4	0.569288	0.793042	0.6876	18.78650	0.5357

Appendix G: VAR

Vector Autoregression Estimates
Date: 05/01/24 Time: 11:41
Sample (adjusted): 2021M04 2023M12
Included observations: 33 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	DRV	DFW	DFC	DINF	DER
DRV(-1)	-0.691867	-0.002633	-8.89E-07	1.01E-05	-0.003228
	(0.24715)	(0.00676)	(4.3E-07)	(2.8E-05)	(0.00718)
	[-2.79934]	[-0.38971]	[-2.07117]	[0.36668]	[-0.44975]
DRV(-2)	-0.473873	-0.001549	-9.75E-07	7.36E-06	0.004834
	(0.24643)	(0.00674)	(4.3E-07)	(2.7E-05)	(0.00716)
	[-1.92296]	[-0.22994]	[-2.27846]	[0.26819]	[0.67549]
DFW(-1)	16.10735	-0.218286	1.07E-05	-0.000568	0.045335
	(8.48998)	(0.23212)	(1.5E-05)	(0.00095)	(0.24654)
	[1.89722]	[-0.94039]	[0.72499]	[-0.60122]	[0.18389]
DFW(-2)	16.54522	-0.149620	2.17E-05	-0.001070	-0.174977
	(8.72650)	(0.23859)	(1.5E-05)	(0.00097)	(0.25341)
	[1.89598]	[-0.62711]	[1.43406]	[-1.10107]	[-0.69049]
DFC(-1)	60053.13	2536.026	-0.662428	-14.97582	-99.48299
	(95575.3)	(2613.09)	(0.16599)	(10.6399)	(2775.41)
	[0.62833]	[0.97051]	[-3.99070]	[-1.40752]	[-0.03584]
DFC(-2)	84816.19	-75.23837	-0.170099	-12.77116	114.8605
	(94928.9)	(2595.42)	(0.16487)	(10.5679)	(2756.64)
	[0.89347]	[-0.02899]	[-1.03171]	[-1.20849]	[0.04167]
DINF(-1)	2431.956	38.74779	0.010235	-0.331384	10.16931
	(2362.26)	(64.5859)	(0.00410)	(0.26298)	(68.5978)
	[1.02950]	[0.59994]	[2.49464]	[-1.26012]	[0.14825]
DINF(-2)	452.1460	25.17220	0.006960	0.142816	15.72218
	(1933.40)	(52.8605)	(0.00336)	(0.21523)	(56.1440)
	[0.23386]	[0.47620]	[2.07283]	[0.66354]	[0.28003]
DER(-1)	-5.508767	-0.097716	-4.52E-05	-0.001057	0.129448
	(9.96837)	(0.27254)	(1.7E-05)	(0.00111)	(0.28947)
	[-0.55262]	[-0.35854]	[-2.61208]	[-0.95274]	[0.44719]
DER(-2)	10.99392	0.019151	2.60E-05	-0.002020	-0.285974
	(9.62683)	(0.26320)	(1.7E-05)	(0.00107)	(0.27955)
	[1.14201]	[0.07276]	[1.55377]	[-1.88468]	[-1.02297]
C	4715.352	58.36523	0.004556	0.691490	275.3554
	(6103.47)	(166.873)	(0.01060)	(0.67946)	(177.239)
	[0.77257]	[0.34976]	[0.42976]	[1.01770]	[1.55358]

R-squared	0.348414	0.172038	0.652924	0.363513	0.146404
Adj. R-squared	0.052239	-0.204308	0.495162	0.074201	-0.241594
Sum sq. resids	2.18E+10	16285462	0.065716	269.9981	18371488
S.E. equation	31468.71	860.3768	0.054654	3.503233	913.8204
F-statistic	1.176378	0.457127	4.138664	1.256472	0.377333
Log likelihood	-381.9075	-263.1280	55.78732	-81.50644	-265.1167
Akaike AIC	23.81258	16.61382	-2.714383	5.606451	16.73435
Schwarz SC	24.31141	17.11266	-2.215547	6.105287	17.23318
Mean dependent	3768.485	16.42424	0.000636	0.116212	251.5054
S.D. dependent	32324.33	784.0069	0.076921	3.640915	820.1081

Determinant resid covariance (dof adj.)	7.55E+18
Determinant resid covariance	9.94E+17
Log likelihood	-917.8875
Akaike information criterion	58.96288
Schwarz criterion	61.45706
Number of coefficients	55

System: UNTITLED
Estimation Method: Least Squares
Date: 05/03/24 Time: 08:27
Sample: 2021M04 2023M12
Included observations: 33
Total system (balanced) observations 165

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	-0.691867	0.247153	-2.799345	0.0060
C(2)	-0.473873	0.246429	-1.922960	0.0571
C(3)	16.10735	8.489982	1.897218	0.0604
C(4)	16.54522	8.726496	1.895976	0.0606
C(5)	60053.13	95575.26	0.628333	0.5311
C(6)	84816.19	94928.92	0.893471	0.3736
C(7)	2431.956	2362.263	1.029502	0.3055
C(8)	452.1460	1933.399	0.233861	0.8155
C(9)	-5.508767	9.968368	-0.552625	0.5816
C(10)	10.99392	9.626826	1.142009	0.2559
C(11)	4715.352	6103.472	0.772569	0.4414
C(12)	-0.002633	0.006757	-0.389705	0.6975
C(13)	-0.001549	0.006738	-0.229938	0.8186
C(14)	-0.218286	0.232122	-0.940392	0.3491
C(15)	-0.149620	0.238589	-0.627107	0.5319
C(16)	2536.026	2613.095	0.970506	0.3339
C(17)	-75.23837	2595.424	-0.028989	0.9769
C(18)	38.74779	64.58593	0.599942	0.5498
C(19)	25.17220	52.86050	0.476200	0.6349
C(20)	-0.097716	0.272542	-0.358536	0.7206
C(21)	0.019151	0.263204	0.072762	0.9421
C(22)	58.36523	166.8732	0.349758	0.7272
C(23)	-8.89E-07	4.29E-07	-2.071171	0.0407
C(24)	-9.75E-07	4.28E-07	-2.278464	0.0246
C(25)	1.07E-05	1.47E-05	0.724986	0.4700
C(26)	2.17E-05	1.52E-05	1.434058	0.1544
C(27)	-0.662428	0.165993	-3.990700	0.0001
C(28)	-0.170099	0.164870	-1.031713	0.3045
C(29)	0.010235	0.004103	2.494639	0.0141
C(30)	0.006960	0.003358	2.072834	0.0405
C(31)	-4.52E-05	1.73E-05	-2.612082	0.0103
C(32)	2.60E-05	1.67E-05	1.553766	0.1231
C(33)	0.004556	0.010600	0.429759	0.6682
C(34)	1.01E-05	2.75E-05	0.366682	0.7146
C(35)	7.36E-06	2.74E-05	0.268191	0.7891
C(36)	-0.000568	0.000945	-0.601217	0.5489
C(37)	-0.001070	0.000971	-1.101066	0.2733
C(38)	-14.97582	10.63985	-1.407522	0.1621
C(39)	-12.77116	10.56790	-1.208487	0.2295
C(40)	-0.331384	0.262977	-1.260124	0.2103
C(41)	0.142816	0.215234	0.663535	0.5084
C(42)	-0.001057	0.001110	-0.952738	0.3428
C(43)	-0.002020	0.001072	-1.884676	0.0621
C(44)	0.691490	0.679465	1.017699	0.3111
C(45)	-0.003228	0.007177	-0.449748	0.6538
C(46)	0.004834	0.007156	0.675486	0.5008
C(47)	0.045335	0.246541	0.183886	0.8544
C(48)	-0.174977	0.253409	-0.690493	0.4913
C(49)	-99.48299	2775.411	-0.035844	0.9715
C(50)	114.8605	2756.642	0.041667	0.9668
C(51)	10.16931	68.59778	0.148245	0.8824
C(52)	15.72218	56.14401	0.280033	0.7800

C(53)	0.129448	0.289472	0.447188	0.6556
C(54)	-0.285974	0.279554	-1.022967	0.3086
C(55)	275.3554	177.2388	1.553584	0.1232

Determinant residual covariance	9.94E+17

Equation: DRV = C(1)*DRV(-1) + C(2)*DRV(-2) + C(3)*DFW(-1) + C(4)
*DFW(-2) + C(5)*DFC(-1) + C(6)*DFC(-2) + C(7)*DINF(-1) + C(8)*DINF(
-2) + C(9)*DER(-1) + C(10)*DER(-2) + C(11)

Observations: 33

R-squared	0.348414	Mean dependent var	3768.485
Adjusted R-squared	0.052239	S.D. dependent var	32324.33
S.E. of regression	31468.71	Sum squared resid	2.18E+10
Durbin-Watson stat	1.934236		

Equation: DFW = C(12)*DRV(-1) + C(13)*DRV(-2) + C(14)*DFW(-1) + C(15)
*DFW(-2) + C(16)*DFC(-1) + C(17)*DFC(-2) + C(18)*DINF(-1) + C(19)
*DINF(-2) + C(20)*DER(-1) + C(21)*DER(-2) + C(22)

Observations: 33

R-squared	0.172038	Mean dependent var	16.42424
Adjusted R-squared	-0.204308	S.D. dependent var	784.0069
S.E. of regression	860.3768	Sum squared resid	16285462
Durbin-Watson stat	1.855283		

Equation: DFC = C(23)*DRV(-1) + C(24)*DRV(-2) + C(25)*DFW(-1) + C(26)
*DFW(-2) + C(27)*DFC(-1) + C(28)*DFC(-2) + C(29)*DINF(-1) + C(30)
*DINF(-2) + C(31)*DER(-1) + C(32)*DER(-2) + C(33)

Observations: 33

R-squared	0.652924	Mean dependent var	0.000636
Adjusted R-squared	0.495162	S.D. dependent var	0.076921
S.E. of regression	0.054654	Sum squared resid	0.065716
Durbin-Watson stat	1.600851		

Equation: DINF = C(34)*DRV(-1) + C(35)*DRV(-2) + C(36)*DFW(-1) + C(37)
*DFW(-2) + C(38)*DFC(-1) + C(39)*DFC(-2) + C(40)*DINF(-1) + C(41)
*DINF(-2) + C(42)*DER(-1) + C(43)*DER(-2) + C(44)

Observations: 33

R-squared	0.363513	Mean dependent var	0.116212
Adjusted R-squared	0.074201	S.D. dependent var	3.640915
S.E. of regression	3.503233	Sum squared resid	269.9981
Durbin-Watson stat	1.961967		

Equation: DER = C(45)*DRV(-1) + C(46)*DRV(-2) + C(47)*DFW(-1) + C(48)
*DFW(-2) + C(49)*DFC(-1) + C(50)*DFC(-2) + C(51)*DINF(-1) + C(52)
*DINF(-2) + C(53)*DER(-1) + C(54)*DER(-2) + C(55)

Observations: 33

R-squared	0.146404	Mean dependent var	251.5054
Adjusted R-squared	-0.241594	S.D. dependent var	820.1081
S.E. of regression	913.8204	Sum squared resid	18371488
Durbin-Watson stat	1.899885		

Appendix H: Granger causality test

Pairwise Granger Causality Tests
Date: 05/01/24 Time: 11:48
Sample: 2021M01 2023M12
Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
DFW does not Granger Cause DRV	33	3.09390	0.0611
DRV does not Granger Cause DFW		0.20286	0.8176
DFC does not Granger Cause DRV	33	0.35155	0.7067
DRV does not Granger Cause DFC		1.40315	0.2626
DINF does not Granger Cause DRV	33	0.39040	0.6804
DRV does not Granger Cause DINF		0.25462	0.7770
DER does not Granger Cause DRV	33	0.32414	0.7258
DRV does not Granger Cause DER		0.64125	0.5342
DFC does not Granger Cause DFW	33	1.11642	0.3416
DFW does not Granger Cause DFC		0.38829	0.6818
DINF does not Granger Cause DFW	33	0.36053	0.7005
DFW does not Granger Cause DINF		0.36232	0.6993
DER does not Granger Cause DFW	33	0.06059	0.9413
DFW does not Granger Cause DER		0.32683	0.7239
DINF does not Granger Cause DFC	33	2.11911	0.1390
DFC does not Granger Cause DINF		0.96969	0.3916
DER does not Granger Cause DFC	33	1.04134	0.3663
DFC does not Granger Cause DER		0.23801	0.7898
DER does not Granger Cause DINF	33	2.77096	0.0798
DINF does not Granger Cause DER		0.11784	0.8893

Appendix I: Authorisation letter from BUSE

EX0029

STATISTICS AND MATHEMATICS DEPARTMENT

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

CHAIRPERSON'S OFFICE

20 November 2023

The Manager
Simbisa Brands
17 Morningside Drive
Mt Pleasant
HARARE

Dear Sir/ Madam

REF: SPECIAL REQUEST FOR DENZEL TINOTENDA GOMBARAGO (B200312A) TO BE GRANTED SPECIAL PERMISSION TO ACCESS YOUR INSTITUTION'S DATA FOR EDUCATIONAL PURPOSES.

This letter serves to inform you that **Denzel Tinotenda Gombarago (B200312A)** is a student at Bindura University of Science Education. He is pursuing a Bachelor of Science Degree (Hons.) in Statistics and Financial Mathematics and is now at a level where the University requires him to produce a dissertation of his choice.

We are kindly requesting for your assistance wherever possible, with the information that he may need from your organization. For further information and clarification, please feel free to contact the undersigned.

Yours Faithfully

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

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Appendix J: Approval letter from Simbisa Brands

Simbisa Brands
LIMITED

Approval Letter for Data Collection

Denzel T. Gombarago
52 Cavell drive
Southerton
Harare

Dear **Mr. Gombarago,**

I hope this letter finds you well.

I am pleased to inform you that your request for data collection for your research project at Rocomamas has been granted. The purpose of this approval letter is to acknowledge your proposed data collection of revenue values, food waste values and food cost percentage indices for Rocomamas and to provide you with the necessary endorsement to proceed with its implementation.

Please ensure that the information provided is utilized effectively, in accordance to relevant regulations and guidelines, ethical principles and privacy laws. Should any modifications or changes be required, prior approval must be sought from the appropriate authority.

In case of any inquiries or if you require further assistance, please feel free to email me at misheck.muleya@simbisa.co.zw.

I would be more than willing to support you in any way necessary.

Thank you for your diligence and professionalism in submitting your Data Collection approval. We trust that this endorsement will contribute positively to your research efforts and we look forward to the outcomes that will result from it.

Sincerely,

Misheck Muleya

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