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The Effect of Exchange Rate Dynamics on Food Prices in Urban
Uganda: An Integrated Machine Learning and Econometrics Analysis
of Kampala Markets

By

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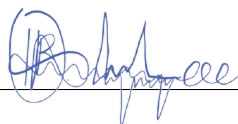
Approval

This research report, conducted and submitted by Econia Racheal, partially fulfills the requirements for the degree of Master of Science in Data Science.

Approved by:

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Date: 15 / 09 / 2026

Declaration

I do declare to the best of my knowledge that the information in this research report on “The Effect of Exchange Rate Dynamics on Food Prices in Urban Uganda: A Case Study of Kampala Markets Using Regression and Causal Analysis” is a result of my effort and has never been presented to any university or higher institution of learning for the award of a degree.

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Abstract

Food price volatility remains a major policy concern in urban Uganda because changes in staple food prices directly affect household welfare, food security, and the purchasing power of low-income consumers. This study investigated the effect of UGX/USD exchange rate dynamics on food prices in Kampala markets using a multi-method analytical framework that combines econometric analysis, causal inference, non-linear modelling, frequency-domain analysis, machine learning, and model deployment. The study used World Food Programme food-price data for Uganda and official Bank of Uganda exchange-rate data, merged on a monthly basis to create an analytical panel covering January 2006 to September 2025.

The analysis began with data preprocessing and exploratory data analysis to examine food-price trends, commodity-level volatility, and consistency between implied and official exchange rates. Causal and dynamic relationships were then evaluated using regression analysis, Granger causality testing, transfer entropy, DCC-GARCH, Markov-switching regression, quantile regression, and wavelet coherence. Predictive performance was assessed using traditional regression models, Random Forest, XGBoost, Prophet, and deep learning models, with model accuracy evaluated using R^2 , RMSE, and MAE. Finally, selected models were operationalized through a Flask API and Progressive Web Application frontend to demonstrate practical food-price prediction.

The findings show that exchange rate movements contain meaningful information for understanding and forecasting urban food prices, but the relationship is non-linear, commodity-specific, and time-varying. Causal evidence indicates a predominantly one-directional influence from exchange rates to food prices, while regime and quantile results show that pass-through effects intensify during high-volatility and high-price episodes. Wavelet analysis further shows strong short-term co-movement at the 3–6 month horizon, with weaker associations at longer horizons. In predictive modelling, XGBoost achieved the strongest panel-level performance with an R^2 of 0.7944, RMSE of 646.25, and MAE of 401.60, followed closely by Random Forest with an R^2 of 0.7815. These results demonstrate that machine learning models using exchange-rate and commodity information can substantially improve food-price prediction compared with linear baselines.

The study contributes theoretically by extending exchange rate pass-through analysis to urban food markets, methodologically by integrating causal, non-linear, time-frequency, and predictive approaches, and practically by deploying a web-based decision-support tool for commodity price prediction. The findings suggest that food-price stabilization policies in Uganda should combine exchange-rate monitoring with commodity-specific market intelligence and early warning systems.

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List of Acronyms

UGX	Ugandan Shilling
USD	United States Dollar
IMF	International Monetary Fund
UNCTAD	United Nations Conference on Trade and Development
VECM	Vector Error Correction Model
DID	Difference-in-Differences
RMSE	Root Mean Square Error

Chapter 1

Introduction

1.1 Introduction to the Study

Food price volatility in urban Uganda represents a critical intersection between macroeconomic dynamics and household welfare, with exchange rate fluctuations playing a pivotal role in price transmission mechanisms. The theoretical foundation of this relationship stems from Purchasing Power Parity frameworks, though its practical manifestation is mediated by localized market structures and commodity-specific characteristics (Terborgh, 1926; International Monetary Fund, 2003). As shown in figure 4.3, the Ugandan Shilling has exhibited substantial depreciation against the US Dollar during the study period and since the 2008 Global Financial Crisis (Reserve Bank of Australia, nd), with documented recent depreciation pressure also reported in Uganda (Daily Monitor, 2023). Broader Sub-Saharan African evidence also shows that commodity dependence and market sentiment can generate time-varying currency pressure across different horizons (Woode et al., 2026), creating persistent pressure on domestic price levels through multiple transmission channels. This research investigated these dynamics through an integrated analytical framework that combined causal inference methods with machine learning techniques, focusing specifically on Kampala's markets where the concentration of economic activity and dependence on imported inputs creates heightened sensitivity to exchange rate movements. The study addressed three significant gaps in the existing literature. First, while previous studies by international organizations including the IMF and UNCTAD established broad correlations between exchange rates and food prices at aggregate levels (International Monetary Fund, 2003; United Nations Conference on Trade and Development, 2022), they insufficiently accounted for urban-specific transmission mechanisms and commodity-level variations. Second, the predominant reliance on linear econometric models in earlier work, including Mawejje's analysis of Ugandan food prices (Mawejje, 2016), overlooked potentially significant non-linear, regime-dependent, and time-scale-varying relationships that better explain price volatility patterns. Third, there remained a critical lack of predictive frameworks that could inform timely policy interventions, particularly for urban markets where supply chain inefficiencies may exacerbate exchange rate effects. The methodology employed in this research overcame these limitations through a multi-method analytical approach. The investigation utilized Granger causality tests, transfer entropy analysis, and regression modeling to establish directional relationships and quantify effects between USD/UGX fluctuations and food price movements. Complementing these causal inference techniques, the research implemented regime-switching models, quantile regression, and frequency domain analysis to capture non-linear dynamics and time-varying relationships. The predictive component incorporated ensemble machine learning algorithms alongside traditional time series models to assess the practical forecasting utility of exchange rate information. This comprehensive methodology

was applied to an integrated dataset spanning 2006–2025, incorporating detailed price observations from Kampala’s markets alongside exchange rate and macroeconomic indicators from the Bank of Uganda and World Food Programme (Bank of Uganda, 2025; World Food Programme, 2025). The study made three primary contributions to the understanding of exchange rate pass-through in developing economies. Theoretically, it extended Purchasing Power Parity frameworks by demonstrating how urban market structures and commodity characteristics mediate exchange rate pass-through effects, with empirical evidence revealing significant state-dependent and quantile-varying transmission patterns. Methodologically, it demonstrated the value of integrating multiple analytical perspectives; encompassing causal inference, non-linear analysis, frequency domain examination, and predictive modeling; to develop a more comprehensive understanding of complex economic relationships. Practically, the findings provided actionable insights for food security policy and exchange rate management, particularly regarding the design of targeted interventions to stabilize urban food markets during periods of currency volatility and price spikes. By rigorously analyzing both the causal mechanisms and predictive relationships between exchange rates and food prices in an urban context, this research advanced the understanding of a critical policy challenge facing import-dependent economies. The integrated analytical framework developed and implemented offered a replicable approach for similar studies in other developing country contexts where urbanization, food security concerns, and macroeconomic instability intersect.

1.2 Background of the Study

Food price stability represents a critical determinant of economic resilience and household welfare in Uganda, with particular significance for urban populations where food expenditures constitute a substantial portion of household budgets. Exchange rate dynamics, characterized by fluctuations in the Ugandan Shilling against major international currencies including the US Dollar, exert considerable influence on the cost structure of agricultural production and food distribution systems. While international and African research has established the importance of exchange rate movements and monetary policy conditions in food inflation patterns (United Nations Conference on Trade and Development, 2022; Ezebilo et al., 2023), the Ugandan context presents unique characteristics shaped by regional supply chains, domestic production cycles, and market infrastructure that mediate these global influences. Urban markets, particularly Kampala’s Owino Market as the largest retail market in Uganda, function as critical hubs for both imported and locally produced food commodities, creating environments where exchange rate transmissions manifest with particular clarity. The concentration of economic activity and dependence on imported agricultural inputs in urban centers makes these markets ideal microcosms for investigating how macroeconomic shocks translate to micro-level price outcomes, consistent with evidence on exchange-rate effects on commodity prices and food commodity prices (Gilbert, 1986; Umoru and Amedu, 2022). This research leveraged the food price dataset from the World Food Programme, accessed through the Humanitarian Data Exchange (World Food Programme, 2025), which provided detailed monthly price observations for staple commodities including maize, rice, beans, and various processed foods across Ugandan urban markets. The analytical framework was strengthened through the integration of official exchange rate data from the Bank of Uganda (Bank of Uganda, 2025), creating a unified dataset that enabled rigorous examination of the relationship between currency movements and food price dynamics. This integration addressed a significant limitation in previous studies that relied solely on implied exchange rates or lacked high-frequency official currency data. The focus on Kampala proved particularly relevant given the city’s economic structure, where despite domestic sourcing of many food commodities, production remains heavily dependent on imported inputs including fertilizers, pesticides, and fuel, creating multiple channels for exchange

rate effects to permeate the food system. The background context informed the research design that ultimately examined how exchange rate dynamics propagate through urban supply chains, affecting both staple food items and essential non-food commodities. The comprehensive temporal coverage of the integrated dataset, spanning nearly two decades of monthly observations, provided sufficient historical variation to capture both short-term adjustments and longer-term structural relationships between currency values and commodity prices in Uganda’s evolving market economy.

1.3 Problem Statement

Urban households in Uganda, particularly those residing in Kampala, faced persistent exposure to food price volatility driven by complex interactions between macroeconomic forces and local market conditions. While existing literature established broad correlations between exchange rate movements and national price levels, these studies failed to adequately account for the distinctive transmission mechanisms operating in urban markets. Previous research approaches, including those by the IMF (International Monetary Fund, 2003), predominantly employed linear econometric models that overlooked potentially significant non-linear relationships and regime-dependent behaviors characterizing exchange rate pass-through. The research problem addressed through this investigation centered on understanding how USD-UGX exchange rate dynamics interacted with Kampala’s specific market structures to influence food price formation and volatility. This problem manifested through three interconnected dimensions: the directional causality between exchange rates and prices, the state-dependent nature of transmission intensity, and the practical utility of exchange rate information for price forecasting. The absence of comprehensive analysis integrating these dimensions in previous research created a significant knowledge gap regarding the precise mechanisms through which macroeconomic shocks translate to micro-level welfare outcomes in urban Uganda. The investigation specifically examined the hypothesis that exchange rate pass-through operates through complex, non-linear channels that vary across different economic conditions and commodity types. This problem demanded a methodological approach capable of capturing both the linear dependencies and intricate, time-varying nature of the relationship between currency fluctuations and food price outcomes. The research therefore implemented a multi-faceted analytical framework to address these complexities and provide empirical evidence regarding the nature and magnitude of exchange rate effects on urban food security in Uganda.

1.4 Purpose of the Study

The primary purpose of this study was to determine how UGX/USD exchange-rate dynamics affected and predicted commodity prices in Kampala markets between January 2006 and September 2025, and to translate the strongest predictive models into a functioning decision-support tool. The study pursued four aligned objectives covering descriptive market analysis, causal and dynamic assessment, predictive model evaluation, and practical deployment.

1.5 Significance of the Study

This research holds significance across multiple domains, contributing to both practical policy formulation and academic knowledge advancement. From a policy perspective, the study provides precise empirical estimates of exchange rate pass-through effects on food prices, offering evidence-based guidance for designing targeted interventions to stabilize domestic markets.

The identification of regime-dependent transmission patterns and commodity-specific vulnerabilities enables more effective policy measures, including potential targeted subsidies or adjusted import duty regulations, to mitigate the adverse impacts of currency volatility on urban households. The findings offer particular relevance for Uganda’s National Development Plan and monetary policy framework by illuminating the complex dynamics between exchange rate management and food security objectives. The economic and social significance of this research stems from its focus on urban consumer vulnerability to food price fluctuations. By developing robust forecasting frameworks that demonstrate the predictive utility of exchange rate information, the study contributes to early warning systems that can facilitate proactive measures to protect vulnerable populations from sudden inflationary shocks. The quantification of differential effects across price distribution quantiles provides crucial insights for social protection programs, highlighting the disproportionate impact of exchange rate movements during price spike episodes that most severely affect low-income households.

Academically, this research makes substantive contributions through its methodological integration of traditional econometric approaches with contemporary analytical techniques. The demonstration of complementary insights from causal inference, non-linear analysis, frequency domain examination, and predictive modeling advances the methodological state of research on exchange rate dynamics and price behavior. The study addresses significant literature gaps regarding urban-specific transmission mechanisms and causal relationships, while providing a replicable analytical framework for similar investigations in other emerging market contexts characterized by rapid urbanization and import dependency. Furthermore, the comprehensive approach establishes a foundation for future research by demonstrating the value of multi-methodological frameworks for understanding complex economic relationships. The study encourages subsequent investigations to incorporate similar integrated methods to explore policy-specific outcomes and refine predictive models for improved food security planning. The identification of specific research gaps and methodological limitations provides clear direction for further scholarly inquiry into localized food market dynamics under varying exchange rate conditions, particularly in import-dependent urban centers across developing economies.

The findings are relevant to monetary, agricultural, fiscal, urban-market, humanitarian, commercial, and research stakeholders. These groups can use the study for inflation surveillance, commodity monitoring, food-security planning, market assessment, scenario analysis, procurement planning, and methodological extension. The detailed stakeholder roles and intended uses of the study outputs are presented in Appendix H, while Chapters 5 and 6 discuss their practical interpretation and stakeholder-specific recommendations.

1.6 Study Objectives

1.6.1 Main Objective

The principal objective of this research was to determine how monthly UGX/USD exchange-rate dynamics affected and predicted commodity prices in Kampala markets from January 2006 to September 2025, using an integrated causal, non-linear, time-frequency, and predictive framework, and to operationalize the strongest predictive models in a web-based decision-support system.

1.6.2 Specific Objectives

The study pursued four specific objectives. First, it sought to characterize monthly UGX/USD exchange-rate and commodity-price trends in Kampala from January 2006 to September 2025,

quantify commodity-level volatility, and identify commodities exhibiting the greatest price sensitivity. Second, it aimed to estimate the direction, magnitude, regime dependence, distributional heterogeneity, volatility co-movement, and time-scale characteristics of the exchange-rate–price relationship using linear and non-linear analytical methods. Third, it sought to develop and compare econometric, machine-learning, time-series, and deep-learning models for commodity-price prediction and evaluate their performance on held-out observations using R^2 , RMSE, and MAE. Finally, it aimed to design, deploy, and demonstrate a web-based decision-support system that generates commodity-price estimates from exchange-rate and commodity inputs using the selected predictive models.

1.7 Research Questions

The investigation was guided by four research questions aligned with the revised objectives. First, what trends and commodity-level volatility patterns characterized the monthly UGX/USD exchange rate and commodity prices in Kampala between January 2006 and September 2025? Second, what directional, regime-dependent, distributional, volatility, and time-scale relationships existed between exchange-rate movements and commodity prices in Kampala markets? Third, how accurately did econometric, machine-learning, time-series, and deep-learning models predict commodity prices when evaluated using R^2 , RMSE, and MAE on held-out observations? Finally, how could the selected predictive models be implemented in a web-based decision-support system for practical commodity-price estimation?

1.8 The Scope of the Study

This research delineates its scope across geographical, temporal, methodological, and conceptual dimensions to maintain analytical focus while ensuring comprehensive investigation of the core research problem. Geographically, the study concentrates specifically on urban markets within Kampala, with Owino Market serving as the primary case study due to its prominence as Uganda’s largest retail market and its representative function as a major price-setting institution. While findings may offer insights into other urban contexts, the explicit focus remains on understanding the distinct transmission mechanisms operating within Kampala’s specific market ecosystem. Temporally, the investigation encompasses the period from January 2006 through September 2025, providing nearly two decades of monthly observations that capture multiple business cycles, exchange rate regimes, and structural economic shifts. This extensive timeframe enables robust analysis of both short-term dynamics and long-term relationships while incorporating significant economic events including the global financial crisis, commodity price cycles, and recent inflationary episodes. Methodologically, the scope encompasses a multi-faceted analytical framework integrating causal inference techniques, non-linear modeling, frequency domain analysis, predictive machine learning approaches, and practical model deployment. While comprehensive in methodological coverage, the study acknowledges that each approach possesses inherent limitations and makes no claim to exhaustive treatment of all potential methodologies applicable to exchange rate pass-through analysis.

Conceptually, the research focuses specifically on the transmission mechanisms between exchange rate fluctuations and food price outcomes, examining both direct effects and those mediated through market structures and commodity characteristics. The scope explicitly excludes detailed examination of other inflationary drivers including fiscal policy, climate impacts on agricultural production, or regional trade dynamics, though it acknowledges these as important contextual factors. The commodity scope encompasses both food and essential non-food

items tracked within the Kampala market dataset, enabling comparative analysis of transmission mechanisms across different product categories while maintaining focus on commodities most relevant to household consumption patterns and welfare outcomes. This carefully delineated scope ensures analytical depth while providing clear boundaries for interpreting research findings and their implications for both academic understanding and policy formulation specific to urban Ugandan contexts.

1.9 Conceptual Framework

This study’s analytical framework integrates macroeconomic exchange rate theory with microeconomic market structure analysis to explain the transmission mechanisms between currency fluctuations and food price outcomes in urban Uganda. The framework posits a dynamic, multi-channel relationship where exchange rate movements interact with local market conditions to determine final consumer prices, with effects that vary across time scales, economic regimes, and commodity types.

The conceptual relationships investigated in this research are illustrated below:

1.9.1 Core Theoretical Relationships

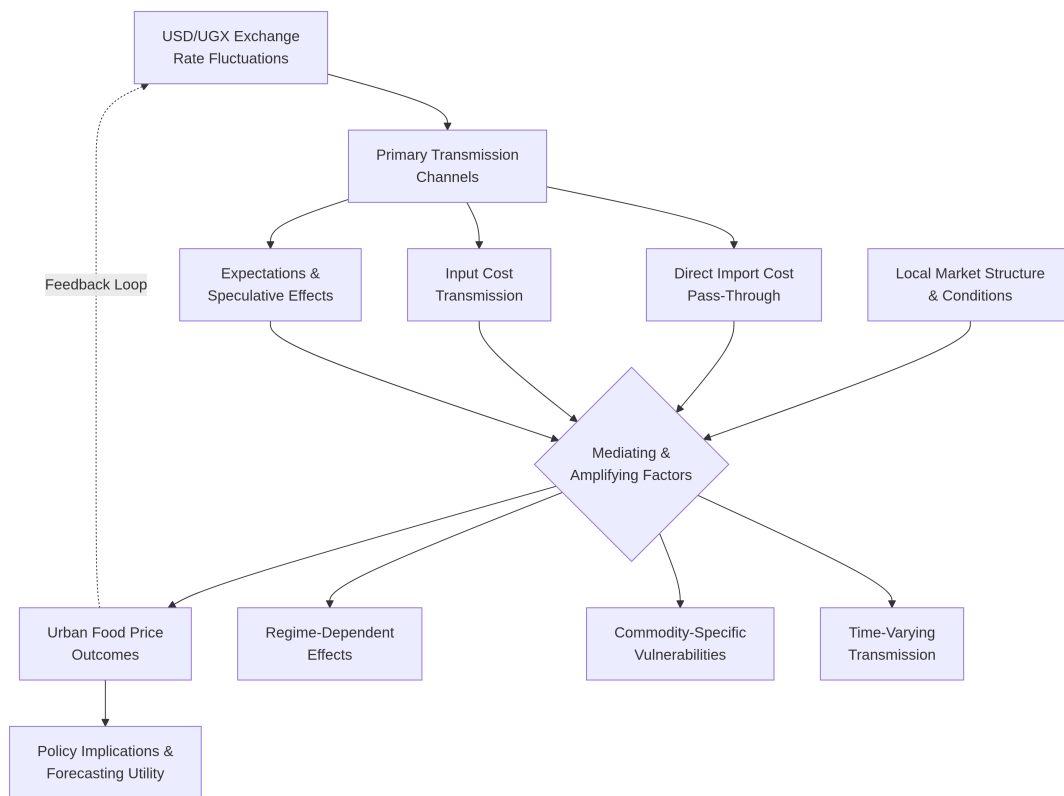


Figure 1.1: Conceptual framework

The framework conceptualizes three primary transmission channels through which exchange rate dynamics influence food prices. The direct import cost channel operates through immediate pass-through effects on imported food items and agricultural inputs, creating first-round

inflationary pressures. The production input channel transmits exchange rate effects through intermediate goods including fertilizers, pesticides, and fuel, which affect domestic production costs and create second-round price effects. The expectations channel captures how currency movements influence trader behavior, inventory decisions, and speculative activities that can amplify or dampen direct cost effects. Local market structures and conditions serve as critical mediating factors that determine the ultimate magnitude and timing of exchange rate pass-through. These include supply chain efficiency, market concentration, storage capacity, and transportation infrastructure, which collectively influence how external shocks translate to retail price outcomes and are consistent with evidence on staple-food market integration and asymmetric price transmission in Uganda (Waiswa and Yavuz, 2023). The framework specifically accounts for the role of seasonal agricultural cycles, which can temporarily decouple domestic prices from exchange rate movements during harvest periods while amplifying effects during lean seasons.

1.9.2 Methodological Integration

The research implemented a comprehensive analytical approach to investigate these conceptual relationships empirically. Causal inference methods, including Granger causality tests and transfer entropy analysis, were employed to establish directional relationships and temporal precedence between exchange rates and prices. Regression techniques, encompassing both linear and non-linear specifications, quantified the magnitude and significance of exchange rate effects while controlling for confounding factors. Non-linear and regime-dependent analysis through Markov-switching and quantile regression models captured the state-varying nature of transmission mechanisms, recognizing that pass-through intensity differs across economic conditions and price distribution segments. Frequency domain analysis using wavelet coherence examined how relationships evolve across different time horizons, distinguishing between short-term adjustments and long-term structural relationships. Predictive modeling with both traditional time series approaches and machine learning algorithms evaluated the practical forecasting utility of exchange rate information, while simultaneously providing insights into the complex interaction patterns that characterize the transmission process. This multi-methodological integration enabled robust examination of both the theoretical propositions and empirical manifestations of exchange rate pass-through in Uganda's urban food economy.

Chapter 2

Literature Review

2.1 Introduction

This chapter presents a comprehensive review of the theoretical and empirical literature that informed and contextualized the investigation into exchange rate pass-through to food prices in urban Uganda. The review synthesizes established economic theories and prior empirical findings to establish the conceptual foundation upon which this research was built. It examines the evolution of relevant theoretical frameworks, assesses the methodological approaches employed in previous studies, and identifies the specific research gaps that this study sought to address through its integrated analytical framework. The chapter concludes by situating the current research within the broader academic discourse on exchange rate transmission mechanisms in developing economies.

2.2 Theoretical Literature Review

This research was theoretically anchored in the Purchasing Power Parity (PPP) framework, which posits that exchange rate movements influence domestic price levels by altering the relative cost of traded goods and services. First articulated in its modern form by Cassel (Cassel, 1916), PPP theory establishes that exchange rates tend toward equilibrium levels that equalize the purchasing power of different currencies across national borders (Terborgh, 1926). The monetary approach to exchange rates complemented this framework, suggesting that inflationary pressures stemming from currency depreciation propagate through commodity markets via import-dependent supply chains (Umoru and Amedu, 2022). However, Terborgh's seminal critique (Terborgh, 1926) highlighted critical limitations of the pure PPP theory that proved particularly relevant for this investigation. First, the assumption that exchange rates are determined solely by relative price levels neglects important non-trade factors including capital flows, tariff structures, and speculative behavior. Terborgh argued that deviations from PPP equilibrium could persist indefinitely due to structural shifts in trade balances or changes in international indebtedness—a phenomenon observed in Uganda's reliance on imported agricultural inputs. Second, PPP's reliance on aggregate price indices conflates traded and non-traded goods, weakening its explanatory power in contexts like Kampala where perishable staples with limited tradability dominate local markets. Despite these limitations, PPP provided a foundational theoretical framework for understanding Uganda's exchange rate-food price nexus. As Terborgh acknowledged (Terborgh, 1926), PPP offers a "rough normative benchmark" for exchange rate valuation, particularly in inflation-prone economies where currency depreciation systematically amplifies import costs. Recent refinements by international institutions includ-

ing the IMF have integrated PPP with market integration frameworks, emphasizing how local market structures and supply chain inefficiencies mediate the pass-through of exchange rate shocks to domestic prices (International Monetary Fund, 2003). The empirical implementation of this research further engaged with these theoretical propositions by testing their applicability in the Ugandan context. The findings regarding state-dependent pass-through effects and quantile-varying transmission intensities demonstrated the limitations of linear PPP assumptions while supporting the theoretical expectation of incomplete and variable exchange rate transmission. The frequency domain results aligning with short-term co-movement patterns provided empirical validation for theoretical propositions about the temporal dimension of price adjustment mechanisms.

Thus, while the PPP framework provided the foundational theoretical orientation, the research design incorporated sufficient flexibility to capture the complex, non-linear relationships that characterize real-world exchange rate pass-through processes.

2.3 Empirical Literature

Empirical investigations have consistently documented significant relationships between exchange rate volatility and food price movements across diverse economic contexts. UNCTAD identified a double burden phenomenon in net food-importing countries, where global food price increases combine with substantial currency depreciation to dramatically inflate import bills (United Nations Conference on Trade and Development, 2022). Research specific to Uganda has yielded particularly relevant insights. Mawejje established that a one percent depreciation of the Ugandan Shilling correlates with a 1.6 percent rise in urban food prices, demonstrating the particular sensitivity of Kampala's markets to exchange rate shocks (Mawejje, 2016). This finding aligns with broader African evidence from Umoru and Amedu, who employed GARCH modeling to demonstrate that exchange rate volatility exerts pronounced and persistent effects on food commodity prices across multiple African economies (Umoru and Amedu, 2022). Nigerian evidence similarly links macroeconomic policy instruments to food inflation, with Ezebilo et al. using a non-linear autoregressive distributed lag approach to examine exchange rate, monetary policy rate, treasury bill rate, and broad money supply effects on food inflation (Ezebilo et al., 2023). Related Ethiopian evidence also supports the relevance of multivariate volatility modeling, with Likassa et al. showing that DCC-GARCH captures time-varying correlations among inflation indicators, food prices, non-food prices, and exchange rates (Likassa et al., 2026). The temporal dimension of exchange rate pass-through has received considerable scholarly attention. Gilbert documented a delayed but persistent response of food prices to exchange rate shocks, especially in urban environments characterized by fragmented supply chains (Gilbert, 1986). This pattern of gradual adjustment has been observed in subsequent studies examining price transmission mechanisms in developing economies. Recent research on food price shocks in Uganda has reinforced these findings by demonstrating how external factors including global commodity price trends interact with domestic market inefficiencies to drive food price volatility.

Recent Sub-Saharan African evidence further demonstrates the value of examining commodity-currency linkages across multiple time horizons. Woode et al. analyzed commodity import and export dependence, market sentiment, and currency pressure in Ghana, The Gambia, and Madagascar using time-frequency wavelet methods, showing that commodity-currency relationships vary across short-, medium-, and long-run horizons and may intensify during crisis periods (Woode et al., 2026). Although their study focused on pressure currencies and broad commodity dependence rather than Ugandan food retail prices, it is relevant to the present research because it confirms that commodity-linked exchange rate dynamics in African economies are

time-varying, country-specific, and sensitive to external market conditions. This supports the use of wavelet coherence in the current study and highlights the remaining need for urban-market evidence on how such macroeconomic dynamics transmit into local food prices.

The empirical literature collectively underscores the importance of exchange rate movements as determinants of food price behavior, yet reveals significant methodological limitations in previous approaches. Many studies relied predominantly on linear econometric models that potentially oversimplified the complex, non-linear relationships characterizing real-world market dynamics. Even where recent African studies have adopted wavelet methods to uncover time-frequency commodity-currency interactions (Woode et al., 2026), the evidence remains concentrated at macroeconomic and cross-country levels rather than at the urban food-market level. Furthermore, the literature exhibited limited integration of causal inference methods with predictive modeling frameworks, creating a knowledge gap regarding both the mechanistic pathways and practical forecasting utility of exchange rate information. The current research addressed these limitations through its comprehensive analytical approach, incorporating methods capable of detecting non-linearities, regime changes, time-scale dependent co-movement, and causal relationships that may have been obscured in previous investigations.

2.4 Gaps and Opportunities Identified

While the theoretical and empirical literature robustly confirms the macroeconomic linkages between exchange rate fluctuations and food prices, several critical gaps remain that this research sought to address. The comprehensive review revealed four principal limitations in existing scholarship that created opportunities for methodological and substantive contributions. First, a significant urban-rural disparity exists in the granularity of existing research. Studies such as those by the IMF and other international institutions (International Monetary Fund, 2003) often generalize findings at the national level, neglecting the unique dynamics of urban markets where population density, supply chain structures, and consumption patterns create distinct transmission mechanisms. Kampala’s markets, where a substantial portion of food commodities rely on imported inputs despite domestic sourcing, represent a particularly compelling context that had not received focused analytical attention in previous research. This gap limited the applicability of national-level findings to urban policy formulation and targeted intervention design. Second, the literature demonstrates a pronounced emphasis on correlational relationships rather than causal mechanisms. Most empirical work, including comprehensive studies by UNCTAD (United Nations Conference on Trade and Development, 2022), establishes statistical associations but provides limited evidence of causal directionality. There exists a scarcity of studies that employ rigorous causal inference methods such as Granger causality tests or information-theoretic approaches to isolate the direct effects of exchange rate changes from local confounding factors including transportation costs, seasonal production cycles, and market-specific inefficiencies. This methodological limitation has constrained the ability to establish mechanistic pathways through which exchange rate shocks transmit to retail prices. Third, the application of predictive modeling and time-frequency techniques remains underdeveloped in the Ugandan context. Although machine learning approaches have been successfully applied in forecasting commodity prices globally, and wavelet methods have recently been used to study broader commodity-currency dependence in Sub-Saharan Africa (Woode et al., 2026), their deployment for understanding exchange rate pass-through in African urban food markets is limited. There exists a significant opportunity to leverage algorithms including Random Forest and XGBoost to capture non-linearities and complex interactions specific to urban supply chains, potentially enhancing both forecasting accuracy and theoretical understanding of the transmission process. Fourth, the literature exhibits insufficient attention to policy nuance and

local supply chain specificities. While broader recommendations exist regarding exchange rate management and food price stabilization, previous research rarely addresses the microeconomic aspects of urban supply chain vulnerabilities, such as those observed in Owino Market, which can substantially mediate the effect of exchange rate changes. The absence of contextualized understanding of how market institutions, trader behaviors, and logistical frameworks influence price transmission has limited the practical utility of existing research for targeted policy intervention. This study systematically addressed these gaps through its focused investigation of Kampala’s urban markets, employing integrated causal inference methods, frequency-domain analysis, and machine learning techniques to improve both explanatory understanding and forecasting accuracy. The research design specifically accommodated the examination of non-linear relationships and regime-dependent behaviors that theoretical literature suggested might be present but previous empirical work had insufficiently captured. By contextualizing the analysis within specific market structures and supply chain characteristics, the study provided a more nuanced, empirically-grounded understanding of how exchange rate dynamics influence food prices, thereby contributing to more effective and targeted policy interventions in urban food markets.

Chapter 3

Methodology

3.1 Introduction

This chapter delineates the methodological framework employed to investigate the dynamic relationship between exchange rate fluctuations and local food prices in Uganda. The primary objective is to move beyond simple correlation and establish a multi-faceted understanding that encompasses causality, non-linear dynamics, and predictive power. The chapter provides a detailed exposition of the research design, the datasets utilized, and the sequential application of a suite of analytical techniques. These techniques range from foundational data preprocessing and exploratory analysis to advanced econometric and machine learning models. The goal of this methodological approach is to ensure the empirical findings are robust, nuanced, and capable of informing both academic discourse and practical policy decisions.

3.2 Research Design

The research design for this study is fundamentally empirical and quantitative, structured around a causal-predictive framework. The approach is designed to systematically unpack the complex interplay between the Ugandan Shilling to US Dollar (UGX/USD) exchange rate and the prices of key commodities. The investigation is executed through a sequential, multi-stage process that begins with data preparation and culminates in predictive modeling. The cornerstone of this research is the utilization of two primary datasets. The first is the Ugandan food price dataset from the World Food Programme (WFP), obtained from Humanitarian Data Exchange (World Food Programme, 2025). The obtained sample of this dataset contains 20,209 monthly price records spanning from January 2006 to September 2025. This dataset provides detailed information, including date, administrative regions, market locations, commodity types, prices in Ugandan Shilling (UGX), and their USD-converted values. The second critical dataset is the historical UGX/USD exchange rate series provided by Bank of Uganda and obtained from OpenData for the Bank of Uganda website (Bank of Uganda, 2025), which was merged with the price data on a year-month basis to create a unified analytical panel. The methodological execution is structured to answer the research questions from different angles. Initially, Exploratory Data Analysis (EDA) is conducted to understand the structure, distribution, and temporal trends within the data, with a specific focus on the key market of Kampala as the urban market. Subsequently, Causality Analysis employs a combination of Granger causality tests and regression models to test for directional influences, following the predictive-causality logic formalized by Granger (Granger, 1969). To capture more complex, non-linear relationships that may be missed by traditional methods, the research incorporates Non-linear

and Regime-Dependent Analysis, including Quantile Regression as introduced by Koenker and Bassett (Koenker and Bassett, 1978). The dynamic co-movement between exchange rates and prices across different time horizons is examined using Frequency Domain Analysis, specifically Wavelet Coherence, which is widely used for localized time-frequency analysis (Torrence and Compo, 1998). Finally, the practical predictive power of the exchange rate is rigorously tested using a suite of Machine Learning models and a weighted ensemble, benchmarked against traditional time series models like SARIMA and Prophet (Breiman, 2001; Chen and Guestrin, 2016; Taylor and Letham, 2018; Hyndman and Khandakar, 2008). This multi-methodological design ensures that the findings are not only statistically sound but also rich in context, capturing both the linear dependencies and the intricate, time-varying nature of the relationship between macroeconomic shocks and micro-level price outcomes.

3.3 Data Preprocessing

The integrity and reliability of the empirical analysis are contingent upon rigorous data preprocessing. This stage involved the transformation of raw, heterogeneous datasets into a clean, consistent, and merged analytical file suitable for time series and causal inference. The process encompassed data cleaning, variable transformation, and the strategic merging of disparate data sources. The primary dataset, sourced from the World Food Programme (WFP), contained 20,209 initial observations of Ugandan food prices. The initial data inspection revealed the first row contained column descriptors rather than data, which was subsequently handled. Key preprocessing steps on this dataset included the conversion of the date column into a datetime format to facilitate time series operations. The price and `usdprice` columns were converted to numeric data types, coercing any non-numeric entries to missing values. Rows with critical missing values in these fields, or in the date, were excluded from the analysis to ensure data quality. The dataset was then sorted chronologically to maintain the temporal order essential for time series analysis. A crucial step involved engineering a derived variable, the `implied_exchange_rate`, from the WFP data. This variable was computed for each price observation using the formula:

$$\text{implied_exchange_rate}_{i,t} = \frac{\text{price}_{i,t}}{\text{usdprice}_{i,t}} \quad (3.1)$$

allowing for a methodological check against the official average monthly exchange rate data obtained from the Bank of Uganda (Bank of Uganda, 2025). The distribution and central tendency of these implied rates were later compared to the official series to assess consistency and identify any systematic biases in the USD price conversions within the WFP dataset. Concurrently, the secondary dataset from the Bank of Uganda, containing the official monthly average UGX/USD exchange rates, was processed. The date information in this dataset was standardized into a datetime format, and year and month components were extracted to serve as merge keys. The final preprocessing step was the integration of these two datasets. The cleaned WFP food price data was merged with the official exchange rate data using the year and month as the primary keys. This merge operation, performed as a left join, successfully appended the official `exchange_rate` value to every corresponding price record in the main dataset without any loss of primary observations, resulting in a unified panel data structure. This consolidated dataset forms the foundation for all subsequent analytical stages outlined in this chapter.

3.3.1 Data Challenges and Mitigation Procedures

Several data challenges affected the design and interpretation of the study. First, the WFP dataset contained a descriptor row within the raw observations, mixed data types in the price fields, and missing or non-numeric values. These issues were addressed by removing the descriptor row, coercing price variables to numeric form, converting dates to a consistent datetime format, excluding observations without valid dates or prices, and sorting the resulting records chronologically.

Second, commodity coverage was uneven across time and markets. Some commodities had long monthly histories, while others appeared intermittently or contained too few observations for stable volatility and time-series analysis. The study therefore applied a minimum-observation threshold for detailed exploratory analysis and interpreted commodity comparisons in relation to their available sample sizes. Monthly averaging was used to reduce duplicate or within-month market noise, but this aggregation may conceal shorter price movements occurring within a month.

Third, the exchange-rate and food-price datasets differed in structure and frequency. Official exchange rates were available as a monthly series, whereas the WFP data contained multiple commodity-market observations per month. Year and month keys were created in both datasets and used for a left merge so that every valid food-price observation retained its commodity and market information while receiving the corresponding official monthly exchange rate. The implied exchange rate calculated from UGX and USD prices was compared with the official series as an internal consistency check.

Fourth, Kampala observations were concentrated in Owino Market and did not provide balanced representation of all markets within the city. The Kampala analysis should therefore be understood as an urban-market case study with strong representation of Owino Market, rather than a statistically representative sample of every Kampala market. This concentration was retained because it provided the most consistent urban time series, but it limits spatial generalization.

Finally, the available merged dataset primarily supported analysis using price, exchange rate, time, market, and commodity information. Variables such as rainfall, fuel and transport costs, harvest volumes, storage conditions, global commodity prices, and policy interventions were not consistently available at a matching monthly market level. Consequently, the models estimate relationships within the observed data structure and do not represent a complete structural model of food-price formation. This limitation is considered when interpreting the results and identifying directions for future extension.

3.4 Exploratory Data Analysis

The Exploratory Data Analysis (EDA) phase was conducted to develop an initial understanding of the data structure, identify underlying patterns, and inform subsequent analytical approaches. This phase employed comprehensive visualization techniques and descriptive statistical measures to characterize the temporal dynamics, distributional properties, and relational patterns within the dataset, with particular emphasis on the Kampala market as the primary urban economic center.

The analysis commenced with temporal trend examination of food prices in both local currency (UGX) and US Dollar (USD) terms. Time series line plots were generated to visualize the evolution of prices over the entire study period, providing initial insights into inflationary trends, seasonal patterns, and potential structural breaks. This dual-currency perspective allowed for

preliminary assessment of exchange rate pass-through mechanisms. To ensure analytical robustness, commodity selection was based on data sufficiency criteria. Commodities with fewer than 100 observations were excluded from detailed analysis, focusing instead on major staples with adequate temporal coverage. This filtering approach ensured that subsequent volatility calculations would be statistically reliable and representative of meaningful market dynamics. Price volatility was quantified using multiple complementary metrics to capture different dimensions of price instability. The coefficient of variation (CV) served as the primary measure of relative volatility, and as shown in the equation 3.2, calculated as the ratio of standard deviation to mean price. This normalized measure facilitated cross-commodity comparison independent of price scale. Additionally, absolute volatility was assessed through price range calculations, while short-term fluctuations were captured using three-month rolling standard deviations. The volatility analysis was conducted on monthly averaged price data to eliminate noise from intra-month variations while preserving meaningful temporal patterns.

$$CV_i = \frac{\sigma_i}{\mu_i} \quad (3.2)$$

where σ_i represents the standard deviation of prices and μ_i represents the mean price for each commodity. Multiple visualization techniques were employed to present the volatility landscape. Bar charts ranked commodities by their coefficient of variation, while scatter plots with bubble sizing illustrated the relationship between average price levels and volatility magnitude. Radar charts provided multidimensional comparisons of normalized volatility metrics across selected commodities, and heatmaps offered a comprehensive view of the correlation structure between different volatility measures. The relationship between local currency and USD-denominated prices was examined through correlation analysis. Pearson correlation coefficients were computed for each major commodity to quantify the strength of linear association between price series in different currency denominations. This analysis provided preliminary evidence regarding the synchronization of local price movements with exchange rate fluctuations. Finally, methodological validation was performed through comparative analysis of exchange rate series. The implied exchange rate derived from commodity transactions was visually and statistically compared against the official Bank of Uganda exchange rate series. This comparison served to verify data consistency and identify potential systematic discrepancies between market-implied and officially reported exchange rates, thereby ensuring the reliability of subsequent analytical procedures. The EDA approach established a solid foundation for the more sophisticated causal and predictive analyses that follow, while ensuring that all subsequent methodological choices would be informed by a thorough understanding of the data's inherent characteristics and limitations.

3.5 Causality Analysis

The causality analysis component employed a multi-methodological framework to rigorously investigate the directional relationships between exchange rate movements and local food prices. This comprehensive approach integrated both linear and non-linear causality detection methods, along with volatility transmission analysis, to provide a robust examination of the underlying causal mechanisms.

3.5.1 Regression Analysis

The analysis commenced with ordinary least squares (OLS) regression to quantify the linear relationship between exchange rates and food prices. The fundamental regression specification

took the form:

$$P_t = \alpha + \beta E_t + \varepsilon_t \quad (3.3)$$

3.5.2 Granger Causality Testing

To examine temporal precedence and predictive causality, the Granger causality framework was implemented (Granger, 1969). This approach tests whether past values of one time series contain information that helps predict another time series beyond what is contained in its own past values. The bivariate vector autoregression (VAR) model was specified as:

$$P_t = \alpha_0 + \sum_{i=1}^p \alpha_i P_{t-i} + \sum_{i=1}^p \beta_i E_{t-i} + \varepsilon_t \quad (3.4)$$

3.5.3 Transfer Entropy Analysis

To capture non-linear and information-theoretic causal relationships that may be missed by linear methods, transfer entropy was implemented, recognizing its close relationship to Granger causality under Gaussian assumptions (Barnett et al., 2009). Transfer entropy quantifies the reduction in uncertainty about future values of one variable given knowledge of another variable's past, beyond what is explained by the first variable's own past. This makes the method suitable for studying asymmetric information flow in exchange-rate and commodity-linked systems, as demonstrated by Maiti and Kayal (Maiti and Kayal, 2023). The transfer entropy from exchange rates (E) to prices (P) was computed as:

$$T_{E \rightarrow P} = \sum p(p_{t+1}, p_t, e_t) \log \frac{p(p_{t+1} | p_t, e_t)}{p(p_{t+1} | p_t)} \quad (3.5)$$

3.5.4 Dynamic Conditional Correlation GARCH Framework

To examine volatility spillovers and time-varying comovement between exchange rates and food prices, the Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroskedasticity (DCC-GARCH) framework was employed. This framework is appropriate for inflation and exchange-rate systems because recent African evidence shows that DCC-GARCH can capture time-varying correlations among consumer prices, food prices, non-food prices, and exchange rates more effectively than more restrictive multivariate GARCH alternatives (Likassa et al., 2026). The model specification begins with univariate GARCH processes for each series:

$$r_t = \mu + \varepsilon_t, \quad \varepsilon_t = \sigma_t z_t, \quad \sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \quad (3.6)$$

where r_t represents returns, σ_t^2 is the conditional variance, and z_t are standardized innovations. The dynamic conditional correlation between the standardized innovations is then modeled as:

$$Q_t = (1 - a - b)\bar{Q} + a\varepsilon_{t-1}\varepsilon'_{t-1} + bQ_{t-1} \quad (3.7)$$

3.6 Non-linear and Regime-Dependent Analysis

To capture the complex, state-dependent relationships between exchange rates and food prices that may be obscured by linear methods, this study employed two complementary non-linear analytical approaches: regime-switching models and quantile regression. These methodologies recognize that the transmission mechanism between exchange rates and prices may vary across different market conditions, volatility regimes, and price distribution segments.

3.6.1 Markov-Switching Regression

The Markov-switching regression framework was implemented to model the potential existence of distinct regimes in the relationship between exchange rates and food prices. This approach allows for parameter instability across different, unobserved states of the economy, capturing the intuition that exchange rate pass-through may be stronger during periods of high volatility or economic stress compared to stable periods. The general specification of the Markov-switching model with two regimes takes the form:

$$P_t = \alpha_{s_t} + \beta_{s_t} E_t + \varepsilon_t, \quad s_t \in \{0, 1\} \quad (3.8)$$

$$Pr(s_t = j \mid s_{t-1} = i) = p_{ij} \quad (3.9)$$

3.6.2 Quantile Regression Analysis

To examine how the relationship between exchange rates and food prices varies across different segments of the conditional price distribution, quantile regression was employed. Unlike ordinary least squares that estimates conditional mean relationships, quantile regression models conditional quantiles, providing a more comprehensive view of the relationship, particularly in the presence of heteroskedasticity or heavy-tailed distributions. The quantile regression model for the τ -th quantile is specified as:

$$Q_{P_t}(\tau \mid E_t) = \alpha_\tau + \beta_\tau E_t \quad (3.10)$$

$$\min_{\alpha_\tau, \beta_\tau} \sum_t \rho_\tau(P_t - \alpha_\tau - \beta_\tau E_t) \quad (3.11)$$

behavior at the lower tail (periods of price stability), median, and upper tail (periods of price spikes) of the conditional price distribution. Together, these non-linear approaches provide an understanding of how exchange rate pass-through operates under different market conditions, acknowledging that the relationship is unlikely to be uniform across time or across different segments of the price distribution.

3.7 Frequency Domain Analysis

To examine the time-frequency dynamics and transient co-movement patterns between exchange rates and food prices, Wavelet Coherence Analysis was employed (Torrence and Compo, 1998). This choice is consistent with recent Sub-Saharan African commodity-currency research that uses time-frequency wavelet methods to examine how commodity import and export dependence relates to currency pressure across short- and long-run horizons (Woode et al., 2026).

This methodology provides a powerful framework for analyzing how the relationship between two time series evolves across different time scales and temporal locations, capturing both the strength and phase of their association in the time-frequency domain. The analysis began with the decomposition of both exchange rate and food price series using the Discrete Wavelet Transform (DWT). The DWT decomposes a time series into different frequency components through a series of scaling and wavelet functions, enabling the examination of localized variations in the time series at multiple resolutions. The decomposition was implemented using the Daubechies wavelet of order 4 (db4), selected for its optimal balance between time-frequency localization and smoothness properties.

$$X(t) = \sum_k c_{J,k} \phi_{J,k}(t) + \sum_{j=1}^J \sum_k d_{j,k} \psi_{j,k}(t) \quad (3.12)$$

$$\rho_j = \text{corr}(d_{j,k}^P, d_{j,k}^E) \quad (3.13)$$

particularly focuses on whether short-term exchange rate volatility transmits more strongly to food prices than long-term trends, or whether certain economic episodes exhibit heightened co-movement across specific frequency domains. The wavelet coherence methodology provides a comprehensive view of the time-scale dependent relationship between macroeconomic variables and commodity prices, overcoming limitations of traditional time-domain methods that assume stationarity and constant relationships over time. This approach is particularly well-suited for economic time series that often exhibit non-stationarity, structural breaks, and time-varying relationships across different business cycle phases.

3.8 Predictive Modeling using Machine Learning

The predictive modeling component was implemented as an extensive supervised learning and time-series forecasting exercise designed to assess how well exchange rate information, commodity identity, and temporal structure can explain and forecast commodity prices in Kampala markets, consistent with the use of machine learning and statistical models for complex time-series forecasting (Hyndman and Khandakar, 2008; Lim and Zohren, 2021). Unlike a purely illustrative forecasting exercise, the notebook implementation trained and compared multiple model families, including classical regression baselines, tree-based machine learning models, a commodity-specific Prophet model, and deep sequence models. The modeling strategy was designed to evaluate both cross-sectional price prediction across commodities and temporal forecasting behavior within commodity price series.

The primary modeling dataset used the cleaned Kampala market panel containing date, commodity, commodity identifier, UGX price, USD price, and official exchange rate variables. A key methodological refinement in the notebook was the inclusion of `commodity_id` as a predictive feature alongside `exchange_rate`. This allowed the models to distinguish structural price differences across commodities rather than attributing all observed variation to exchange rate movements alone. For the tree-based models, the feature matrix was specified as:

$$X_t = \{E_t, C_i\}, \quad y_t = P_{i,t} \quad (3.14)$$

where E_t denotes the official UGX/USD exchange rate, C_i denotes the commodity identifier, and $P_{i,t}$ denotes the observed commodity price in Ugandan Shillings. The use of `commodity_id`

was especially important because the dataset contains heterogeneous commodities with different baseline prices, volatility patterns, storage characteristics, and market structures.

3.8.1 Tree-Based Machine Learning Models

Two main tree-based machine learning models were trained on the commodity panel: Random Forest regression and XGBoost regression, both established ensemble approaches for non-linear prediction tasks (Breiman, 2001; Chen and Guestrin, 2016). The Random Forest model was fitted with 100 estimators and a fixed random state to ensure reproducibility. XGBoost was trained with 100 estimators, a learning rate of 0.1, and the same random seed. The data were split into training and test subsets using an 80/20 split while preserving the corresponding date index for later visualization of predicted and observed prices.

These models were selected because they can capture non-linear relationships and interaction effects between exchange rates and commodity identity. In particular, tree-based ensembles are well suited to the study context because exchange rate pass-through may vary across commodity types rather than operating through a single homogeneous slope. Model performance was evaluated using the coefficient of determination (R^2), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE):

$$MAE = \frac{1}{n} \sum_{t=1}^n |y_t - \hat{y}_t|, \quad RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^n (y_t - \hat{y}_t)^2} \quad (3.15)$$

3.8.2 Classical Regression Benchmarks

Ordinary Least Squares (OLS) and Weighted Least Squares (WLS) models were also estimated as benchmark approaches. These models incorporated `exchange_rate`, `commodity_id`, `year`, and `month` as predictors. The benchmark models provided interpretable linear comparisons against the more flexible machine learning models. WLS was estimated using inverse residual weights to account for heteroskedasticity in commodity price errors.

3.8.3 Prophet Forecasting Framework

The Prophet model was implemented as a commodity-specific forecasting framework based on an additive trend-seasonality decomposition suitable for scalable forecasting tasks (Taylor and Letham, 2018). In the notebook, Prophet was modelled only for maize because fitting Prophet separately for every commodity was computationally expensive. The maize-only Prophet model therefore served as a focused time-series benchmark for one major staple commodity rather than a panel-wide model for all commodities.

Prophet decomposes the target series into trend, seasonal, and error components:

$$y(t) = g(t) + s(t) + h(t) + \varepsilon_t \quad (3.16)$$

where $g(t)$ captures trend, $s(t)$ captures seasonal effects, $h(t)$ captures holiday or event effects where specified, and ε_t is the residual component. The model was trained on maize observations from January 2006 to October 2018 and tested on the subsequent period from December 2018 to May 2022.

3.8.4 Deep Sequence Models

To capture sequential dynamics beyond conventional regression, the notebook also implemented several neural sequence models on transformed monthly commodity series, reflecting the increasing use of deep learning architectures for time-series forecasting (Lim and Zohren, 2021). The data were grouped by commodity, resampled to monthly frequency, interpolated where necessary, and transformed using logarithms and first differences. Exchange rate and price differences, seasonal encodings, and one-hot commodity indicators were included in the sequence feature set. A sliding window approach was then used to create supervised learning sequences.

The deep learning architectures included LSTM with Attention, CNN-BiLSTM with Attention, Transformer Encoder, and Stacked BiLSTM models. These architectures were evaluated on a log-difference scale, which emphasizes directional and proportional changes rather than raw price levels. The sequence dataset contained 84 training samples and 21 test samples with 14 features after preprocessing and scaling.

3.8.5 Model Evaluation and Visualization

Model evaluation combined numerical metrics and diagnostic plots. Scatter plots of true versus predicted values were used to assess calibration, while time-series plots were used to compare observed and predicted prices over the test period. The exported result graphs in the `images/graphs` directory were used to document Random Forest, XGBoost, Prophet, OLS/WLS, LSTM with Attention, CNN-BiLSTM with Attention, Transformer Encoder, and Stacked BiLSTM performance visually.

3.9 Model Deployment Architecture

To translate the predictive modeling outputs into a practical decision-support tool, the trained models were deployed through a web-based prediction system composed of a Progressive Web Application (PWA) frontend and a Flask-based Application Programming Interface (API). This deployment stage extended the research beyond offline model evaluation by demonstrating how exchange rate-driven price prediction can be operationalized for real-time use by market analysts, policymakers, and other stakeholders.

3.9.1 System Architecture

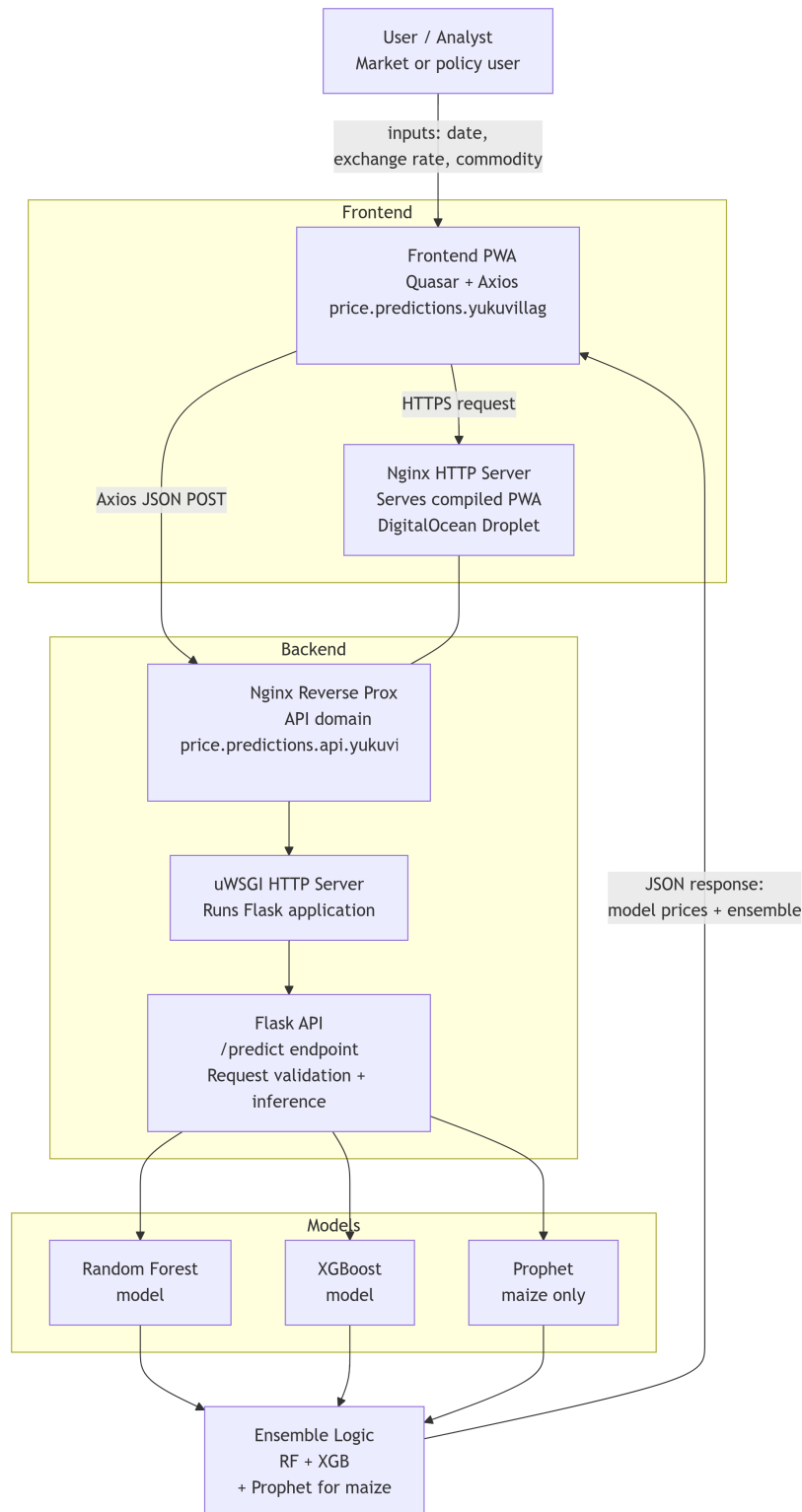


Figure 3.1: System architecture for the deployed food price prediction platform

The deployment architecture followed a client-server design. The frontend PWA is hosted at <https://price.predictions.yukuwillag.com/#/>, while the prediction API is hosted at <https://price.predictions.api.yukuwillag.com>. The frontend was built using the

Quasar framework and Axios. Quasar provided the user interface framework for building a responsive PWA, while Axios was used to send HTTP requests from the frontend to the API. The API was implemented using Flask and exposed a prediction endpoint that receives commodity prediction inputs in JSON format.

Both the frontend and backend services were hosted on DigitalOcean Virtual Private Servers (Droplets) running Ubuntu Server. For the API server, Nginx was configured as a reverse proxy in front of uWSGI, which served the Flask application. This configuration allowed Nginx to handle external HTTP traffic and forward prediction requests to the internal uWSGI-Flask application process. For the frontend, Nginx was used as the HTTP server responsible for serving the compiled Quasar PWA assets.

3.9.2 API Inference Workflow

The uploaded deployment script `prism-uploads/main.py` loads the trained Random Forest, XGBoost, and Prophet model artifacts at application startup. The API exposes a `/predict` endpoint that accepts a JSON payload containing an `inference_type` and a list of prediction `instances`. Each instance contains a prediction date, exchange rate, and commodity identifier. The API validates the request, extracts the feature values, and performs inference using the selected model configuration.

For commodity-aware inference, the API uses models trained with both `exchange_rate` and `commodity_id`. The tree-based prediction function constructs a feature frame containing both variables before calling the Random Forest and XGBoost models. Prophet is used only when `commodity_id = 51`, corresponding to maize, because the Prophet model was trained specifically for maize. For non-maize commodities, the Prophet component is omitted from the ensemble.

3.9.3 Ensemble Prediction Logic

The deployed API implements a simple ensemble class to combine pre-computed model predictions. For maize, the ensemble averages Random Forest, XGBoost, and Prophet predictions. For other commodities, the ensemble averages Random Forest and XGBoost predictions only. This design reflects the modeling decision that Prophet was trained only for maize, while the tree-based models support commodity-aware predictions across the broader commodity set.

The ensemble rule can be expressed as:

$$\hat{P}_{ens} = \begin{cases} \frac{\hat{P}_{RF} + \hat{P}_{XGB} + \hat{P}_{Prophet}}{3}, & \text{if } C_i = 51 \\ \frac{\hat{P}_{RF} + \hat{P}_{XGB}}{2}, & \text{otherwise} \end{cases} \quad (3.17)$$

where $\hat{P}_{RF}$ is the Random Forest prediction, $\hat{P}_{XGB}$ is the XGBoost prediction, $\hat{P}_{Prophet}$ is the Prophet prediction, and C_i is the commodity identifier. The API returns individual model predictions and the ensemble prediction as JSON, allowing the frontend to display both model-specific and combined estimates.

3.9.4 Frontend Design

The frontend PWA provides a user-facing interface for entering prediction inputs and viewing model outputs. Users provide an exchange rate, select or specify the commodity, and submit the

request through the Quasar interface. Axios sends the request to the Flask API and renders the returned Random Forest, XGBoost, Prophet where available, and ensemble predictions. This deployment design makes the research outputs accessible beyond the notebook environment and demonstrates the feasibility of integrating food price forecasting into a lightweight web-based information system.

3.9.5 Intended Users, Functionality, and Operational Context

The deployed tool was designed as a research prototype and decision-support application rather than an automated market-quotation service. Its intended users include food-security analysts, policymakers, humanitarian organizations, agricultural planners, market analysts, traders, and researchers who require a rapid indication of how a specified exchange rate may relate to the expected price of a selected commodity. The tool accepts a prediction date, exchange rate, and commodity identifier, validates the request, generates model-specific predictions, and returns the available Random Forest, XGBoost, Prophet, and ensemble estimates.

The presentation of individual model predictions alongside the ensemble is deliberate. It allows users to observe disagreement among models and discourages interpretation of the ensemble as an exact market price. In operational use, the output can supplement—but not replace—current market observations, trader information, field assessments, and institutional food-security monitoring. Humanitarian organizations may use the prototype to explore adverse exchange-rate scenarios, prioritize commodities for closer monitoring, and support planning for market assessments, cash-based assistance, food interventions, or policy engagement.

The current implementation requires users to enter the exchange rate manually and does not automatically retrieve live market prices or continuously retrain the models. A production implementation would require automated data feeds, scheduled model updating, authentication, prediction logging, model-performance monitoring, uncertainty intervals, and clear governance over how alerts are interpreted and acted upon. These requirements define the boundary between the deployed research demonstration and a fully institutionalized early warning platform.

3.10 Ethical Considerations

While this research utilizes exclusively secondary data sources, it maintains rigorous ethical standards throughout the analytical process. All datasets employed in this study are publicly available from recognized international and national institutions, specifically the World Food Programme through the Humanitarian Data Exchange and the Bank of Uganda through its OpenData portal. These sources provide data explicitly intended for research and analytical purposes, ensuring proper authorization for their use. The research adheres to fundamental ethical principles of data confidentiality and privacy protection. The dataset from the World Food Programme contains only aggregated market-level information without any personally identifiable information, thereby eliminating risks to individual privacy. No data pertaining to individual traders, consumers, or households are included in the analysis, ensuring complete anonymity throughout the research process.

Transparency in methodology represents a core ethical commitment of this study. All analytical approaches, including data preprocessing techniques, statistical methods, and modeling frameworks, have been thoroughly documented to enable reproducibility and critical evaluation. The research maintains intellectual honesty by appropriately citing all data sources and methodological references, acknowledging the contributions of preceding work in this domain.

The analytical framework has been designed to prevent potential misuse or misinterpretation of findings. All conclusions are derived directly from the empirical evidence, with careful attention to methodological limitations and appropriate contextualization of results. The research avoids speculative claims that could potentially influence market behavior or policy decisions without sufficient evidentiary support. Furthermore, the study maintains ethical rigor by ensuring that all analytical procedures are conducted without algorithmic bias or selective reporting. The comprehensive multi- method approach provides multiple perspectives on the research questions, reducing the risk of drawing conclusions from potentially flawed single methodologies. This methodological diversity enhances the reliability and validity of the findings while maintaining ethical standards in research conduct. By adhering to these ethical principles, this study ensures that its contributions to understanding exchange rate pass-through to food prices in Uganda are not only academically rigorous but also ethically sound, maintaining the integrity of the research process and its potential implications for policy and further scholarly inquiry.

Chapter 4

Results

4.1 Introduction

This chapter presents the empirical findings derived from the comprehensive analytical framework outlined in the previous chapter. The results are organized to systematically address the research questions concerning the relationship between exchange rate fluctuations and local food prices in Uganda. The presentation follows the methodological sequence, but this time, beginning with dataset characteristics and progressing through exploratory analysis, causal inference, non-linear relationships, frequency domain analysis, and predictive modeling. All findings are presented objectively through appropriate visualizations and statistical summaries, with detailed interpretation and discussion reserved for the subsequent chapter. The experimental outcomes provide the empirical foundation for evaluating the research hypotheses and drawing substantive conclusions about exchange rate pass-through mechanisms in the Ugandan context.

4.2 The Datasets

The analysis utilized two primary datasets that were systematically integrated to create a comprehensive analytical framework. The primary dataset, obtained from the World Food Programme through the Humanitarian Data Exchange (World Food Programme, 2025), contained 20,209 observational records after preprocessing. This dataset exhibited substantial diversity across multiple dimensions, tracking 38 distinct commodities spanning both food and non-food categories. The commodity spectrum ranged from staple foods including Maize, Rice, and Beans to non-food essentials such as Charcoal, Firewood, and various household items. These commodities were systematically categorized into nine broad groups: cereals and tubers, pulses and nuts, vegetables and fruits, oil and fats, meat fish and eggs, milk and dairy, miscellaneous food, and non-food items. Temporally, the dataset provided coverage from January 2006 through September 2025, offering nearly two decades of monthly price observations. Geographically, the data encompassed multiple administrative regions and markets across Uganda, with this research's particular focus on urban centers. The dataset maintained recording of prices in both Ugandan Shilling (UGX) and US Dollar (USD) denominations, enabling direct currency comparison and facilitating the computation of implied exchange rates for validation purposes. The secondary dataset, sourced from the Bank of Uganda's OpenData portal (Bank of Uganda, 2025), contained 250 monthly observations of the official UGX/USD exchange rate. This time series provided the benchmark exchange rate data against which the market-implied rates from the primary dataset could be compared. The complete integration of these datasets resulted

in a unified analytical panel containing 20,209 records with complete temporal, commodity, and exchange rate information. The merged dataset exhibited robust data quality following preprocessing, with no missing values in critical fields including date, price, and USD price. All currency values were converted to appropriate numeric formats, and temporal sorting ensured proper time series analysis structure.

4.3 Exploratory Data Analysis Results

The exploratory data analysis revealed significant insights into the structural characteristics and temporal dynamics of food prices in Uganda, with particular focus on the Kampala market. The analysis encompassed 20,209 price records spanning from January 2006 to September 2025, with the Kampala market represented exclusively by Owino Market, which tracked ten major commodities constituting 95.19% of the observational data.

4.3.1 Temporal Price Dynamics

The temporal analysis of food prices revealed distinct patterns across the study period.

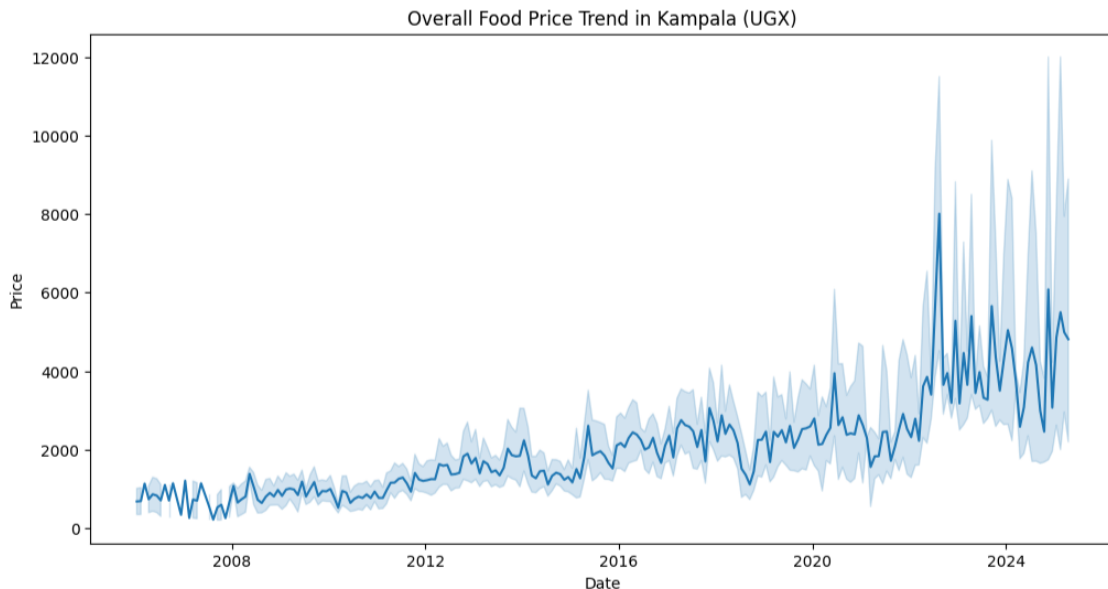


Figure 4.1: Overall food price trend in Ugandan Shilling

Figure 4.1 illustrates the overall food price trend in Ugandan Shilling, demonstrating relative stability from 2006 through 2021, followed by pronounced volatility and substantial price increases from 2022 through 2025. This pattern suggests structural breaks or external shocks affecting the food price system during the latter period. The USD-denominated price series, depicted in Figure 4.2, exhibits a similar volatility pattern, indicating that the observed fluctuations cannot be attributed solely to currency movements but reflect genuine commodity market dynamics. The exchange rate trend, presented in Figure 4.3, shows a distinct evolutionary pattern characterized by a steep appreciation of the US Dollar against the Ugandan Shilling from approximately 2009 to 2016, followed by a period of relative stability with minor oscillations. This temporal pattern provides important context for understanding potential exchange rate pass-through mechanisms to food prices, a relationship also emphasized in commodity-price and food-price exchange-rate studies (Gilbert, 1986; Umoru and Amedu, 2022).

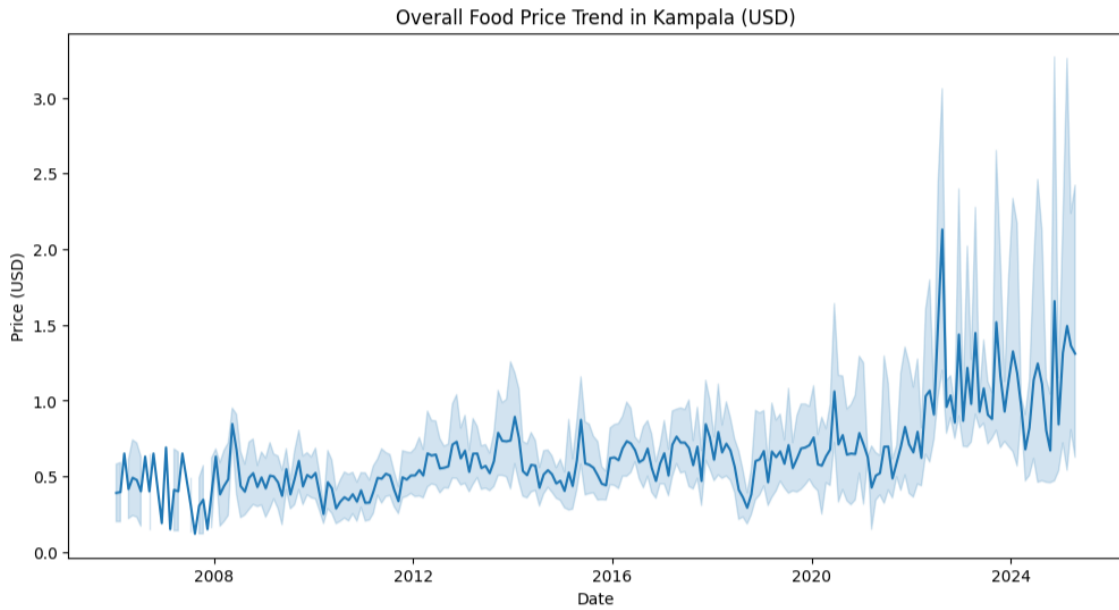


Figure 4.2: Overall food price trend in US dollars

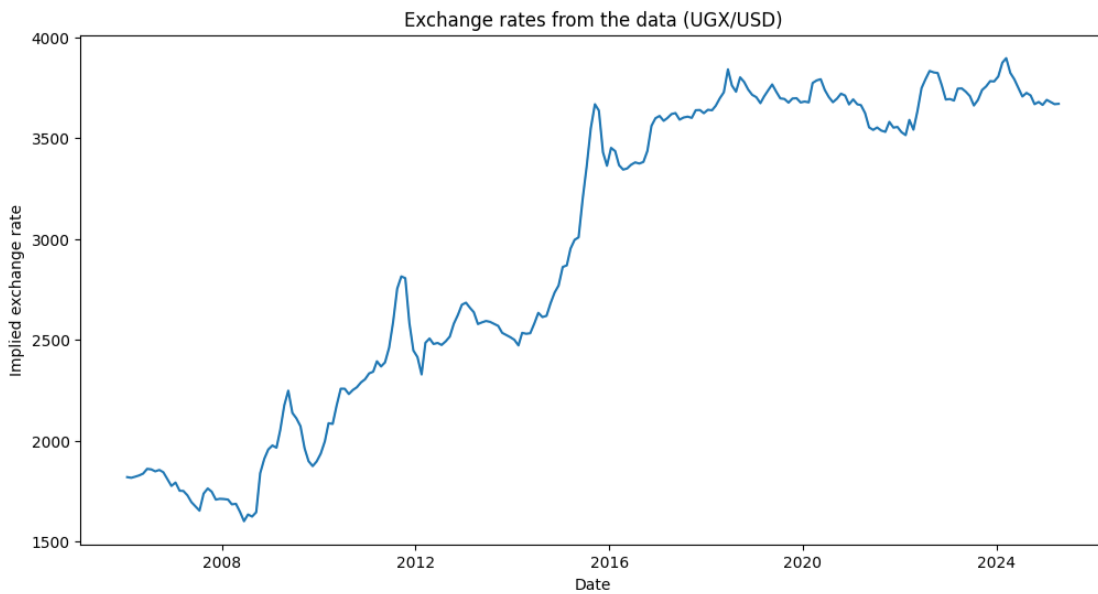


Figure 4.3: Average monthly exchange rate from Bank of Uganda

4.3.2 Commodity Price Volatility

The volatility analysis across major commodities revealed substantial heterogeneity in price stability characteristics. Table 4.1 presents the comprehensive volatility metrics for the nine major commodities tracked in Kampala, ranked by coefficient of variation (CV).

Table 4.1: Commodity Price Volatility Metrics (2006–2025)

Commodity	Mean Price (UGX)	Std. Dev.	CV	Price Range (UGX)
Plantains	1,129.90	1,011.70	0.895	5,819.42
Sorghum	1,977.25	984.74	0.498	3,366.00
Cassava flour	1,326.16	620.74	0.468	2,583.33
Beans	2,450.86	1,048.50	0.428	4,703.99
Maize	757.08	305.00	0.403	1,338.02
Millet	2,523.41	978.74	0.388	3,707.00
Maize (white)	1,384.86	518.91	0.375	2,251.00
Rice	2,495.70	861.35	0.345	3,087.21
Maize flour	1,984.13	602.49	0.304	3,237.50

Plantains exhibited the highest relative volatility with a coefficient of variation of 0.895, indicating substantial price instability relative to its average price level. This was followed by Sorghum (CV=0.498) and Cassava flour (CV=0.468). In contrast, Maize flour demonstrated the most stable pricing behavior with a coefficient of variation of 0.304, suggesting more predictable price patterns.

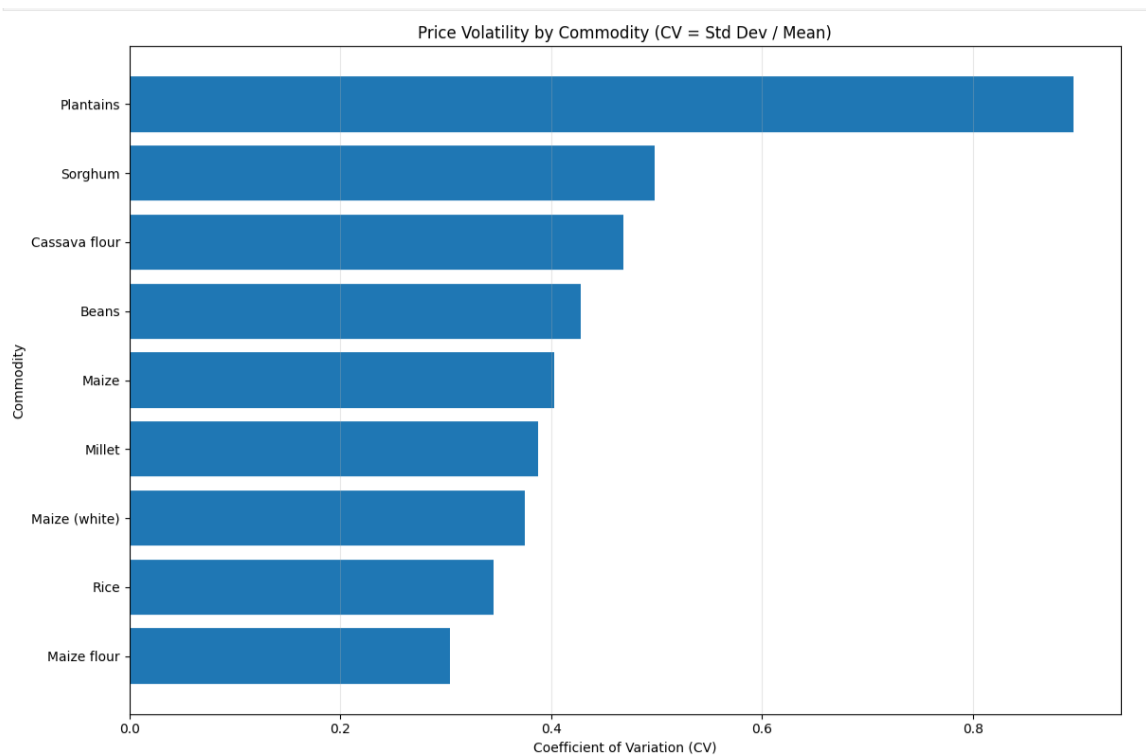


Figure 4.4: Volatility levels in different commodities

The visualization of these volatility patterns through bar charts (Figure 4.4), volatility radar (Figure 4.5) and bubble plots (Figure 4.6) revealed no consistent relationship between average price levels and volatility measures. Some high-priced commodities like Maize flour exhibited low volatility, while medium-priced commodities like Plantains showed extreme volatility, indicating commodity-specific factors beyond simple price level effects.

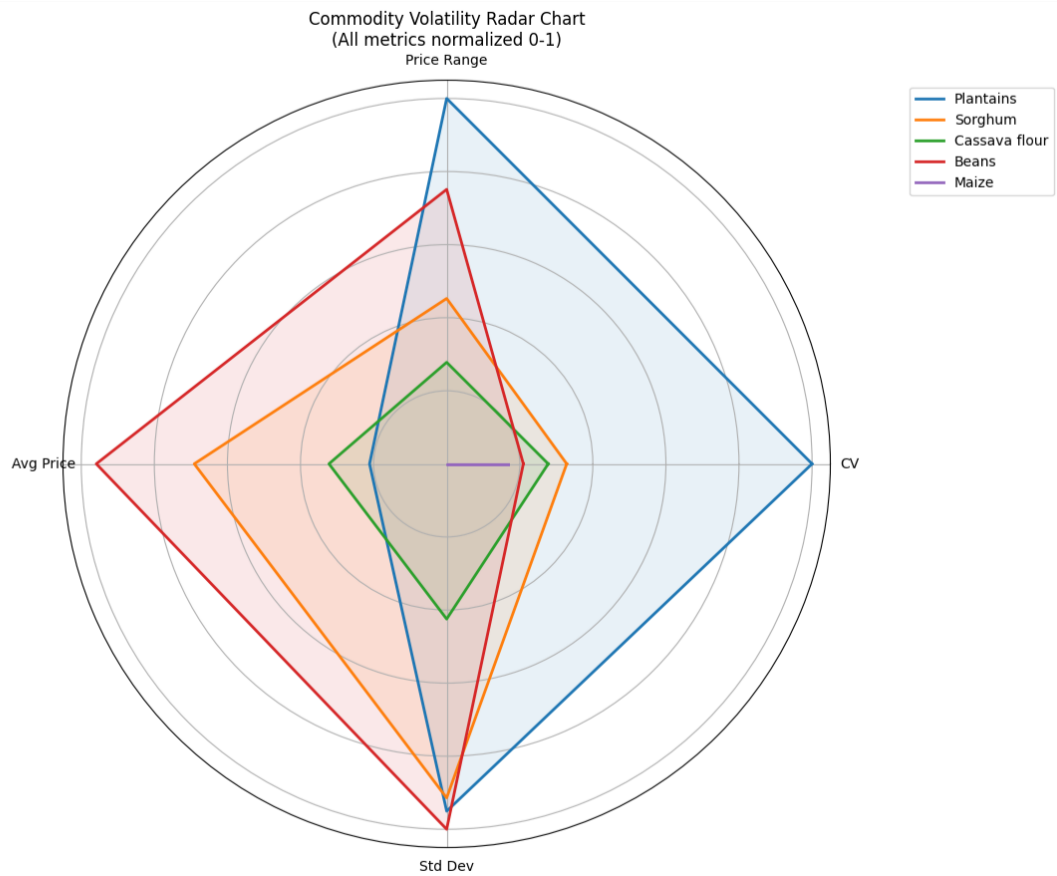


Figure 4.5: Commodity volatility metrics

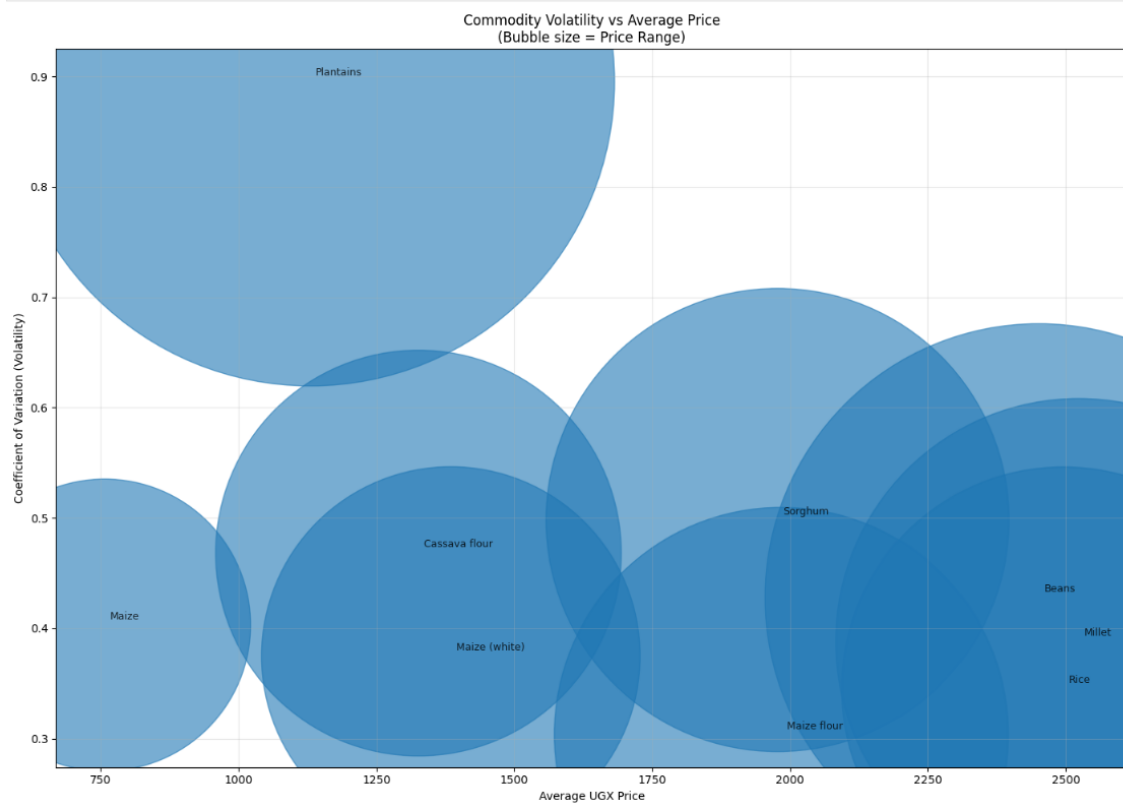


Figure 4.6: Relationship between volatility and mean commodity price

4.3.3 Exchange Rate Validation

A crucial methodological validation was performed by comparing the implied exchange rates derived from commodity transactions against the official Bank of Uganda exchange rate series. Figure 4.7 demonstrates a near-perfect superimposition of the implied exchange rate series over the official exchange rate series throughout the study period. This remarkable alignment provides strong evidence for the internal consistency of the dataset and validates the methodological approach of using market transactions to derive currency conversion factors.

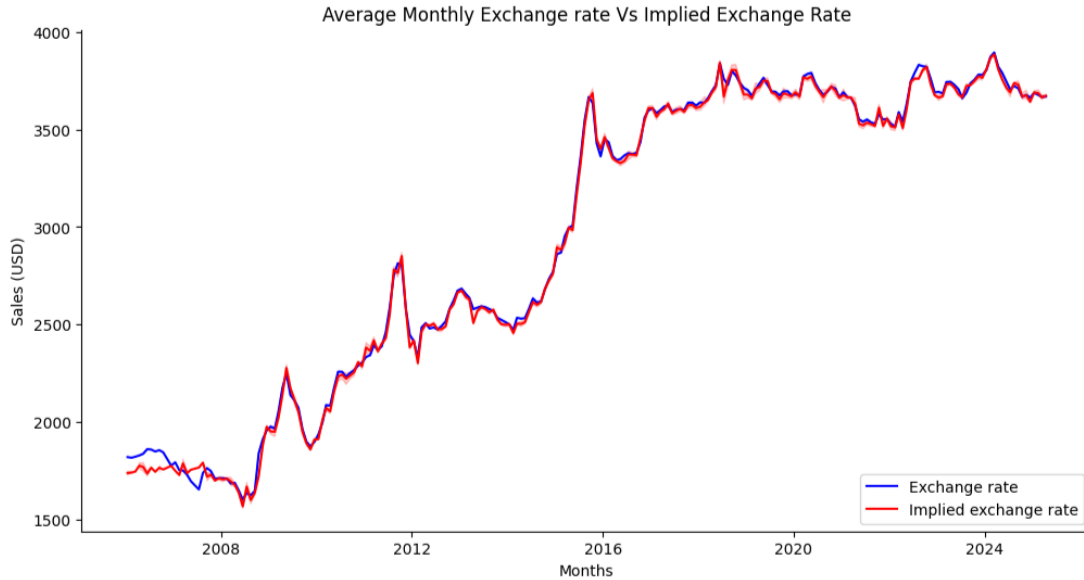


Figure 4.7: Comparison of implied and official exchange rate series

The close correspondence between these series suggests that

the USD price conversions in the WFP dataset accurately reflect prevailing market exchange rates, thereby enhancing confidence in subsequent analytical procedures. The exploratory analysis collectively established a foundation of data quality and reveals important preliminary patterns that inform the more sophisticated causal and predictive analyses that follow. The identified volatility patterns and temporal trends provide crucial context for interpreting the relationship between exchange rate movements and food price dynamics.

4.4 Causality Analysis Results

The causality analysis employed multiple methodological approaches to systematically investigate the directional relationships and dynamic interactions between exchange rate movements and local food prices. The results provide compelling evidence of significant

causal linkages, with particular strength in the direction from exchange rates to food prices.

4.4.1 Regression Analysis Results

The ordinary least squares regression analysis revealed a statistically significant positive relationship between exchange rates and food prices. Table 4.2 presents the comprehensive regression results, indicating that exchange rate fluctuations explain approximately 20.4% of the variation in local food prices ($R^2 = 0.204$).

Table 4.2: OLS Regression Results for Exchange Rate on Food Prices

Parameter	Coefficient	Std. Error	t-statistic	p-value	95% CI
Constant	-1457.98	178.42	-8.17	¡0.001	[-1807.95, -1108.01]
Exchange Rate	1.13	0.06	19.75	¡0.001	[1.02, 1.25]

The exchange rate coefficient of 1.13 indicates that a one-unit increase in the UGX/USD exchange rate is associated with an average increase of 1.13 UGX in food prices, holding other factors constant. The highly significant p-value ($p \leq 0.001$) provides strong evidence against the null hypothesis of no relationship. However, diagnostic statistics reveal potential issues with the model specification, including significant non-normality of residuals (Jarque-Bera $p \leq 0.001$) and a large condition number (1.45×10^4), suggesting possible multicollinearity or numerical instability.

4.4.2 Granger Causality Test Results

The Granger causality tests provided robust evidence of temporal precedence running from exchange rates to food prices. Table 4.3 summarizes the test results across different lag specifications, with all tests rejecting the null hypothesis that exchange rates do not Granger-cause food prices at the 1% significance level.

Table 4.3: Granger Causality Test Results

Lag Order	F-statistic	p-value	Chi-square	p-value
1	218.33	¡0.001		¡0.001
2	84.39	¡0.001		¡0.001

The consistently significant results across multiple lag structures and test statistics provide strong evidence that past values of exchange rates contain valuable information for predicting current food prices beyond what is contained in past food prices alone. The diminishing F-statistics with increasing lag orders suggest that more recent exchange rate movements exert stronger influence on current price levels.

4.4.3 Transfer Entropy Analysis Results

The information-theoretic analysis through transfer entropy revealed asymmetric information flow between exchange rates and food prices. The results demonstrate substantially greater information transfer from exchange rates to food prices ($TE_{x \rightarrow y} = 1.89$) compared to the reverse direction ($TE_{y \rightarrow x} = 0.20$). This yields a net transfer entropy of 1.69, indicating strong directional causality from exchange rate movements to food price changes. The magnitude of the transfer entropy from exchange rates to food prices suggests that knowledge of past exchange rate values reduces uncertainty about future food price movements by approximately 1.89 bits, significantly more than the reduction achieved by knowing past food prices alone. This non-linear causality measure complements the linear Granger causality results, providing evidence that the relationship extends beyond simple linear dependencies.

4.4.4 Dynamic Conditional Correlation Results

The correlation analysis between returns series revealed minimal contemporaneous linear association, with a correlation coefficient of 0.005 between exchange rate returns and food price returns. This near-zero correlation suggests that while causal relationships exist in the levels and directional sense, the day-to-day co-movement in volatility is relatively weak. The DCC-GARCH framework, though implemented in simplified form, indicates that the primary transmission mechanism between exchange rates and food prices operates through mean transmission rather than volatility spillovers. This finding suggests that exchange rate changes systematically influence the level of food prices rather than creating synchronized volatility patterns.

4.5 Non-linear and Regime-Dependent Analysis Results

The non-linear and regime-dependent analysis revealed significant state-varying relationships between exchange rates and food prices, demonstrating that the transmission mechanism operates differently across economic regimes and segments of the price distribution. These findings provide crucial nuance beyond the linear relationships identified in previous analyses.

4.5.1 Markov-Switching Regression Results

The Markov-switching regression identified two distinct regimes characterizing the relationship between exchange rates and food prices, with strongly asymmetric parameter estimates across states. Table 4.4 presents the comprehensive regime-dependent parameter estimates.

Table 4.4: Markov-Switching Regression Results

Parameter	Regime 0	Regime 1	Transition Probabilities
Constant	-963.69	-2233.41	$p_{00} = 0.982$
Exchange Rate Coefficient	0.922	3.495	$p_{10} = 0.965$
Standard Error (σ^2)	1,035,000	–	–

Regime 0, characterized by a moderate exchange rate pass-through coefficient of 0.922, represents the predominant state with a high persistence probability of 0.982. This suggests that approximately 98.2% of the time, the system remains in this state of moderate exchange rate sensitivity. The constant term of -963.69 in this regime indicates a baseline price level adjustment. In contrast, Regime 1 exhibits dramatically different dynamics, with an exchange rate coefficient of 3.495, nearly four times larger than in Regime 0. This high-pass-through regime, though less frequent, demonstrates substantially stronger sensitivity of food prices to exchange rate movements. The large negative constant term of -2233.41 in this regime suggests different baseline pricing conditions, potentially corresponding to periods of economic stress or market dislocation. The transition probabilities reveal asymmetric regime persistence, with both regimes showing high self-persistence (0.982 and an implied $p[1\ 1]$ of approximately 0.035). This $\rightarrow$ indicates that while the high-pass-through regime is rare, once entered, it tends to persist for multiple periods before transitioning back to the moderate regime.

4.5.2 Quantile Regression Results

The quantile regression analysis demonstrated substantial heterogeneity in exchange rate pass-through across different segments of the conditional food price distribution. Table 4.5 presents the exchange rate coefficients and their statistical significance at five key quantiles.

Table 4.5: Quantile Regression Results Across Price Distribution

Quantile	Exchange Rate Coefficient	p-value
0.10	0.251	≤ 0.001
0.25	0.345	≤ 0.001
0.50	0.555	≤ 0.001
0.75	0.804	≤ 0.001
0.90	1.108	≤ 0.001

The results reveal a clear monotonic pattern: exchange rate pass-through intensifies progressively across the conditional price distribution. At the 10th quantile (representing periods of relatively low food prices), the exchange rate coefficient is 0.251, indicating that a one-unit increase in the exchange rate is associated with a 0.251 UGX increase in food prices. This effect more than quadruples at the 90th quantile (periods of relatively high food prices), where the coefficient reaches 1.108. The statistical significance of all coefficients ($p \leq 0.001$) confirms that the relationship between exchange rates and food prices is robust across the entire price distribution. However, the magnitude variation demonstrates that exchange rate movements exert substantially stronger influence during periods of elevated food prices compared to normal or low-price conditions.

This pattern suggests that the transmission mechanism between exchange rates and food prices is state-dependent, with amplified effects during high-price regimes. The increasing coefficients across quantiles indicate that exchange rate fluctuations contribute disproportionately to price spikes rather than affecting all price levels uniformly.

4.6 Frequency Domain Analysis Results

The frequency domain analysis through wavelet coherence revealed distinctive patterns of co-movement between exchange rates and food prices across different time scales, providing insights into the time-varying nature of their relationship across various investment and adjustment horizons.

4.6.1 Wavelet Coherence Results

The wavelet decomposition across five distinct scales revealed significant heterogeneity in the strength and direction of association between exchange rates and food prices. Table 4.6 presents the scale-specific correlation coefficients derived from the wavelet coherence analysis, with each scale corresponding to different frequency components of the time series.

Table 4.6: Wavelet Coherence Across Time Scales		
Scale	Correlation Coefficient	Time Horizon
1	0.770	Short-term (3–6 months)
2	-0.079	Medium-term (6–12 months)
3	0.077	Medium-to-long-term (1–2 years)
4	-0.035	Long-term (2–4 years)
5	0.024	Very long-term (>4 years)

The analysis reveals a strongly positive correlation coefficient of 0.770 at Scale 1, representing the highest frequency components corresponding to short-term fluctuations (approximately 3-6 month horizons). This indicates substantial co-movement between exchange rates and food prices in the short run, suggesting immediate pass-through effects and rapid adjustment to currency movements. In contrast, Scales 2 and 3 exhibit near-zero correlation coefficients (-0.079 and 0.077 respectively), representing medium-term horizons (6 months to 2 years). These minimal correlations suggest that intermediate-term price dynamics are dominated by factors other than exchange rate movements, potentially including seasonal agricultural cycles, domestic policy interventions, or supply chain adjustments that decouple food prices from currency fluctuations at these frequencies. The longer-term scales (4 and 5) show progressively weaker correlations (-0.035 and 0.024), indicating that the relationship between exchange rates and food prices diminishes substantially over extended horizons. This pattern suggests that while short-term price movements are strongly influenced by exchange rate fluctuations, long-term price trends are driven by more fundamental structural factors including technological change, productivity growth, and long-term agricultural development. The alternating signs of the correlation coefficients across scales indicate complex phase relationships between the series, with periods of in-phase and out-of-phase co-movement depending on the time horizon. This complex pattern suggests that the transmission mechanism between exchange rates and food prices operates through multiple channels with different adjustment speeds and directional effects.

The dominance of short-term co-movement aligns with the previous causal analysis findings, providing additional evidence that exchange rate effects on food prices are most pronounced in the immediate to near-term horizon. This frequency-dependent relationship underscores the importance of considering time scale when analyzing exchange rate pass-through mechanisms and designing appropriate policy responses.

4.7 Predictive Modeling Results

The predictive modeling results show that incorporating commodity identity alongside exchange rate information materially improved the ability of machine learning models to explain commodity price variation. The notebook implementation used `commodity_id` as a feature together with `exchange_rate`, allowing the models to account for commodity-specific baseline price differences and heterogeneous pass-through patterns.

Table 4.7: Predictive Model Performance from the Notebook

Model	R^2	RMSE	MAE
XGBoost	0.7944	646.25	401.60
Random Forest	0.7815	666.30	427.76
Prophet (maize only)	-1.3911	324.16	258.14
OLS with commodity and time features	-0.0710	2676.98	1579.96
WLS with commodity and time features	-0.0949	2706.69	1589.19

The strongest panel-level performance was obtained by XGBoost, which achieved an R^2 of 0.7944, RMSE of 646.25, and MAE of 401.60. Random Forest performed similarly, with an R^2 of 0.7815, RMSE of 666.30, and MAE of 427.76. These results indicate that the combination of exchange rate and `commodity_id` features explains a substantial proportion of price variation across commodities. The close performance of the two tree-based models suggests that the predictive relationship is robust across ensemble methods rather than being specific to one algorithm.

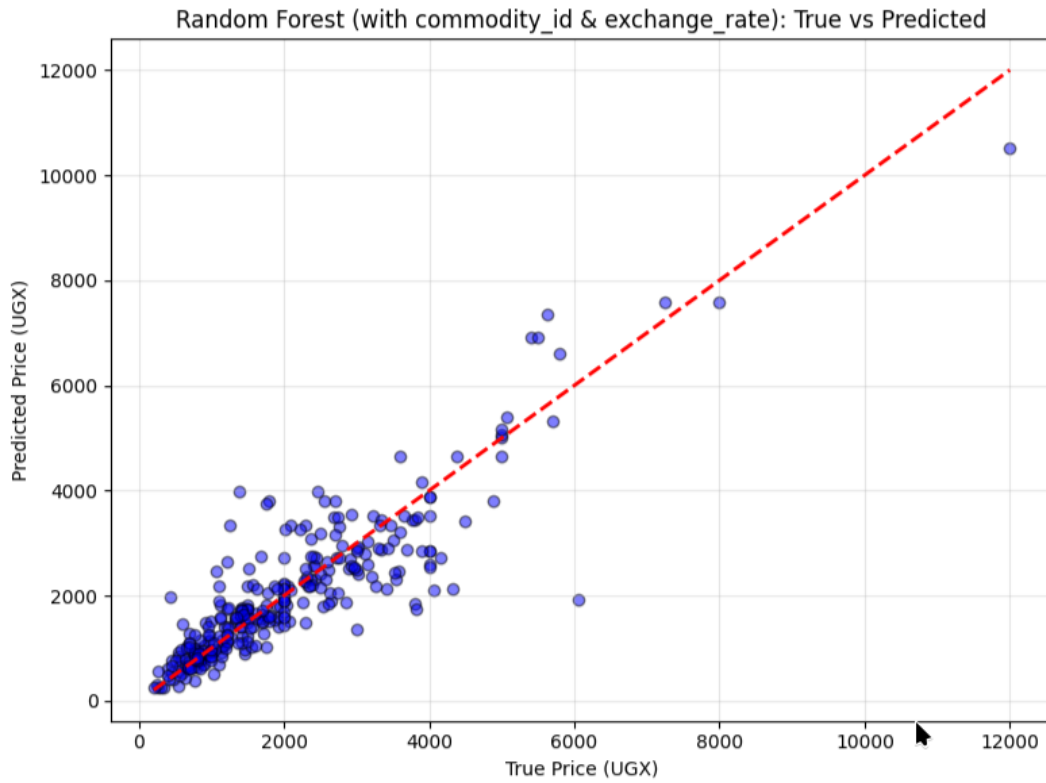


Figure 4.8: Random Forest true versus predicted commodity prices

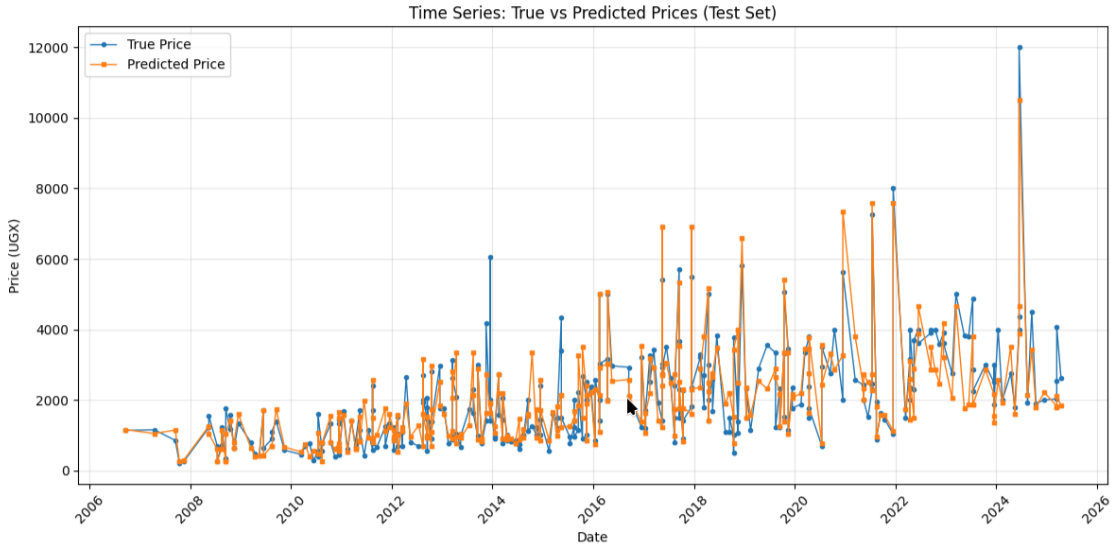


Figure 4.9: Random Forest true versus predicted commodity prices over time

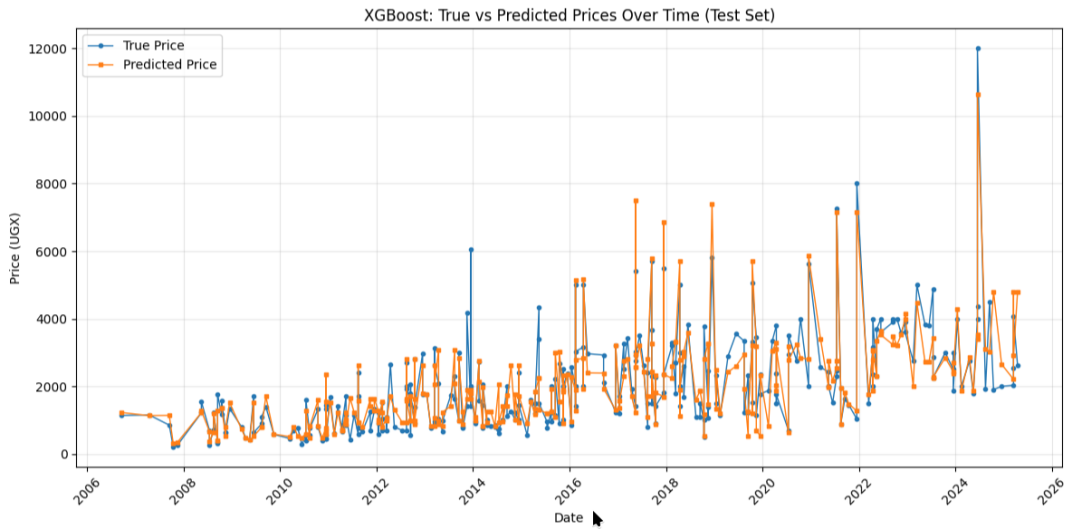


Figure 4.10: XGBoost true versus predicted commodity prices over time

The benchmark OLS and WLS models performed substantially worse than the tree-based models, producing negative R^2 values and RMSE values above 2600 UGX. This contrast demonstrates that linear additive models were unable to capture the non-linear and commodity-specific structure in the price data. The OLS coefficient for exchange rate was positive, but the poor predictive accuracy indicates that a linear specification is insufficient for forecasting heterogeneous commodity prices.

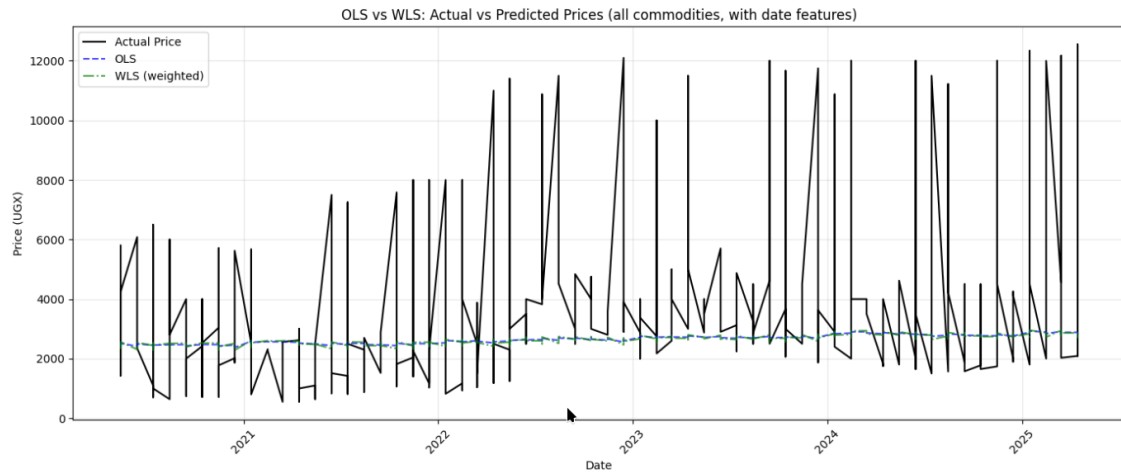


Figure 4.11: OLS and WLS true versus predicted commodity prices

The Prophet model was estimated only for maize because fitting Prophet separately for every commodity was computationally expensive. Its results should therefore be interpreted as a maize-specific time-series benchmark rather than a direct panel-wide comparison with Random Forest or XGBoost. The Prophet model produced an RMSE of 324.16 and MAE of 258.14 for maize, but its negative R^2 indicates that it did not outperform a naive baseline for the selected test period. This suggests that maize prices experienced dynamics during the test period that were not fully captured by Prophet's trend and seasonal components alone.

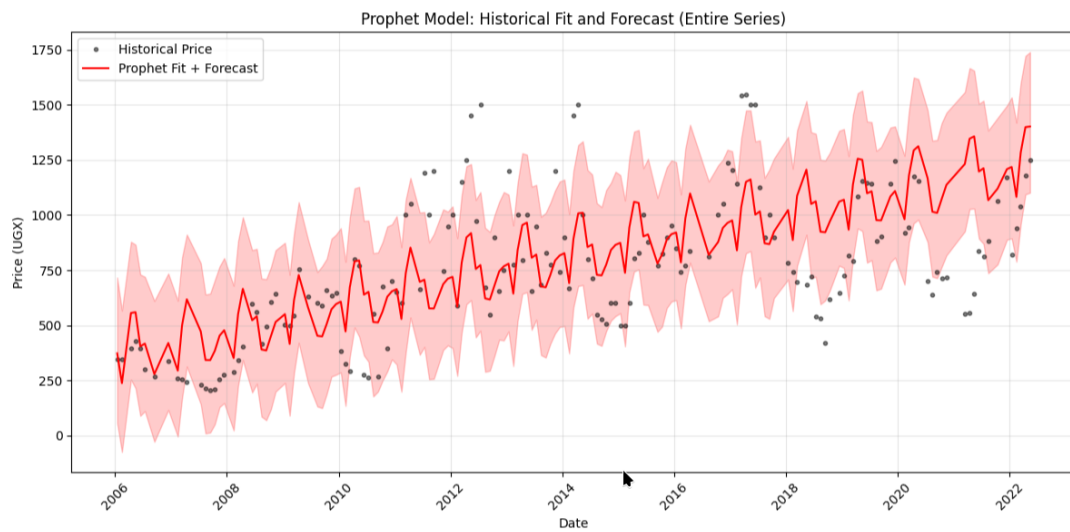


Figure 4.12: Prophet historical fit and forecast for maize

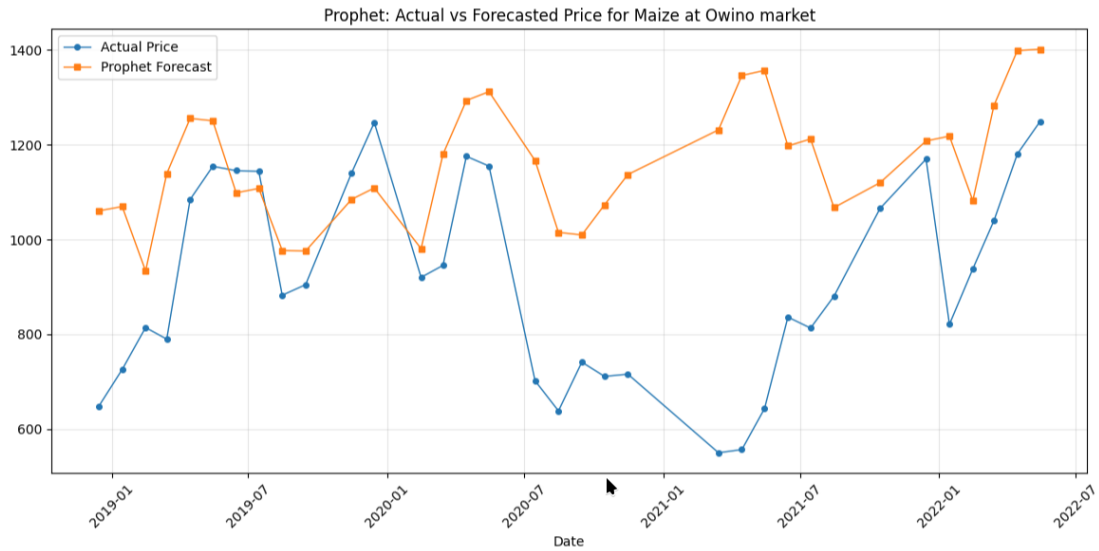


Figure 4.13: Prophet true versus forecasted maize prices

The deep sequence models were evaluated on a log-difference scale rather than raw UGX price levels. Among these models, LSTM with Attention achieved the lowest RMSE (0.1224) and MAE (0.0922), closely followed by the Transformer Encoder (RMSE = 0.1237; MAE = 0.0940) and Stacked BiLSTM (RMSE = 0.1230; MAE = 0.0933). CNN-BiLSTM with Attention performed less well, with RMSE of 0.1541 and MAE of 0.1075. The negative R^2 values across sequence models indicate that while the absolute errors on the transformed scale were small, the models did not fully explain the variance in log-differenced prices in the small test set.

Table 4.8: Deep Sequence Model Performance on Log-Difference Scale

Model	R^2	RMSE	MAE
LSTM with Attention	-0.0057	0.1224	0.0922
Stacked BiLSTM	-0.0167	0.1230	0.0933
Transformer Encoder	-0.0283	0.1237	0.0940
CNN-BiLSTM with Attention	-0.5943	0.1541	0.1075

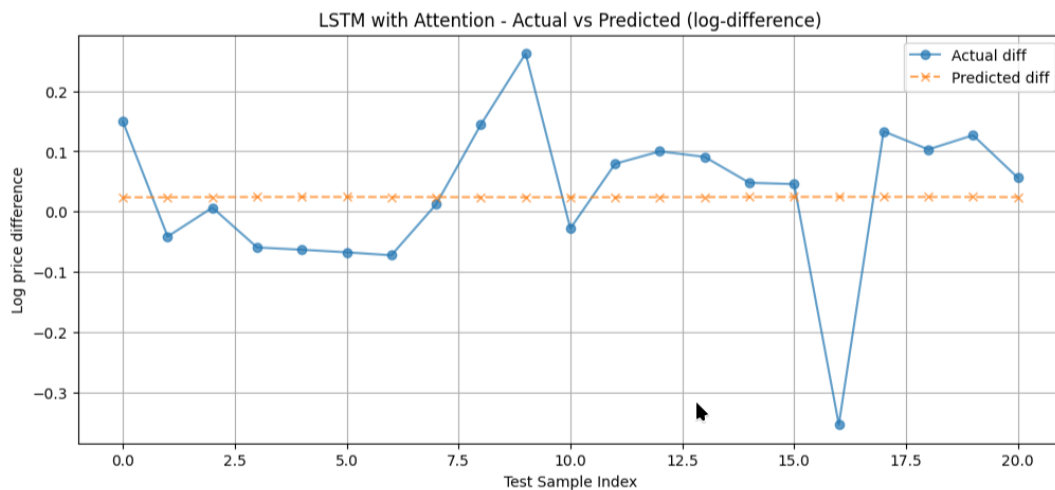


Figure 4.14: LSTM with Attention true versus predicted log-difference prices

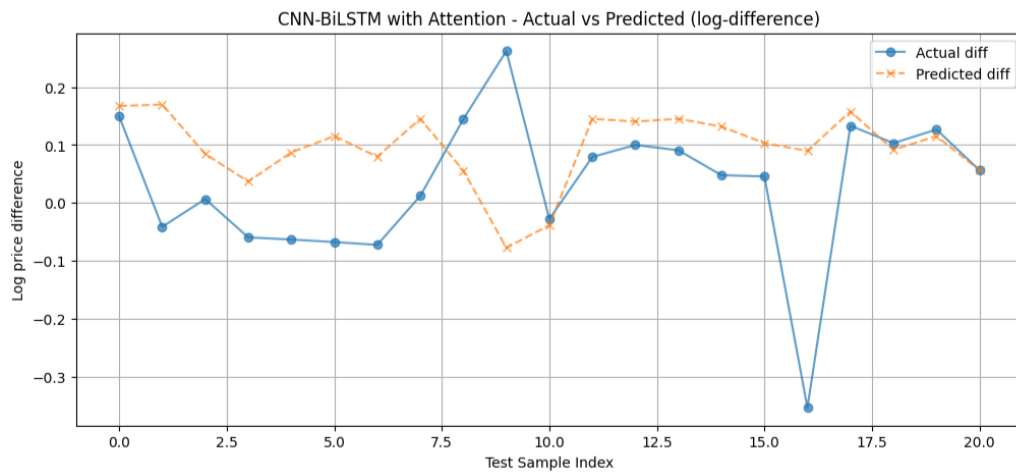


Figure 4.15: CNN-BiLSTM with Attention true versus predicted log-difference prices

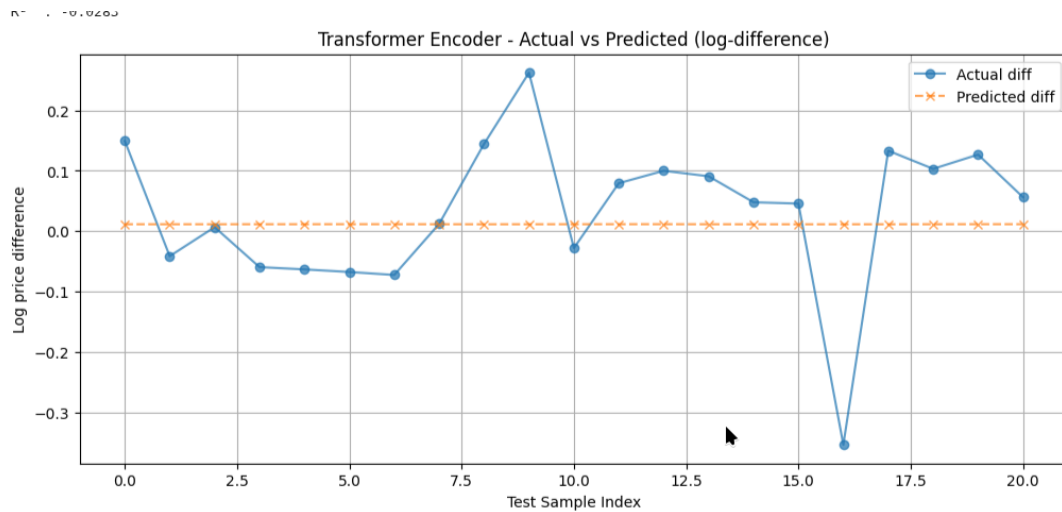


Figure 4.16: Transformer Encoder true versus predicted log-difference prices

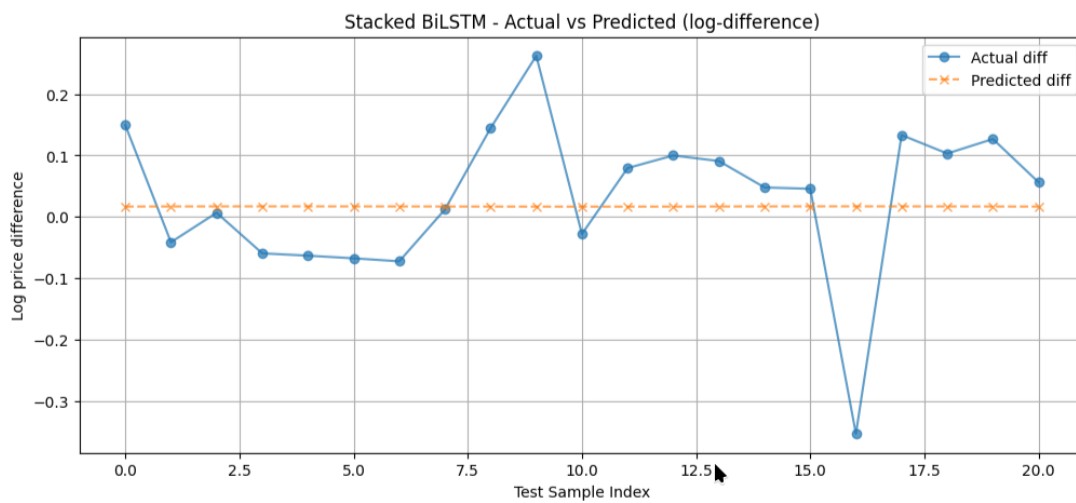


Figure 4.17: Stacked BiLSTM true versus predicted log-difference prices

Overall, the predictive modeling results support the importance of combining macroeconomic information with commodity-specific structure. Exchange rate information alone is not sufficient to explain all price movements, but when paired with `commodity_id`, ensemble machine learning models captured much of the observed variation in commodity prices. This reinforces the broader finding that exchange rate pass-through is heterogeneous across commodities and that predictive models must explicitly account for commodity identity.

4.8 Deployment Results and Live Prediction Demonstration

The trained predictive models were deployed as a live web application to demonstrate their practical usability beyond the notebook environment. The deployed frontend is available as a PWA at <https://price.predictions.yukuville.com/#/>, and the Flask API is available at <https://price.predictions.api.yukuville.com>. The frontend communicates with the API through Axios, while the API performs model inference using the deployed Random Forest, XGBoost, Prophet, and ensemble logic.

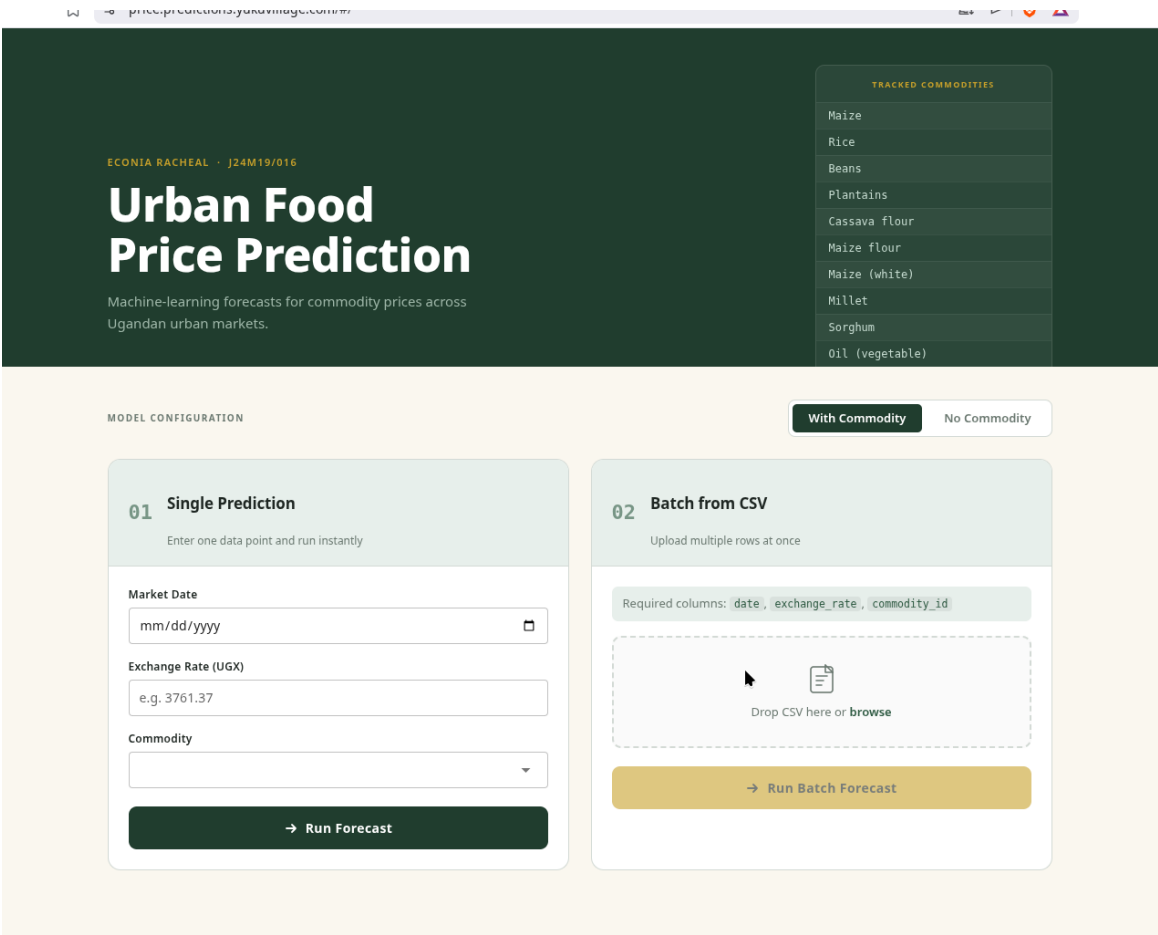


Figure 4.18: Frontend PWA interface for commodity price prediction

A live prediction demonstration was conducted for per kilogram maize on 02 July 2026 using an exchange rate of 3665.77 UGX/USD. The deployed system produced an ensemble maize price prediction of UGX 1,149.82, with Random Forest predicting UGX 718.88 and XGBoost predicting UGX 1,309.77. The live prediction response demonstrates that the deployed API successfully returns individual model outputs and the combined ensemble estimate.

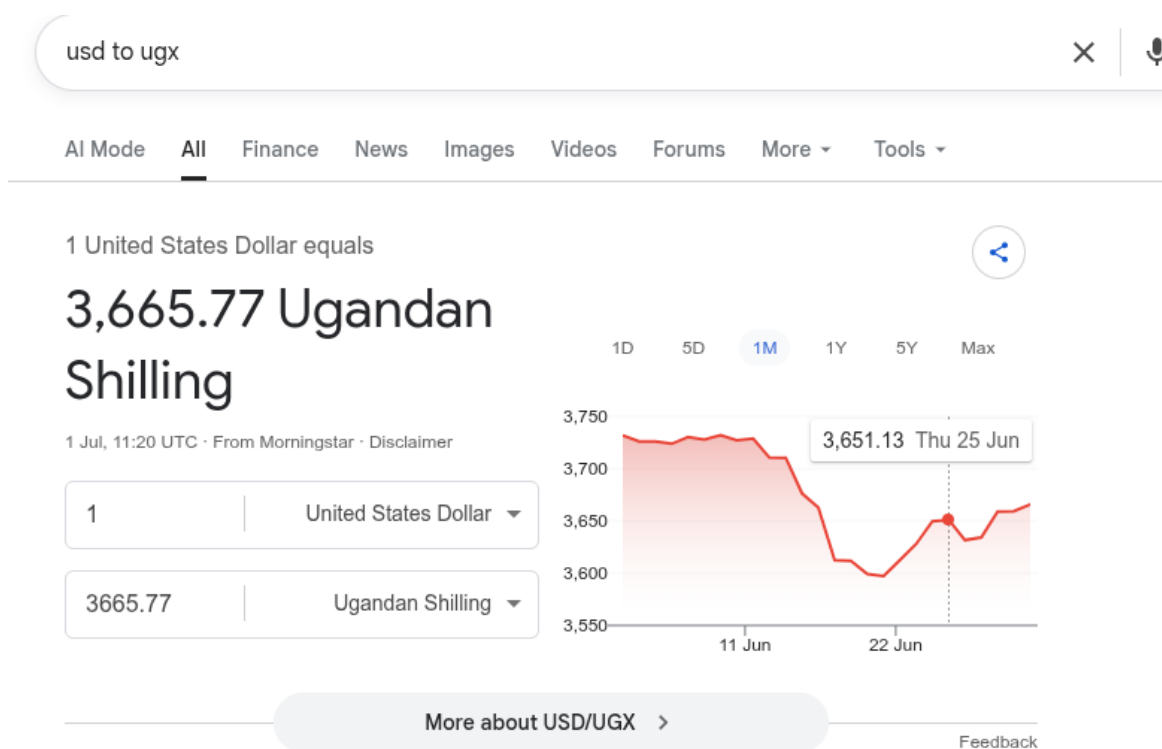


Figure 4.19: Exchange rate input used for the 02 July 2026 live prediction demonstration

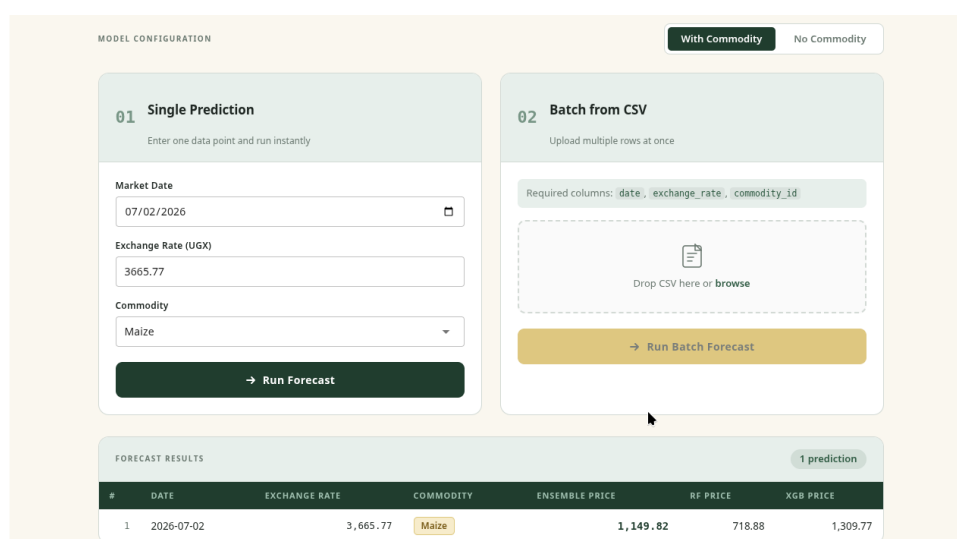


Figure 4.20: Prediction from deployed models for maize on 02 July 2026

The prediction was compared against observed market prices from AfriSokoConnect for the same date. The reported maize prices were UGX 1,360 in Owino Market, UGX 1,360 in Kisenyi Market, UGX 1,380 in Nakawa Market, and UGX 1,400 in Kalerwe Market. The ensemble prediction of UGX 1,149.82 was below the observed market range, while the XGBoost prediction of UGX 1,309.77 was closer to the reported prices. This comparison indicates that the deployed system can produce interpretable live predictions, while also showing that model outputs should be interpreted as decision-support estimates rather than exact market quotations.

Table 4.9: Live Maize Prediction and Market Price Comparison on 02 July 2026

Source	Price per kg (UGX)
Random Forest prediction	718.88
XGBoost prediction	1,309.77
Ensemble prediction	1,149.82
Owino Market actual price	1,360.00
Kisenyi Market actual price	1,360.00
Nakawa Market actual price	1,380.00
Kalerwe Market actual price	1,400.00



Commodity	Unit	Owino Market	Kisenyi Market	Nakawa Market	Kalerwe Market
Beans Rosecoco	Kg	UGX 2,000	UGX 1,900	UGX 2,100	UGX 2,100
Cassava Chips	Kg	UGX 800	UGX 900	UGX 800	UGX 800
Cassava flour	Kg	UGX 1,100	UGX 1,100	UGX 1,150	UGX 1,200
Fish Nile Perch	Kg	UGX 10,000	UGX 10,000	UGX 9,500	UGX 9,500
Fish Tilapia	Kg	UGX 7,500	UGX 7,500	UGX 7,500	UGX 7,500
Fresh Cassava	Kg	UGX 255	UGX 255	UGX 270	UGX 240
Ginger	Kg	UGX 1,500	UGX 1,500	UGX 1,800	UGX 1,800
Greengram	Kg	UGX 2,800	UGX 2,700	UGX 2,800	UGX 2,800
Groundnuts	Kg	UGX 4,800	UGX 4,800	UGX 4,800	UGX 5,000
Irish potatoes	Kg	UGX 1,200	UGX 1,200	UGX 1,300	UGX 1,300
Maize Flour	Kg	UGX 1,360	UGX 1,360	UGX 1,380	UGX 1,400
Maize Grain	Kg	UGX 800	UGX 750	UGX 800	UGX 800
Matooke	Kg	UGX 521	UGX 521	UGX 565	UGX 521
Milk	Ltr	UGX 1,000	UGX 1,000	UGX 1,000	UGX 1,000
Millet flour	Kg	UGX 2,600	UGX 2,600	UGX 2,700	UGX 2,700

Figure 4.21: Actual maize market prices from AfriSokoConnect for 02 July 2026

The deployment results therefore validate the end-to-end system workflow: user input is captured through the frontend, transmitted to the API, processed by the trained models, and returned as readable predictions. This operational demonstration supports the applied contribution of the study by showing how exchange rate-based predictive modeling can be transformed into a functioning digital tool for food price monitoring.

Chapter 5

Discussion

5.1 Introduction

This chapter synthesizes the empirical findings presented in Chapter 4 to develop a comprehensive understanding of the relationship between exchange rate fluctuations and food prices in urban Uganda. The discussion integrates evidence from multiple analytical perspectives to evaluate the nature, strength, and dynamics of exchange rate pass-through mechanisms. By examining the convergent and complementary findings across causal, non-linear, frequency domain, and predictive analyses, this chapter provides a nuanced interpretation of how macroeconomic shocks transmit to micro-level price outcomes in a developing economy context.

5.2 Distinct Contributions of Causal and Predictive Analyses

The causal and predictive components addressed different aspects of the research problem and should not be interpreted as interchangeable. The causal component examined temporal precedence, directional predictability, and asymmetric information flow. Granger causality tested whether past exchange-rate values improved the explanation of current food prices beyond lagged food prices, while transfer entropy assessed whether past exchange-rate information reduced uncertainty about future prices in a non-linear setting. These methods provide evidence of predictive or temporal causality, but they do not by themselves establish a fully identified structural causal effect equivalent to a randomized experiment or an econometric design with an external instrument.

The predictive component addressed a separate practical question: whether exchange-rate and commodity information could generate accurate held-out price estimates. Random Forest, XGBoost, Prophet, linear baselines, and sequence models were evaluated using R^2 , RMSE, and MAE. Their contribution is therefore operational rather than causal. A model may predict prices accurately by exploiting stable patterns without identifying why those patterns occur, while a causal test may establish temporal direction without producing the most accurate forecast.

Table 5.1: Distinct contributions of causal and predictive analyses

Component	Question addressed	Main methods	Contribution
Causal and directional analysis	Do exchange-rate movements temporally precede and provide directional information about food-price movements?	Granger causality, transfer entropy, regression, regime and quantile analysis	Supports interpretation of exchange rates as an upstream monitoring signal and clarifies direction, asymmetry, regimes, and distributional differences.
Predictive analysis	How accurately can available exchange-rate and commodity information estimate held-out commodity prices?	Random Forest, XGBoost, Prophet, OLS/WLS, and deep sequence models	Identifies models suitable for decision support, quantifies forecast errors, and enables implementation of the deployed prototype.

Establishing directional evidence was important to the study’s policy interpretation. If no temporal or information-flow relationship had been found, the descriptive objective and predictive modelling objective would still have remained valid, and the deployment tool could still have been evaluated as a forecasting prototype. However, the study could not reasonably have argued that exchange-rate monitoring represents an upstream food-price warning signal or that exchange-rate-focused interventions address a leading component of the observed relationship. The conclusions would instead have been limited to correlation and prediction, with stronger emphasis on unidentified domestic or global factors. The causal analysis therefore strengthened the explanatory contribution, while the predictive analysis established practical usefulness.

5.3 The Nature of Exchange Rate Pass-Through

The integrated findings reveal a complex, multi-dimensional relationship between exchange rates and food prices that transcends simple linear association. Evidence across the fitted models indicates that exchange-rate movements are associated with and temporally precede changes in domestic food prices, but the relationship is characterized by important asymmetries and state dependencies. The OLS regression established a baseline positive association, explaining approximately 20% of price variation, while Granger causality and transfer entropy provided directional predictive evidence from exchange rates to prices. The strength of this relationship, however, varies substantially across different market conditions. The Markov-switching regression identified two distinct regimes: a predominant moderate-pass-through state (covering 98% of observations) and an infrequent but economically significant high-pass-through state where the exchange-rate coefficient quadruples. This regime-dependent behavior is consistent with gradual transmission under normal conditions and stronger sensitivity during periods of economic stress or market dislocation. The quantile regression results further refine this un-

derstanding by demonstrating that exchange-rate coefficients intensify during periods of high food prices. The progressive increase from lower to upper quantiles indicates that currency depreciation is more strongly associated with price spikes than with low-price periods. These estimates should nevertheless be interpreted as conditional relationships within the observed variables rather than as complete structural effects isolated from every other driver of food prices.

5.4 Temporal Dynamics and Adjustment Mechanisms

The time-scale analysis through wavelet coherence provides crucial insights into the adjustment dynamics of exchange rate pass-through. The strong short-term co-movement (0.770 correlation at 3–6 month horizons) indicates immediate transmission of exchange rate shocks to food prices, likely through import channels and expectations formation. The subsequent decoupling at medium-term horizons (6–24 months) suggests that domestic factors, including harvest cycles, storage dynamics, and policy interventions, temporarily dominate price formation before exchange rate effects reassert themselves in the long term.

This temporal pattern is consistent with the predictive modeling results, where tree-based models incorporating exchange-rate information outperformed the linear and univariate time-series benchmarks. The reduction in prediction errors demonstrates practical forecasting value within the evaluated sample. Granger causality and transfer entropy complement this result by indicating directional precedence and asymmetric information flow. The net transfer entropy of 1.69 bits indicates that past exchange-rate information reduced uncertainty about future prices more than the reverse direction. This supports treating exchange rates as a useful leading indicator in the observed data, but it does not prove that exchange-rate movements are fully exogenous or that all alternative causal pathways have been excluded.

5.5 Predictive Modeling Interpretation

The predictive modeling results provide an additional lens for interpreting exchange rate pass-through because they test whether exchange rate information improves practical price prediction when combined with commodity-level structure. The notebook results show that tree-based machine learning models performed strongest when `commodity_id` was included alongside `exchange_rate`. XGBoost achieved an R^2 of 0.7944 and Random Forest achieved an R^2 of 0.7815, demonstrating that a substantial share of commodity price variation can be captured when macroeconomic and commodity-specific information are modeled jointly.

The inclusion of `commodity_id` is important for interpreting these results. It shows that exchange rate effects are not uniform across the food basket; rather, the exchange rate signal interacts with structural differences among commodities. These differences may reflect storage potential, perishability, import exposure, substitution possibilities, and market organization. Therefore, predictive performance improved not simply because exchange rates matter, but because models were able to condition the exchange rate relationship on commodity identity.

The weaker performance of OLS and WLS confirms the limitations of linear modeling for this prediction task. Although the linear models included exchange rate, commodity identifier, year, and month, they produced negative R^2 values and substantially higher prediction errors. This supports the broader conclusion that price formation in Kampala markets is non-linear and heterogeneous. Tree-based models were better able to capture threshold effects, interactions, and commodity-specific patterns that linear specifications missed.

The Prophet results provide a more focused interpretation for maize. Because Prophet was only estimated for maize due to the computational cost of fitting separate Prophet models for every commodity, its findings are best understood as a staple-specific forecasting benchmark. Its negative R^2 suggests that trend and seasonal decomposition alone did not fully explain maize price movements during the test period, reinforcing the importance of incorporating external variables and commodity-market context in food price forecasting.

The deep sequence models add further nuance. Their relatively small MAE and RMSE values on the log-difference scale suggest that recurrent, attention-based, and Transformer architectures can track some short-run movements in transformed prices. However, their negative R^2 values indicate that the available sequence sample was too limited to explain variance reliably. This suggests that deep learning may become more useful with longer commodity-level histories, richer exogenous variables, and larger training samples.

Overall, the predictive modeling evidence strengthens the study’s central argument: exchange rate dynamics contain meaningful information for food price prediction, but the relationship must be modeled as commodity-specific, non-linear, and temporally structured. The strongest practical implication is that early warning systems should combine exchange rate monitoring with commodity identifiers and market-specific features rather than relying on aggregate exchange rate movements alone.

5.6 Model Deployment and Practical Utility

The deployment of the predictive models substantially strengthens the practical contribution of the study. By hosting the frontend PWA and Flask API on DigitalOcean Ubuntu droplets, the research demonstrates that food price prediction can move from offline statistical analysis into an accessible web-based decision-support system. This is important because policy usefulness depends not only on model accuracy, but also on whether predictions can be generated and interpreted by users in real time.

The deployment architecture also reflects an appropriate separation of concerns. The Quasar frontend handles user interaction and visualization, while the Flask API handles model loading, request validation, inference, and JSON response generation. Nginx provides a production-facing HTTP layer for both the frontend and API, and uWSGI provides a stable server interface for the Flask application. This design improves maintainability because the models can be updated on the API server without redesigning the user interface.

The 02 July 2026 maize prediction illustrates both the usefulness and limitations of the deployed system. The XGBoost estimate was close to the observed AfriSokoConnect market prices, while the ensemble was lower and the Random Forest estimate was substantially lower. This pattern suggests that live forecasts should be interpreted comparatively across models rather than as a single definitive market price. In practice, displaying individual model estimates alongside the ensemble is useful because it reveals uncertainty and model disagreement.

From a policy and market-monitoring perspective, the deployed system provides a foundation for early warning dashboards. A future operational version could connect automatically to daily exchange rate feeds and market price sources, store historical predictions, monitor forecast errors, and flag cases where predicted prices diverge sharply from observed prices. Such functionality would support food security planning by helping analysts identify potential price pressures before they fully materialize in retail markets.

5.7 Stakeholder Decision Support

The practical value of the findings differs by stakeholder. The Bank of Uganda can use the short-horizon relationship as supplementary evidence in food-inflation surveillance, while recognizing that monetary action alone cannot address structural supply constraints. Agricultural and finance ministries can use commodity-specific volatility and upper-quantile sensitivity to prioritize temporary market, storage, tariff, production, or social-protection responses during periods of combined depreciation and elevated prices. Kampala market authorities can use the outputs to identify commodities requiring closer monitoring and engagement with traders and logistics providers.

Humanitarian organizations are relevant stakeholders because their food-security decisions depend on the timing, location, and severity of market-price deterioration. The model outputs can complement household surveys, market assessments, and field observations by supporting scenario analysis, prioritization of monitored commodities, anticipatory planning, and the timing of cash or food assistance. They can also use observed model disagreement as an indication that additional market verification is required. The tool is therefore most useful as one input within a broader evidence system, not as an independent trigger for humanitarian action.

For traders and market analysts, model-specific predictions can support inventory and procurement scenarios, but they should not be treated as guaranteed future prices. Researchers and system developers can use the documented architecture and open notebooks to replicate the analysis, test other regions, and improve the feature set and validation design.

5.8 Commodity-Specific Vulnerabilities and Market Structure

The exploratory analysis revealed substantial heterogeneity in price volatility across commodities, with Plantains exhibiting the highest relative volatility ($CV=0.895$) and Maize flour the most stable pricing behavior ($CV=0.304$). This variation reflects differences in market structure, storage characteristics, and import dependence across commodity types. The absence of a consistent relationship between average price levels and volatility measures indicates that commodity-specific factors—including perishability, trade exposure, and substitution possibilities—significantly influence how exchange rate shocks transmit to individual markets.

The near-perfect alignment between implied and official exchange rates validates the methodological approach and suggests efficient arbitrage in currency markets. However, the persistent commodity-level volatility differences indicate that market integration and price transmission mechanisms operate differently across the food system. This heterogeneity has important implications for targeted policy interventions, suggesting that blanket approaches to managing exchange rate effects on food prices may be insufficient.

5.9 Contradictory and Complementary Findings

Several results appear contradictory at first sight but measure different properties of the data. First, the positive level regression and directional Granger and transfer-entropy results coexist with a near-zero contemporaneous correlation between exchange-rate and food-price returns and weak DCC volatility spillovers. The level and causality results concern longer adjustment patterns and predictive information, whereas the return correlation and DCC analysis concern

synchronized short-run volatility. Together, they suggest that exchange rates are more relevant to changes in price levels and delayed adjustment than to simultaneous month-to-month volatility.

Second, XGBoost and Random Forest achieved relatively strong panel-level R^2 values, while OLS, WLS, Prophet, and the deep sequence models produced weak or negative R^2 results. This difference does not imply that every machine-learning architecture is superior. The tree models benefited from commodity identity and flexible interactions across the pooled panel, whereas Prophet was fitted only to maize and the deep models were trained on a much smaller transformed sequence sample. Model performance therefore depended on the prediction task, sample construction, feature representation, and scale of evaluation.

Third, wavelet analysis indicated strong short-horizon co-movement but weak medium- and long-horizon relationships. This qualifies the broader claim of exchange-rate pass-through: the exchange rate is an important short-run signal, while harvest cycles, storage, domestic supply, policy responses, and structural market factors become more influential over longer horizons.

Finally, the live demonstration showed that XGBoost was closer to observed maize prices than Random Forest or the simple ensemble. The ensemble’s underprediction shows that averaging models does not automatically improve accuracy when one component is systematically weaker for a particular observation. The deployed output should therefore display individual estimates and model disagreement, and future ensemble weights should be based on validated out-of-sample performance.

5.10 Study and Analytical Model Limitations

The study has several limitations that qualify its conclusions. Geographically, the Kampala sample was dominated by Owino Market. The findings therefore describe the observed Kampala case and should not be generalized automatically to rural markets, border markets, other cities, or regions with different production, transport, consumption, and market structures. Validation in additional Ugandan regions is required before the framework can support nationwide inference.

The monthly frequency enabled integration of the two datasets but may conceal within-month price shocks and rapid exchange-rate adjustment. Commodity histories were also uneven, and filtering for sufficient observations may favor commodities with better reporting continuity. The implied exchange-rate validation supports internal consistency, but it does not remove all measurement error in the underlying market-price observations.

Each analytical model also has specific limitations. OLS summarizes an average linear association and is sensitive to functional-form assumptions and unobserved influences. Granger causality establishes temporal predictive content rather than structural causality. Transfer entropy depends on discretization choices and available sample size. The simplified DCC-GARCH implementation provides indicative evidence about volatility co-movement but is not equivalent to a fully estimated multivariate structural volatility model. Markov-switching results depend on the assumed number of regimes and model convergence, while quantile regression estimates conditional associations at selected quantiles. Wavelet results depend on the selected wavelet, scales, smoothing, and boundary treatment.

Predictive-model performance is similarly conditional on the evaluation design. The tree models used a limited feature set dominated by exchange rate and commodity identity, so their predictions do not incorporate many known food-price drivers. The held-out split does not

fully reproduce every challenge of genuine rolling future forecasting. Prophet was estimated only for maize, preventing a direct commodity-wide comparison. The deep-learning models used a small sequence sample, which limited their ability to estimate high-capacity architectures reliably. The deployed ensemble used a simple average rather than performance-based weights and did not provide prediction intervals. The live application is therefore a research prototype whose estimates require comparison with observed market information and regular model monitoring.

These limitations do not invalidate the observed relationships, but they restrict the strength and scope of the claims. The findings are best interpreted as convergent evidence from the available Kampala data and as a basis for broader validation, richer model specification, and operational testing.

5.11 Policy Implications and Economic Significance

The collective evidence points toward several important policy considerations. First, the identification of a high-pass-through regime in the Markov-switching model highlights the need for contingency planning during economic stress periods. The quadrupling of exchange rate effects in this regime suggests that standard policy tools may be inadequate during crises, requiring more aggressive or targeted interventions. Second, the quantile regression results indicating amplified effects during price spikes suggest that exchange rate management could play a crucial role in food price stabilization. Policies that mitigate currency depreciation during periods of already elevated food prices may help prevent dangerous inflationary spirals that disproportionately affect low-income households. Third, the short-term dominance of exchange rate effects identified in the frequency domain analysis suggests that monetary policy and exchange rate management can provide effective short-term stabilization, while long-term food price security requires addressing structural factors including agricultural productivity, storage infrastructure, and supply chain efficiency.

Chapter 6

Conclusion and Recommendation

6.1 Conclusion

This study examined how monthly UGX/USD exchange-rate dynamics were associated with, temporally preceded, and predicted commodity prices in Kampala markets between January 2006 and September 2025. The multi-method design produced two distinct contributions. The causal and dynamic analyses assessed direction, asymmetry, regimes, distributional differences, volatility co-movement, and time-scale dependence. The predictive analyses assessed whether the available exchange-rate and commodity information could estimate held-out prices accurately enough to support a practical decision-support prototype.

The directional analyses showed that past exchange-rate values contained useful information about subsequent food-price movements, with substantially stronger transfer entropy from exchange rates to prices than in the reverse direction. This supports the use of exchange rates as an upstream monitoring indicator within the observed data. The result should, however, be interpreted as temporal and predictive causal evidence rather than proof of a fully isolated structural effect. Other domestic and global factors remain important in food-price formation.

The relationship was heterogeneous rather than constant. Markov-switching estimates indicated moderate- and high-pass-through regimes, while quantile regression showed larger exchange-rate coefficients in the upper part of the price distribution. Wavelet analysis identified stronger co-movement over short horizons and weaker relationships at longer horizons. These findings imply that exchange-rate monitoring is most relevant for short-term warning and periods of elevated prices, while longer-term food-price stability depends increasingly on production, storage, transport, market organization, climate, and other structural conditions.

The predictive findings complemented, but did not establish, the directional results. XGBoost and Random Forest performed substantially better than the linear baselines and the maize-specific Prophet benchmark when exchange rate and commodity identity were used together. Their performance demonstrated that commodity-specific, non-linear patterns have practical forecasting value. At the same time, weak results from the linear and deep sequence models, together with disagreement among models in the live demonstration, showed that predictive performance is conditional on feature availability, sample design, model choice, and validation procedure.

The deployed Flask API and Quasar PWA demonstrated how the analytical work could be translated into an accessible research prototype. Its practical contribution is the ability to display model-specific and ensemble estimates for scenario analysis and market monitoring.

The application is not an official price quotation or a substitute for field data. Its outputs are most defensible when combined with current market observations, institutional analysis, and human judgment.

Overall, the study provides convergent evidence that exchange-rate dynamics are relevant to short-term food-price monitoring in Kampala and that machine-learning models can transform this relationship into useful predictive information. The scientific contribution lies in distinguishing directional evidence from forecasting performance, while the applied contribution lies in demonstrating a deployable decision-support workflow. Generalization beyond the observed Kampala markets requires validation with data from other cities, rural markets, border regions, and additional explanatory variables.

6.2 Stakeholder-Specific Recommendations

6.2.1 Bank of Uganda

The Bank of Uganda should incorporate commodity-specific food-price indicators into exchange-rate and inflation surveillance. Particular attention should be given to periods in which depreciation coincides with already elevated food prices, because the quantile and regime results indicate stronger sensitivity under those conditions. Exchange-rate projections and food-market indicators should be shared through regular analytical coordination with agricultural, finance, urban-management, and food-security institutions. The findings do not imply that monetary policy alone can stabilize food prices; they support its use as one component of a coordinated short-term response.

6.2.2 Ministry of Agriculture, Animal Industry and Fisheries

The Ministry should use commodity-level volatility and sensitivity results to prioritize commodities for production support, storage planning, market-information services, and supply-chain monitoring. Highly volatile commodities require closer examination of harvest timing, perishability, storage constraints, and transport exposure. The Ministry should also support the collection of consistent regional market data so that the Kampala framework can be validated across Uganda.

6.2.3 Ministry of Finance, Planning and Economic Development

The Ministry should develop contingency options for periods of combined exchange-rate pressure and food-price escalation. Depending on verified market conditions, these may include time-limited social-protection support, carefully targeted tariff or tax measures, strategic reserve decisions, and financing for supply-chain bottlenecks. Intervention thresholds should combine model signals with observed prices and welfare indicators rather than relying on a prediction alone.

6.2.4 Kampala Capital City Authority and Market Administrators

Kampala authorities and market managers should strengthen routine collection and publication of commodity prices across multiple city markets. The deployed tool can be used to identify scenarios or commodities requiring verification, after which administrators can consult traders, transporters, and consumer-protection units. Expanding data beyond Owino Market would improve both the representativeness of future analysis and the usefulness of city-level alerts.

6.2.5 Humanitarian and Food-Security Organizations

Humanitarian organizations should use the study’s predictions as a supplementary early-warning input alongside household vulnerability data, field market assessments, nutrition information, and observed price series. Scenario outputs can help prioritize commodities and locations for monitoring, anticipate deterioration in food access, plan market assessments, and inform the timing or scale of cash and food assistance. Model disagreement or unusually large predicted changes should trigger additional verification rather than automatic intervention. Humanitarian actors can also use aggregated findings to support policy dialogue on food-security preparedness and market stabilization.

6.2.6 Commodity Traders and Market Analysts

Traders and analysts may use the model-specific estimates for procurement, inventory, and price-risk scenarios. They should compare Random Forest, XGBoost, and ensemble outputs rather than treating a single prediction as certain. Decisions should continue to incorporate current wholesale and retail quotations, seasonal supply information, transport costs, and commodity quality.

6.2.7 System Owners and Institutional Users

Before operational adoption, the prediction platform should be extended with authenticated access, automated exchange-rate and market-price feeds, prediction logging, model-version control, uncertainty intervals, and routine error monitoring. Institutional users should define who is responsible for data updates, model approval, alert interpretation, and communication of limitations. The application should clearly label predictions as decision-support estimates rather than official market prices.

6.2.8 Researchers and Model Developers

Future research should validate the framework in other Ugandan regions and compare urban, rural, and border markets. The dataset should be expanded with consistently measured variables such as rainfall, fuel and transport costs, harvest volumes, global commodity prices, import exposure, and policy interventions. Future model development should also evaluate rolling time-based validation, commodity-specific models, calibrated prediction intervals, performance-weighted ensembles, and systematic hyperparameter optimization. These extensions would strengthen predictive robustness and clarify how much of the observed relationship remains after accounting for additional food-price drivers.

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Appendix A

Budget

The budget for this research is primarily associated with model inference and deployment. Since the trained models are deployed through a Flask API and a Quasar frontend hosted on an Ubuntu Virtual Private Server (VPS), the main recurring cost is the server infrastructure required to keep the prediction system available online.

Table A.1: Deployment and Inference Budget

Item	Monthly Cost (UGX)	Duration	Total Cost (UGX)
Ubuntu VPS hosting for deployed prediction system (4 vCPU, 8 GB RAM)	190,000	6 months	1,140,000
Total Deployment Budget			1,140,000

The estimated total deployment budget is therefore **UGX 1,140,000**. This cost covers the Ubuntu VPS infrastructure used to host the API and frontend services for six months, supporting live inference for the food price prediction system.

Appendix B

Research Project timelines

This appendix presents the project implementation timeline from proposal development through model training, deployment, reporting, presentation, and post-presentation improvement. The timeline reflects the main research and development phases followed in completing the study and operationalizing the food-price prediction system.

B.1 Project Timeline

Table B.1: Research project timeline

Period	Phase	Main activities and deliverables
November–December 2025	Project proposal documentation and presentation	Developed the research proposal, refined the research topic, formulated the problem statement, objectives, research questions, scope, significance, and initial methodology. Prepared and delivered the proposal presentation for academic review and feedback.
January–March 2026	Model training and financial analytics	Collected and cleaned food-price and exchange-rate datasets, merged WFP food-price data with Bank of Uganda exchange-rate data, conducted exploratory data analysis, implemented causal and non-linear analytical methods, trained predictive models, and evaluated model performance using financial analytics and forecasting metrics.
April–June 2026	Model deployment and frontend application development	Prepared trained model artifacts for deployment, developed the Flask prediction API, configured backend inference logic, built the frontend Progressive Web Application, integrated frontend requests with backend predictions, and configured hosting infrastructure for the deployed system.

Period	Phase	Main activities and deliverables
June–July 2026	Reporting, documentation, and presentation	Completed the research report, documented the methodology, results, discussion, deployment architecture, conclusions, recommendations, appendices, and references. Prepared final presentation materials and refined the report based on feedback.

B.2 Post-Presentation Plan

Following the academic presentation, the project will continue as an applied decision-support initiative. The post-presentation period will focus on demonstrating the system, maintaining the deployed infrastructure, and improving model performance based on stakeholder feedback.

Table B.2: Post-presentation activity plan

Period	Activity area	Planned activities
August 2026– August 2027	Stakeholder demonstration	Demonstrate the food-price prediction application to relevant stakeholders, including potential users, policymakers, market analysts, food-security actors, and potential clients. Collect feedback on usability, interpretability, model outputs, and practical decision-support needs.
August 2026– August 2027	Hosting infrastructure management	Monitor and manage the hosting environment for the API and frontend application, including server uptime, domain access, reverse proxy configuration, model-serving reliability, and basic maintenance of the deployed system.
August 2026– August 2027	Model improvement	Improve the prediction models based on demo feedback, updated datasets, observed prediction errors, and stakeholder needs. Possible improvements include adding more recent price records, refining commodity-specific models, improving feature engineering, and adjusting the ensemble logic.

B.3 Dependencies and Deliverables

Table B.3: Key dependencies and deliverables by project phase

Phase	Key dependencies	Main deliverables
Proposal documentation	Topic approval, supervisor guidance, preliminary literature review	Approved proposal document and proposal presentation.
Model training and analytics	Availability of WFP food-price data, Bank of Uganda exchange-rate data, data preprocessing, and model-development environment	Clean analytical dataset, exploratory results, causal analysis outputs, trained models, and model performance comparisons.
Deployment and frontend development	Trained model artifacts, API code, frontend framework, hosting server, domain configuration, and reverse proxy setup	Deployed Flask API, frontend PWA, model inference workflow, and operational prediction interface.
Reporting and presentation	Completed analysis, generated figures, validated results, and compiled documentation	Final research report, appendices, references, final presentation slides, and documented deployment architecture.
Post-presentation improvement	Stakeholder feedback, continued hosting access, updated data, and monitoring of deployed application performance	Demonstration feedback, maintained infrastructure, improved model versions, and refined decision-support functionality.

Overall, the project was managed as a phased research-and-development process. The academic component culminated in the final report and presentation, while the post-presentation plan extends the work into practical stakeholder engagement, infrastructure maintenance, and continuous model improvement.

Appendix C

Declaration of AI use

This appendix provides a declaration of how generative artificial intelligence (AI) and large language model (LLM) tools were used ethically during the preparation of this research. The tools were used as a study assistant for literature discovery, methodological orientation, troubleshooting, and visual design support. AI-generated outputs were not accepted as final research content without verification, interpretation, rewriting, and integration by the researcher.

Declaration Statement:

I, Econia Racheal, declare that I used DeepSeek (<https://chat.deepseek.com>) as an AI-assisted study tool during this research. The tool was used to support literature search, identify potentially relevant methodological sources, troubleshoot selected deployment issues, and assist with draft system-architecture visualization ideas. The final thesis content, analysis, interpretation, and conclusions remain my responsibility.

AI Tool Used

Table C.1: Summary of AI/LLM use in the research

AI tool	Purpose	How outputs were used and modified
DeepSeek (https://chat.deepseek.com)	Literature-search assistance	Used to identify possible peer-reviewed papers and methodological directions. Search results were checked against actual papers, bibliography details were verified, and only relevant sources were incorporated into the literature review.
DeepSeek	Methodological orientation	Used to explore existing approaches for Granger causality, transfer entropy, Markov-switching regression, quantile regression, wavelet coherence, DCC-GARCH, and machine-learning forecasting. The final methodological design was adapted to the available Ugandan food-price and exchange-rate data.

AI tool	Purpose	How outputs were used and modified
DeepSeek	Deployment troubleshooting	Used to help reason through uWSGI server issues encountered while loading machine-learning models, especially problems that caused the HTTP server to hang for a long time. The final fixes were tested and implemented manually.
DeepSeek	Diagram support	Used to generate ideas and MermaidJS-style drafts for system architecture diagrams. The final architecture was reviewed, adapted, and presented in a form consistent with the deployed Flask API and PWA frontend.

Major AI Prompts Used

The following are the main prompts used for AI-assisted literature discovery and methodological review.

I. Granger Causality Analysis

Search for peer-reviewed academic papers that apply Granger causality tests to examine the relationship between exchange rates and food prices or agricultural commodity prices. Prioritize studies published in the last five years (2020–2025) with high citation counts. Return results in a structured table format including: authors, publication year, title, journal name, specific methodology used (e.g., linear vs. frequency-domain Granger), and key empirical findings. Exclude purely theoretical reviews.

II. Transfer Entropy Analysis

Search for academic papers that utilize Transfer Entropy (TE) or Effective Transfer Entropy (ETE) to quantify information flow and asymmetric causal relationships between exchange rates and commodity or food prices. Focus on studies published after 2020. Provide full bibliographic details (authors, title, journal, volume, DOI) and explicitly mention whether the study uses symbolic or kernel-based transfer entropy.

III. Markov-Switching Regression

Search for journal articles that employ Markov-Switching Regression (MSR) models to analyze regime-dependent exchange rate pass-through (ERPT) to food prices or inflation. Prioritize empirical studies focusing on developing economies or emerging markets. The results should highlight differences in pass-through coefficients across identified regimes (e.g., high-volatility vs. low-volatility states). Return a list with full citations and a brief summary of the regime findings.

IV. Quantile Regression

Search for empirical papers applying Quantile Regression to study the asymmetric and heterogeneous effects of exchange rate fluctuations on food prices or food inflation. Papers must report coefficient estimates across multiple quantiles (e.g., 0.10, 0.25, 0.50, 0.75, 0.90) to show how pass-through intensity changes during price spikes vs. price troughs. Provide full citations and explicitly state the range of quantile coefficients found.

V. Wavelet Coherence Analysis

Search for academic papers that use Wavelet Coherence and phase-difference analysis to investigate the time-frequency dynamics and multi-scale co-movement between exchange rates and agricultural/food commodity prices. Papers should include wavelet coherence spectra or contour maps. Focus on studies that distinguish between short-term (e.g., 3–6 months) and long-term horizons. Return full citations and describe the dominant coherence scales found.

VI. DCC-GARCH Models

Search for journal articles that implement Dynamic Conditional Correlation GARCH (DCC-GARCH) models to analyze time-varying conditional correlations and volatility spillovers between exchange rates and food prices. Prioritize papers that report the dynamic correlation trajectories over time and discuss implications for volatility transmission. Provide a structured list with authors, year, title, journal, and summary of the DCC estimates.

VII. Machine Learning and Predictive Modeling

Search for academic papers that use Machine Learning methods (specifically Random Forest, XGBoost, LSTM, GRU, or Transformer architectures) to forecast food or commodity prices, with the exchange rate included as a key predictive feature. Papers should report standard regression metrics (R^2 , RMSE, MAE, MAPE). Include studies on African or emerging markets if available. Return full citations and a brief note on the best-performing algorithm in each study.

VIII. Review and Survey Papers

Search for review articles and systematic literature reviews on Exchange Rate Pass-Through (ERPT) to food prices or headline inflation. The reviews should synthesize findings across multiple methodologies (linear, non-linear, time-series, and panel data approaches) and discuss determinants of pass-through heterogeneity (e.g., market structure, import share, inflation environment). Provide full citations and indicate the primary conclusion regarding the magnitude of ERPT in developing countries, if possible in Uganda.

Additional AI-Assisted Activities

Beyond literature-search support, DeepSeek was also used for the following technical and design-support tasks:

- i. Troubleshooting uWSGI server issues that occurred while loading trained model artifacts, including issues that caused the HTTP server to hang for a long time.
- ii. Generating initial MermaidJS-style ideas for system architecture drawings used to conceptualize the deployed prediction platform.
- iii. Generating research poster for appendix I.

Human Verification and Modification

All AI-assisted outputs were reviewed and modified by the researcher. For paper-search outputs, a secondary search was conducted using the Brave Search Engine (<https://search.brave.com/>) to access the actual source pages of the papers, download available full texts, and read them for verification before use. Bibliographic suggestions were checked against accessible papers before being cited. Methodological suggestions were compared with the available dataset and the actual Python notebook implementation. Deployment suggestions were tested in the application environment before being accepted. Diagram suggestions were adapted to match the actual deployed architecture consisting of a Quasar PWA frontend, Flask API, uWSGI, Nginx, and hosted model artifacts.

No AI tool was used as a substitute for the researcher's analysis, interpretation, or academic judgment. The AI tools supported brainstorming, literature discovery, troubleshooting, and drafting assistance only.

Signature:  Date: 2/07/2026

Appendix D

List of 10 Major Journal Publications reviewed

This appendix summarizes ten major publications and technical sources reviewed for this study. The selected works were prioritized because they directly inform the theoretical framing, empirical context, and methodological design of the investigation into exchange rate dynamics and food prices in urban Uganda. The list combines journal articles, methodological papers, and policy-oriented sources because the study draws on both academic methods and applied food-security evidence.

Table D.1: Major publications and sources reviewed for the study

No.	Publication	Source type	Main focus	Contribution to this study
1	Mawejje (Mawejje, 2016)	Journal article	Food prices, energy, and climate shocks in Uganda	Provides Uganda-specific empirical grounding for food-price vulnerability and supports the focus on local food-price dynamics.
2	Umoru and Amedu (Umoru and Amedu, 2022)	Journal article	Exchange-rate variation and food commodity prices in selected African countries	Supports the regional argument that dollar exchange-rate movements can influence African food commodity prices.
3	Waiswa and Yavuz (Waiswa and Yavuz, 2023)	Journal article	Market integration and asymmetric price transmission in Ugandan staple-food markets	Informs the discussion of local market structures, asymmetric transmission, and commodity-specific pass-through in Uganda.

No.	Publication	Source type	Main focus	Contribution to this study
4	Ezebilo, Akanegbu, and Yakubu (Ezebilo et al., 2023)	Journal article	Monetary policy and food inflation in Nigeria using a NARDL approach	Strengthens the African empirical review by linking exchange rates, monetary policy instruments, and food inflation.
5	Likassa et al. (Likassa et al., 2026)	Journal article	DCC-GARCH modelling of inflation indicators and exchange rates in Ethiopia	Supports the use of multivariate volatility methods for studying time-varying relationships among food prices, inflation, and exchange rates.
6	Woode et al. (Woode et al., 2026)	Journal article	Commodity dependence, market sentiment, and pressure currencies in Sub-Saharan Africa	Justifies the use of time-frequency methods by showing that commodity-currency linkages vary across horizons and crisis periods.
7	Maiti and Kayal (Maiti and Kayal, 2023)	Journal article	Transfer entropy and asymmetric information flow among exchange rates, oil, and gold	Supports the use of information-theoretic causality tools for detecting asymmetric information flow in exchange-rate and commodity systems.
8	Granger (Granger, 1969)	Foundational journal article	Predictive causality in econometric models	Provides the theoretical basis for Granger causality testing used to establish temporal precedence between exchange rates and food prices.
9	Torrence and Compo (Torrence and Compo, 1998)	Methodological journal article	Practical wavelet analysis	Provides the methodological foundation for wavelet coherence and frequency-domain analysis in the study.
10	UNCTAD (United Nations Conference on Trade and Development, 2022)	Policy report	Food-price increases, currency depreciation, and import bills	Provides policy context on how currency depreciation and global food-price increases jointly affect food-importing countries.

Overall, the reviewed literature was sufficient to support Appendix D because it covers the study's four core pillars: Uganda-specific food-price evidence, broader African exchange-rate and food-inflation evidence, causal and volatility methods, and time-frequency analysis. However, the appendix should be interpreted as a list of major publications and technical sources reviewed, rather than only journal publications, because some highly relevant sources for this study are policy reports or foundational methodological works.

Appendix E

Scopus Search Strings used during the literature review

This appendix documents the main keywords and Scopus-style search strings used during the literature review. The searches were designed to identify studies on exchange rate pass-through, food prices, African commodity markets, causal inference, volatility modelling, time-frequency analysis, and predictive modelling. Because the study combines econometric, information-theoretic, and machine learning methods, the search strategy used several complementary strings rather than a single broad query.

Search Scope

The literature search prioritized peer-reviewed journal articles, methodological papers, and policy-oriented sources relevant to exchange rate dynamics and food prices in developing economies. Searches were concentrated on the period from 2000 onward, while older foundational works were retained where they introduced core methods or theories, such as purchasing power parity, Granger causality, quantile regression, and wavelet analysis.

Table E.1: Core keyword groups used in the literature search

Keyword group	Search terms and variants
Exchange rate terms	exchange rate, currency depreciation, currency volatility, foreign exchange, real effective exchange rate, exchange rate pass-through, dollar exchange rate, UGX, USD
Food-price terms	food price, food inflation, commodity price, staple food, agricultural commodity, retail food price, food security, price volatility
Geographical terms	Uganda, Kampala, East Africa, Sub-Saharan Africa, Africa, developing countries, low-income countries, food-importing countries
Econometric methods	Granger causality, vector autoregression, VAR, GARCH, DCC-GARCH, NARDL, quantile regression, Markov-switching, regime switching
Information-flow methods	transfer entropy, information flow, asymmetric causality, non-linear causality, entropy-based causality

Keyword group	Search terms and variants
Time-frequency methods	wavelet coherence, wavelet analysis, frequency domain, time-frequency analysis, co-movement, scale-dependent relationship
Prediction methods	machine learning, random forest, XGBoost, forecasting, predictive modelling, SARIMA, Prophet, deep learning, LSTM

Scopus Search Strings

The following search strings were used as the principal query templates. Minor adjustments were made during searching to account for spelling variants, singular and plural forms, and database result volume.

Search String 1: Exchange Rate Pass-Through and Food Prices

```
TITLE-ABS-KEY(
  ("exchange rate" OR "currency depreciation" OR "currency volatility"
   OR "exchange rate pass-through")
  AND
  ("food price" OR "food inflation" OR "commodity price"
   OR "staple food")
  AND
  (Africa OR "Sub-Saharan Africa" OR Uganda OR Kampala
   OR "developing countries")
)
```

This search identified empirical studies linking exchange-rate movements to food prices, commodity prices, and food inflation in African and developing-economy contexts.

Search String 2: Uganda and Staple-Food Market Transmission

```
TITLE-ABS-KEY(
  (Uganda OR Kampala OR "East Africa")
  AND
  ("food price" OR "staple food" OR "agricultural commodity"
   OR "food market")
  AND
  ("price transmission" OR "market integration" OR volatility
   OR "exchange rate")
)
```

This search supported the Uganda-specific review, especially literature on staple-food markets, market integration, asymmetric transmission, and local food-price volatility.

Search String 3: Monetary Policy, Exchange Rates, and Food Inflation

```
TITLE-ABS-KEY(
  ("monetary policy" OR "money supply" OR "policy rate"
   OR "treasury bill rate" OR "exchange rate")
  AND
```

```

("food inflation" OR "consumer price index" OR CPI
 OR "food price index")
AND
(Africa OR Nigeria OR Ethiopia OR Uganda OR "developing economies")
)

```

This search captured studies that connect food inflation to monetary policy and exchange-rate conditions, including NARDL and multivariate volatility studies.

Search String 4: Volatility and Multivariate GARCH Methods

```

TITLE-ABS-KEY(
  (GARCH OR "DCC-GARCH" OR "BEKK-GARCH"
   OR "multivariate GARCH" OR "dynamic conditional correlation")
  AND
  (inflation OR "food price" OR "exchange rate" OR "commodity price")
  AND
  (Africa OR "developing countries" OR Ethiopia OR Nigeria OR Uganda)
)

```

This search informed the volatility-transmission component of the methodology and helped locate African applications of DCC-GARCH and related models.

Search String 5: Causality and Information Flow

```

TITLE-ABS-KEY(
  ("Granger causality" OR "transfer entropy" OR "information flow"
   OR "nonlinear causality" OR "asymmetric causality")
  AND
  ("exchange rate" OR currency OR "commodity price"
   OR "food price" OR inflation)
)

```

This search supported the causal-inference design by identifying foundational and applied studies on predictive causality and entropy-based information transfer.

Search String 6: Wavelet and Time-Frequency Commodity-Currency Analysis

```

TITLE-ABS-KEY(
  ("wavelet coherence" OR "wavelet analysis"
   OR "time-frequency" OR "frequency domain")
  AND
  ("exchange rate" OR currency OR "commodity price"
   OR "food price" OR "market sentiment")
  AND
  (Africa OR "Sub-Saharan Africa" OR "developing economies"
   OR commodity)
)

```

This search identified studies using wavelet coherence and time-frequency analysis to examine commodity-currency co-movement across short- and long-run horizons.

Search String 7: Predictive Modelling and Machine Learning

```
TITLE-ABS-KEY(  
  ("machine learning" OR "random forest" OR XGBoost OR LSTM  
  OR "deep learning" OR forecasting OR "predictive modelling")  
AND  
  ("food price" OR "commodity price" OR inflation)  
AND  
  ("exchange rate" OR macroeconomic OR Africa OR "developing countries")  
)
```

This search informed the predictive modelling component of the study, particularly the comparison between traditional time-series methods and machine learning models.

Screening and Selection Criteria

The search results were screened using the following criteria:

1. **Topical relevance:** studies had to address exchange rates, food prices, commodity prices, inflation, market integration, volatility, or forecasting.
2. **Geographical relevance:** priority was given to Uganda, East Africa, Sub-Saharan Africa, and other developing-economy contexts with comparable food-security and exchange-rate challenges.
3. **Methodological relevance:** studies using Granger causality, transfer entropy, GARCH-type models, NARDL, quantile regression, wavelet analysis, machine learning, or forecasting models were prioritized.
4. **Policy relevance:** reports and studies were retained where they provided evidence on food-import bills, currency depreciation, food-security vulnerability, or monetary policy implications.
5. **Foundational value:** older works were included where they introduced theories or methods central to the study, even if they fell outside the main date range.

The final reviewed literature therefore combined Uganda-specific evidence, broader African food-inflation studies, methodological foundations, and applied forecasting literature. This combination was necessary because the research problem required both substantive understanding of food-price pass-through and methodological tools capable of capturing causality, non-linearity, volatility, time-frequency co-movement, and predictive performance.

Appendix F

Research alignment with specialization, SDG, NDPIV & Vision 2040

This appendix explains how the study aligns with the student’s programme specialization, Uganda’s national development priorities, Uganda Vision 2040, and the global Sustainable Development Goals (SDGs). The research topic, *The Effect of Exchange Rate Dynamics on Food Prices in Urban Uganda: A Multi-Method Analysis of Kampala Markets*, is positioned at the intersection of data science, financial analytics, food security, and evidence-based public policy.

F.1 Alignment with Programme Specialization

The study aligns most strongly with the Data Science specialization track of **Business Intelligence and Financial Analytics**. The research applies data-driven techniques to a financial and economic policy problem: understanding how exchange rate dynamics affect food prices in Kampala’s urban markets. This makes the study relevant to financial analytics because exchange rates are macro-financial variables, while food prices represent market-level welfare outcomes that can be monitored and forecast using data science tools.

The alignment is demonstrated in four ways. First, the study integrates heterogeneous data sources, including World Food Programme food-price data and Bank of Uganda exchange-rate data, into a unified analytical dataset. Second, it uses statistical and econometric methods such as regression, Granger causality, quantile regression, DCC-GARCH, and wavelet coherence to understand relationships among economic variables. Third, it applies machine learning and forecasting models, including Random Forest, XGBoost, SARIMA, Prophet, and neural-network-based approaches, to evaluate the predictive value of exchange-rate information. Fourth, the study extends beyond analysis by deploying a web-based prediction system that translates model outputs into a practical decision-support tool.

Therefore, the research contributes to the specialization by showing how business intelligence and financial analytics can support real-world decision-making in food-price monitoring, market-risk assessment, and policy planning. The study also demonstrates the practical value of data science in transforming public datasets into actionable insights for government agencies, market analysts, and food-security stakeholders.

F.2 Alignment with Sustainable Development Goals

The study contributes directly and indirectly to several Sustainable Development Goals (SDGs), particularly those concerned with poverty reduction, food security, economic resilience, innovation, and sustainable urban development (United Nations Development Programme, 2026). Its strongest alignment is with SDG 2, SDG 1, SDG 8, SDG 9, and SDG 11.

Table F.1: Alignment of the study with selected Sustainable Development Goals

SDG	Goal focus	Research alignment
SDG 1	No Poverty	Urban food-price inflation reduces household purchasing power and disproportionately affects low-income households. By identifying exchange-rate-driven food-price risks, the study supports evidence-based interventions that can protect vulnerable urban consumers.
SDG 2	Zero Hunger	The study directly supports food-security planning by examining the drivers of staple-food price movements in Kampala markets. Better price forecasting can strengthen early warning systems and improve the timing of food-security responses.
SDG 8	Decent Work and Economic Growth	Exchange-rate instability and food-price volatility affect business costs, real wages, and household welfare. The study contributes to economic resilience by helping policymakers understand how macro-financial shocks transmit into local markets.
SDG 9	Industry, Innovation and Infrastructure	The deployed prediction platform demonstrates how digital innovation, analytics infrastructure, and applied machine learning can support public-sector and market decision-making.
SDG 11	Sustainable Cities and Communities	Kampala's urban markets are central to food access for city residents. The study supports more resilient urban food systems by generating evidence on price risks in a major urban market setting.

The research is especially relevant to SDG 2 because food-price volatility directly affects access to affordable food. It is also relevant to SDG 9 because the study operationalizes predictive analytics through a web-based system, demonstrating how digital tools can support development planning and public decision-making.

F.3 Alignment with the National Development Plan IV

The Fourth National Development Plan (NDPIV) is Uganda’s medium-term development framework for advancing socio-economic transformation and implementing the longer-term national vision through prioritized programmes and public investment planning (Ministry of Finance, Planning and Economic Development, 2025). This study aligns with NDPIV because it supports evidence-based planning in food security, macroeconomic management, digital transformation, urban development, and household welfare.

First, the study contributes to food-security and household-welfare priorities by focusing on staple-food price movements in urban markets. Food-price volatility can weaken household resilience, particularly for urban residents who depend heavily on market purchases rather than own production. By identifying commodities that are most sensitive to exchange-rate movements, the study provides evidence that can inform targeted price-stabilization and social-protection measures.

Second, the research supports macroeconomic stability by examining the relationship between the UGX/USD exchange rate and local food prices. Exchange-rate depreciation can affect food prices through imported food items, fuel, fertilizers, transport costs, and expectations. Understanding this transmission mechanism can support better coordination between monetary policy, agricultural policy, trade policy, and food-security planning.

Third, the study aligns with digital transformation and data-driven governance. The analytical workflow integrates official exchange-rate data with humanitarian food-price data, applies advanced modelling techniques, and deploys a web-based prediction tool. This demonstrates how public and open datasets can be converted into practical intelligence for planning, monitoring, and early warning.

Fourth, the research supports urban development priorities by focusing on Kampala markets, where food access, price stability, and household welfare are closely linked. Urban markets are important economic nodes, and their stability affects consumers, traders, transporters, and policymakers. The study therefore contributes evidence for improving urban market resilience and managing the effects of macroeconomic shocks on city households.

F.4 Alignment with Uganda Vision 2040

Uganda Vision 2040 aims to transform Uganda from a predominantly peasant and low-income society into a modern and prosperous country within 30 years (National Planning Authority, 2013). The Vision emphasizes strengthening the fundamentals of the economy, including infrastructure, science, technology, engineering and innovation, human resources, urban development, and macroeconomic stability. This study aligns with those priorities in several ways.

First, the study supports the Vision 2040 emphasis on science, technology, engineering, and innovation by applying data science, machine learning, econometrics, and web-based deployment to a national development problem. It demonstrates how advanced analytical methods can generate practical knowledge for food-price monitoring and economic planning.

Second, the study contributes to macroeconomic management by examining exchange-rate pass-through to domestic prices. Vision 2040 recognizes the importance of strengthening economic fundamentals and improving competitiveness. Understanding how currency movements affect food prices can help policymakers design more responsive interventions during periods of exchange-rate pressure.

Third, the research aligns with the Vision’s focus on agriculture and food systems. Although the study is urban-market focused, Kampala food prices are linked to agricultural production, input costs, fuel prices, transport systems, imports, and market structure. Evidence on price transmission can therefore support broader agricultural commercialization and food-system resilience.

Fourth, the study contributes to urban development by focusing on Kampala, a major urban market environment. As Uganda urbanizes, stable and efficient food markets will be increasingly important for household welfare, social stability, and inclusive growth. The study’s urban focus therefore supports Vision 2040’s broader transformation agenda by linking macroeconomic management to practical outcomes in urban livelihoods.

F.5 Summary of Alignment

Table F.2: Summary of research alignment with specialization, national agenda, and global goals

Alignment area		How the study contributes
Programme	specialization	Applies business intelligence, financial analytics, econometrics, machine learning, and deployment to an economic policy problem.
Sustainable Development Goals	Develop-	Supports food security, poverty reduction, innovation, economic resilience, and sustainable urban communities.
NDPIV		Provides evidence for food-security planning, macroeconomic policy coordination, digital transformation, and urban market resilience.
Uganda Vision 2040		Supports science and innovation, macroeconomic stability, agricultural transformation, and urban development.

In summary, the study is strongly aligned with the Data Science programme and with Uganda’s national and global development priorities. Its main contribution is the use of data-driven financial analytics to understand and forecast food-price risks, thereby supporting more timely, targeted, and evidence-based interventions for urban food security.

Appendix G

Algorithms, Code of interest

This appendix summarizes the main algorithms and code workflows used in the empirical analysis and predictive modelling components of the study. The content was derived from the project GitHub repository, <https://github.com/econiaracheal/UCUMsDSA>, specifically the notebooks `econia-price-p.ipynb`, which contains the main exploratory, causal, non-linear, frequency-domain, and initial machine-learning analysis; and `predictive-modelling-02.ipynb`, which contains the expanded predictive modelling workflow, including tree-based models, Prophet, ensemble learning, linear baselines, and deep learning models.

G.1 Notebook Sources

Table G.1: Notebook sources used for Appendix G

Notebook	Main analytical content
<code>econia-price-p.ipynb</code>	Data preprocessing, Kampala-focused exploratory data analysis, volatility metrics, implied exchange-rate validation, regression, Granger causality, transfer entropy, DCC-GARCH, Markov-switching regression, quantile regression, wavelet coherence, rolling-window robustness checks, and initial predictive modelling.
<code>predictive-modelling-02.ipynb</code>	Predictive modelling using Random Forest, XGBoost, Prophet, ensemble learning, OLS/WLS baselines, Support Vector Regression, LSTM with attention, CNN-BiLSTM with attention, Transformer Encoder, and Stacked BiLSTM.

G.2 Overall Analytical Pipeline

The project followed a sequential analytical pipeline, beginning with data preparation and ending with model comparison and deployment-oriented prediction outputs.

1. Load WFP food-price data and Bank of Uganda exchange-rate data.
2. Clean date, price, USD price, exchange-rate, commodity, and market fields.

3. Construct month-year merge keys and merge food-price records with official exchange-rate data.
4. Filter the analysis to commodities and markets with sufficient observations, with Kampala used as the main urban-market focus.
5. Compute exploratory statistics, volatility measures, and implied exchange rates.
6. Estimate linear and non-linear causal relationships using OLS, Granger causality, transfer entropy, and DCC-GARCH.
7. Estimate regime-dependent and distribution-sensitive models using Markov-switching regression and quantile regression.
8. Analyze time-frequency co-movement using wavelet coherence.
9. Train and compare predictive models using traditional regression, machine learning, time-series, and deep learning approaches.
10. Export model diagnostics, graphs, and prediction outputs for interpretation and deployment.

G.3 Core Algorithms

G.3.1 Data Preprocessing and Merge Algorithm

The preprocessing algorithm converted raw food-price and exchange-rate files into a unified analytical panel. The essential logic is shown below.

Input: WFP food price data, Bank of Uganda exchange rate data
Output: Clean merged analytical dataset

1. Load food price dataset.
2. Remove non-data descriptor rows where present.
3. Convert date fields to datetime format.
4. Convert price and usdprice columns to numeric values.
5. Drop observations with missing date, price, or usdprice.
6. Create `implied_exchange_rate = price / usdprice`.
7. Extract year and month from the food price date.
8. Load Bank of Uganda exchange rate series.
9. Convert exchange rate date fields to datetime format.
10. Extract year and month from the exchange rate series.
11. Merge food prices with official exchange rates by year and month.
12. Sort the merged dataset chronologically.

This workflow ensured that all subsequent models used consistent monthly exchange-rate information aligned with commodity price observations.

G.3.2 Commodity Volatility Metrics

The exploratory analysis computed relative and absolute volatility indicators for major commodities. The coefficient of variation was used as the main scale-free volatility measure.

For each commodity:

```
mean_price = mean(price)
standard_deviation = std(price)
```

```

coefficient_of_variation = standard_deviation / mean_price
price_range = max(price) - min(price)
rolling_volatility = rolling_standard_deviation(price, window=3 months)

```

Rank commodities by coefficient_of_variation.

The results were visualized using bar charts, radar charts, bubble plots, and heatmaps to compare commodity-level instability.

G.3.3 Granger Causality Algorithm

Granger causality was used to test whether lagged exchange-rate values improved prediction of food prices beyond food prices' own past values.

Input: Monthly food price series P_t , exchange rate series E_t

Output: Lag-specific Granger causality test statistics and p-values

1. Align P_t and E_t by month.
2. Select maximum lag length p .
3. Estimate restricted model using lagged values of P_t only.
4. Estimate unrestricted model using lagged values of P_t and E_t .
5. Compare restricted and unrestricted models using F-tests.
6. Reject non-causality if lagged E_t terms jointly improve prediction of P_t .

In the notebooks, this was implemented using `statsmodels.tsa.stattools.grangercausalitytests`.

G.3.4 Transfer Entropy Algorithm

Transfer entropy was included to capture non-linear information flow that may not be detected by linear causality tests.

Input: Exchange rate series E_t , food price series P_t

Output: Transfer entropy from E to P

1. Discretize E_t and P_t into quantile-based bins.
2. Estimate joint probabilities of future P , past P , and past E .
3. Estimate conditional probability $P(P_{\text{future}} | P_{\text{past}}, E_{\text{past}})$.
4. Estimate conditional probability $P(P_{\text{future}} | P_{\text{past}})$.
5. Sum probability-weighted log ratios across observed states.
6. Interpret larger transfer entropy as stronger information flow.

The main notebook implemented this using helper functions for quantile discretization, conditional entropy, and manual transfer entropy calculation.

G.3.5 DCC-GARCH Volatility Framework

The DCC-GARCH workflow was used to examine whether exchange-rate and food-price returns exhibited time-varying volatility co-movement.

Input: Exchange rate returns and food price returns

Output: Conditional volatility and dynamic correlation estimates

1. Convert price and exchange rate levels into returns.
2. Fit univariate GARCH models to each return series.
3. Extract standardized residuals from each fitted model.
4. Estimate dynamic conditional correlations among standardized residuals.

5. Interpret whether volatility transmission is synchronized over time.

This framework supported the distinction between mean transmission and volatility spillovers.

G.3.6 Non-linear and Regime-Dependent Models

The notebooks used Markov-switching and quantile regression to capture non-linear relationships.

Markov-switching regression:

1. Specify food price as the dependent variable.
2. Use exchange rate as a regime-varying explanatory variable.
3. Estimate separate coefficients for low- and high-pass-through regimes.
4. Use regime probabilities to identify periods of stronger transmission.

Quantile regression:

1. Select target quantiles such as 0.25, 0.50, 0.75, and 0.90.
2. Estimate exchange-rate effects separately at each quantile.
3. Compare coefficients across quantiles.
4. Interpret stronger upper-quantile effects as evidence of amplified pass-through during high-price episodes.

These models helped identify whether exchange-rate effects differ across market conditions and price levels.

G.3.7 Wavelet Coherence Algorithm

Wavelet coherence was used to analyze how exchange-rate and food-price co-movement changes across time and frequency.

Input: Exchange rate series E_t , food price series P_t

Output: Time-frequency coherence matrix

1. Standardize both time series.
2. Apply wavelet decomposition across selected scales.
3. Compute cross-wavelet power between E_t and P_t .
4. Smooth wavelet power spectra across time and scale.
5. Calculate coherence as normalized cross-wavelet power.
6. Visualize coherence to identify short-, medium-, and long-run co-movement.

The main notebook implemented wavelet-related analysis using `pywt` and custom coherence logic.

G.4 Predictive Modelling Workflow

The predictive modelling notebook compared several model families. The general workflow is summarized below.

Input: Clean model-ready dataset

Output: Model predictions and performance metrics

1. Select features such as `exchange_rate` and `commodity_id`.
2. Select target variable: commodity price.
3. Encode categorical variables where needed.

4. Split data into training and test sets.
5. Scale numerical features for models that require scaling.
6. Train baseline econometric models: OLS and WLS.
7. Train machine learning models: Random Forest and XGBoost.
8. Train time-series benchmark: Prophet for maize-specific forecasting.
9. Train deep learning models where sample structure permits.
10. Generate test-set predictions.
11. Evaluate models using MAE, RMSE, and R-squared.
12. Plot observed versus predicted values and time-series prediction traces.

G.4.1 Model Families Implemented

Table G.2: Predictive model families implemented in the notebooks

Model family	Implementation source	Purpose in the study
OLS and WLS	<code>statsmodels</code>	Baseline linear models for comparison against machine learning models.
Random Forest	<code>sklearn.ensemble.RandomForestRegressor</code>	Non-linear tree-based model used to capture feature interactions and commodity-specific effects.
XGBoost	<code>xgboost.XGBRegressor</code>	Gradient-boosted tree model used for high-performing non-linear prediction.
Prophet	<code>prophet.Prophet</code>	Time-series benchmark used for maize-specific trend and seasonality forecasting.
Support Vector Regression	<code>sklearn.svm</code>	Kernel-based benchmark for non-linear regression.
LSTM with attention	<code>tensorflow.keras</code>	Deep learning model for sequential dependency learning with attention weighting.
CNN-BiLSTM with attention	<code>tensorflow.keras</code>	Hybrid deep learning model combining local pattern extraction with bidirectional sequence learning.
Transformer Encoder	<code>tensorflow.keras</code>	Attention-based sequence model used as an advanced deep learning benchmark.
Stacked BiLSTM	<code>tensorflow.keras</code>	Deep recurrent architecture for modelling sequential price patterns.

G.4.2 Evaluation Metrics

The notebooks evaluated prediction performance using standard regression metrics:

```
MAE = mean_absolute_error(y_true, y_pred)
RMSE = sqrt(mean_squared_error(y_true, y_pred))
```

```
R2 = r2_score(y_true, y_pred)
```

Mean Absolute Error measured average prediction deviation in price units, RMSE penalized larger prediction errors more strongly, and R-squared measured the proportion of target variation explained by each model.

G.5 Ensemble Prediction Logic

The deployment-oriented workflow combined predictions from the strongest model components. The ensemble logic used in the deployment script and predictive modelling workflow can be summarized as follows:

```
If commodity_id is maize:
    ensemble_prediction = mean(RandomForest_prediction,
                               XGBoost_prediction,
                               Prophet_prediction)
Else:
    ensemble_prediction = mean(RandomForest_prediction,
                               XGBoost_prediction)
```

This rule reflects the fact that the Prophet model was trained specifically for maize, while the tree-based models supported commodity-aware prediction using exchange-rate and commodity features.

G.6 Reproducibility Note

The notebooks contain the executable code used to generate the analysis, model comparisons, and visual outputs discussed in the report. This appendix does not reproduce every code cell; instead, it documents the major algorithms and implementation logic needed to understand and reproduce the analytical workflow. The complete code sources remain available at <https://github.com/econiaracheal/UCUMsDSA>.

Appendix H

Stakeholder Matrix and Intended Use of the Findings

This appendix provides the detailed stakeholder matrix supporting the concise stakeholder discussion in Chapter 1 and the practical interpretation and recommendations presented in Chapters 5 and 6. It identifies the principal institutional and operational users of the study and explains how the analytical findings and deployed prediction tool may support their activities.

Table H.1: Key stakeholders and intended uses of the study

Stakeholder	Primary role	Use of study outputs
Bank of Uganda	Monetary and exchange-rate surveillance	Incorporate short-term food-price sensitivity and exchange-rate indicators into inflation monitoring, scenario analysis, and communication with food-security and agricultural authorities.
Ministry of Agriculture, Animal Industry and Fisheries	Agricultural policy, production support, and food-system coordination	Identify commodities with elevated volatility or pass-through exposure and target production, storage, market-information, or supply-chain interventions.
Ministry of Finance, Planning and Economic Development	Fiscal policy, development planning, and public expenditure coordination	Assess when exchange-rate pressure may raise food-security risks and inform temporary fiscal, tariff, social-protection, or market-stabilization responses.
Kampala Capital City Authority and market administrators	Urban market management and consumer welfare	Monitor price pressures in Kampala markets, communicate emerging risks, and support market-level responses involving traders, logistics, and consumer protection.

Stakeholder	Primary role	Use of study outputs
Humanitarian and food-security organizations	Early warning, vulnerability assessment, humanitarian planning, and market intervention	Combine the study's forecasts with field assessments to identify potential food-access deterioration, prioritize market monitoring, plan cash or food assistance, time interventions, and contribute evidence to food-security policy formulation.
Commodity traders and market analysts	Procurement, inventory, pricing, and risk management	Use model-specific predictions and exchange-rate scenarios as supplementary information for inventory planning, price-risk assessment, and procurement timing.
Researchers and data-science practitioners	Methodological validation and extension	Replicate the framework, test it in other regions, add explanatory variables, and evaluate alternative causal and predictive models.

Appendix I

Research poster layout



Figure I.1: Research poster summarizing the study