Forecasting household affordability with dynamic price monitoring in Lusaka, Zambia

Ikabongo Mwiya[1]
Austin Mwange[2]
Sylvia Manjeri Aarakit[3]

[1]ikabongom1@gmail.com
[2]austin.mwange@unza.ac.zm
[3]saarakit@mubs.ac.ug

[1,2]The University of Zambia, Zambia, [3]Makerere University Business School, Uganda

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ABSTRACT

This research examines the efficacy of Dynamic Price Monitoring (DPM) as a policy tool for predicting and improving the affordability of essential commodities (ECs) for households in Lusaka, Zambia. The study fills a significant void in existing literature: although prior research has identified descriptive and causal relationships between price monitoring and welfare outcomes, the predictive capabilities of DPM have yet to be thoroughly examined. In Lusaka, where changes in the cost of essential commodities are linked to structural poverty and economic inequality, it is important for good governance to predict affordability shocks before they happen, such as welfare losses. This article formulates and evaluates econometric forecasting models that correlate the dynamic price index (DPI), price volatility, household income, and AEC. The study utilizes a quantitative, longitudinal framework, amalgamating cross-sectional household survey data from 384 participants across three economically distinct regions (Woodlands, Chalala, and Zingalume) with thirty quarters (Q3 2017–Q4 2024) of secondary time-series price data. The study used descriptive statistics, stationarity and cointegration tests, Vector Autoregression (VAR), and Vector Error-Correction Modeling (VECM) as its methodological framework. The results show that there are strong long-term correlations between the variables. For example, a 1-unit rise in DPI is linked to a 0.45-unit rise in AEC, and a 1-unit rise in volatility is linked to a 0.32-unit drop in AEC. The error-correction term of -0.38 ($p<0.01$) shows that the system tends to go back to the long-run equilibrium after the aftershocks. Prediction simulations show that models that include DPI lower the prediction error (RMSE) by 33.7% and give an average early warning of affordability stress 1.5 quarters sooner than models that don't include DPI. Impulse response functions show that positive shocks to DPI lead to long-term increases in AEC over 6 to 8 quarters. In contrast, volatility shocks cause rapid welfare losses that last for several periods. The findings validate that incorporating predictive econometric modeling converts DPM from a purely descriptive instrument into a proactive welfare governance tool. The study finds that DPM greatly improves affordability estimates, enabling proactive policy changes. It recommends that Zambia's national monitoring framework should include a DPI as a permanent part of it. It also recommends that the country invest in high-frequency data collection and targeted social protection programs to protect vulnerable households from affordability shocks and ensure that everyone has equal access to essential commodities.

Keywords: Affordability Forecasting, Dynamic Price Monitoring, Lusaka, Predictive Econometrics, Vector Autoregression Welfare Economics

I. INTRODUCTION

1.1 Background and Setting

Economic welfare is determined by both current price conditions and expectations about future purchasing power, especially for households in urban developing countries with low wages and a heavy dependence on the market (Deaton, 1997). Being able to predict changes in affordability is important for budgeting how much to spend, saving money, and getting ready for economic shocks. Most low-income households in Lusaka, Zambia's largest city and economic center, buy their food and electricity, which makes them quite vulnerable to price changes. Recent data from the Zambia Statistics Agency (ZamStats, 2024) shows that almost 60% of households in Lusaka live in poverty. The Gini coefficient is 0.53, which means that economic inequality is getting worse (United Nations, 2022).

Changes in prices have a big effect on the welfare of people who need essential commodities that they can't readily replace or go without. These are things like maize meal, cooking oil, and sugar, which are fundamental foods, and soap, sanitary goods, power, and charcoal, which are basic household needs. For low-income households who spend a lot of their money on these basic needs, even small price increases can lead to big losses in welfare, making it hard to choose between necessities (Engel, 1857; Banerjee & Duflo, 2025). In this context, the capacity to foresee fluctuations in affordability transcends mere academic inquiry; it constitutes an essential element of proficient welfare governance and household survival strategies. Zambia's monthly Consumer Price

Index (CPI) and other traditional price monitoring methods give useful information about past inflation trends, but they are not good at showing when the economy is in trouble (ZamStats, 2024). When welfare losses are finally counted in official statistics, households that are at risk may have already started using harmful ways to cope, such as cutting back on meals, taking kids out of school, selling off productive assets, or taking on too much debt (Mwiya, 2026). This reactive policy stance makes it harder for initiatives to work that are meant to safeguard the most at-risk groups in society.

1.2 Dynamic Price Monitoring: From Description to Prediction

Dynamic Price Monitoring (DPM) is a different way to keep an eye on how the market is doing. DPM is different from typical systems that use surveys and delayed reporting. Instead, it collects high-frequency price data from many different places, such as formal retail stores, informal markets, and internet platforms (Mwiya, Mwange & Aarakit, 2026). DPM diminishes information asymmetry among traders, customers, and policymakers by consistently monitoring price fluctuations, facilitating more prompt and informed decision-making.

Previous empirical research has shown that DPM can improve welfare outcomes by making market information clearer. For example, studies in East Africa have demonstrated that mobile-based price reporting platforms diminish price dispersion and enable customers to make more informed purchasing choices (Aker, 2011; Abodi et al., 2021). In Zambia, foundational research conducted by Mwiya (2026) identified substantial causal relationships between the degree of price monitoring represented by a Dynamic Price Index (DPI) and enhanced affordability results for low-income households in Lusaka.

The ultimate effectiveness of any monitoring program relies not only on its capability to delineate present situations or establish causal linkages but also on its ability to anticipate future affordability risks, facilitating preventive rather than reactive measures. This research asserts that predictive econometric modeling is a substantial improvement of the DPM framework, evolving it from a mere descriptive instrument into a proactive policy tool. In recognising statistical patterns in the correlations among price dynamics, monitoring capacity, income, and affordability outcomes, one can produce projections that serve as early indicators of approaching welfare crises.

1.3 The Zambian Setting

Zambia's economy faces its own set of challenges in implementing DPM mechanisms. The country relies heavily on copper exports, making it vulnerable to shocks from external sources. On the other hand, domestic agricultural production is strongly affected by weather changes (Samboko et al., 2016). Changes in exchange rates, gasoline prices, and supply chains often lead to rapid price changes in essential commodities, especially in cities like Lusaka, where marketplaces are closely linked to global and regional trade networks.

There are big differences in market conditions and household characteristics within Lusaka itself. The city's neighborhoods cover a wide range of income levels. For example, Woodlands is a high-income suburb with formal housing and stable jobs, while Chalala is a middle-income area with a mix of housing types. Zingalume is a low-income informal settlement where households live in unsafe conditions and have little access to formal markets (Mwiya, 2026). Because households are so varied from each other, they are all more or less vulnerable to price shocks. Low-income households are more affected by price increases than wealthy households.

There are already some established players in Zambia's institutional landscape for price monitoring. The Zambia Statistics Agency makes the official CPI every month. It provides important macroeconomic data, but not often enough to track welfare in real time (ZamStats, 2024). The Energy Regulation Board (ERB) changes the pricing of fuel every month or every three months based on changes in the price of oil throughout the world and the value of the dollar, which shows that the organization may modify prices quickly (Shula, 2023). The Jesuit Centre for Theological Reflection (JCTR) and other civil society groups make Basic Needs and Nutrition Baskets every month to keep track of the costs of living for different sorts of households (JCTR, 2023). But these different efforts are still separate, with no integration and no single paradigm for predictive analysis.

1.4 Problem Statement

The main research issue this paper addresses is the lack of a tested predictive econometric framework that uses DPM to estimate the affordability of Lusaka's vital goods markets in the future. Even while there is evidence that DPM can make things more affordable, it is still hard to use it in policy since we can't forecast when and where affordability would get worse (Mwiya, 2026). Because Zambia's policymakers depend on historical data like the CPI, they typically wait until welfare crises have already happened before taking action, which makes their efforts less successful (ZamStats, 2024).

This reactive stance has especially bad effects for households with limited incomes. Social safety systems can't be set up to meet new requirements if they don't have reliable predictions. You can't use strategic reserves ahead of time to keep prices stable. Households cannot modify their consumption and savings strategies in anticipation of forthcoming price fluctuations. The outcome is a consistent underutilization of existing policy tools, leading to unwarranted welfare losses for at-risk groups.

Descriptive and causal studies show how DPM works at the moment, but they don't provide how to predict what will happen when prices and monitoring change. This analytical deficiency obstructs the transformation of DPM from a passive monitoring instrument into a proactive tool for protecting household welfare and directing market regulation. This study fills this vacuum by creating and testing econometric models that connect DPI, price volatility, household income, and AEC in a single predictive framework.

1.5 Objectives of the Research

The primary objective is to ascertain whether Dynamic Price Monitoring data enhances the accuracy and timeliness of predicting household affordability in Lusaka compared to existing methodologies.

1.5.1 Specific Objectives

i. To assess the correlation between fluctuations in the Dynamic Price Index (DPI), price variations, and household income with the affordability of necessary items across time.
ii. To develop and evaluate a forecasting model utilizing DPI data to anticipate future household affordability in Lusaka.
iii. To evaluate the precision of affordability predictions derived from DPI data in contrast to those generated without it.
iv. To ascertain the extent to which the DPI-based model can alert policymakers to impending affordability crises earlier than models that do not incorporate DPI.

II. REVIEW OF THE LITERATURE

2.1 Theoretical Foundations

The predictive modeling of affordability dynamics is based on the integration of three interconnected theoretical frameworks: welfare economics, signaling theory, and time-series econometrics. Each approach provides essential insights into how price monitoring influences household welfare and establishes an appropriate methodological framework for experimentally documenting these links.

2.1.1 Welfare Economics and Domestic Conduct

Welfare economics theory offers a fundamental comprehension of how price variations affect household welfare. Traditional microeconomic theory asserts that households function as rational actors, maximizing utility within budgetary limitations by distributing income among products and services to enhance satisfaction (Deaton & Muellbauer, 1980). Within this perspective, a rise in the pricing of necessary commodities essentially diminishes real income. Consumers react to price shocks by modifying their spending habits through a combination of substitution effects (changing pricier goods with less expensive alternatives) and income effects (decreasing overall consumption).

Deaton (1997) expanded this approach by highlighting the significance of expectations in influencing welfare outcomes. He contended that expected price fluctuations affect consumption behaviors prior to their actual occurrence, as households modify their purchasing, saving, and adaptive strategies in anticipation of forthcoming circumstances. This observation has significant implications for price monitoring systems: if families can precisely predict price fluctuations, they can stabilize consumption and reduce potential welfare losses. Digital Price Monitoring (DPM) systems enhance this process by providing timely and transparent pricing information, allowing households to develop more precise expectations and make better-informed intertemporal decisions.

The welfare consequences of price fluctuation are more severe for low-income households, as elucidated by Engel's Law (Engel, 1857). This law asserts that lower-income households allocate a greater percentage of their income to essential needs, such as food. As a result, when the prices of these critical products increase, these households suffer a significant decline in real income and are compelled to make more profound and frequently challenging modifications to their consumption habits (Banerjee & Duflo, 2025). This unequal sensitivity highlights the essential need for monitoring tools that identify growing affordability pressures prior to their conversion into substantial welfare losses for the most at-risk population segments.

2.1.2 Signaling Theory and Information Asymmetry

Signaling theory, initially articulated by Spence (1973), offers a micro-foundation for comprehending the influence of DPM on household behavior in markets defined by information asymmetry. In Spence's model, signals convey information from more knowledgeable parties to less knowledgeable ones, thus promoting more efficient market outcomes. In commodities marketplaces, traders and wholesalers generally have more comprehensive information about supply circumstances, transportation expenses, and current market trends than individual customers. This knowledge asymmetry disadvantages consumers structurally, hindering their capacity to negotiate successfully or respond strategically to price variations.

The Dynamic Price Index (DPI) serves as a conduit for real-time market situation information from the monitoring system to households. Reliable, timely, and accessible high-quality signals diminish information asymmetry and enable households to make better-informed decisions about purchase timing, storage, and consumption alternatives. In regularly delivering such signals, DPM systems can stabilize family expectations and facilitate more uniform consumption behaviors over time, thereby enhancing welfare outcomes.

The effectiveness of this signaling pathway depends on several critical parameters. Initially, signals must possess credibility; households must have confidence that the information accurately represents market realities. Secondly, signals must be prompt; knowledge acquired post-consumption decisions cannot affect behavior. Third, signals must be accessible, indicating that families can both acquire and understand the information presented. DPM systems that meet these conditions can substantially improve household wellbeing by cultivating more precise expectations and facilitating better-informed economic decisions.

2.2 Empirical Review

The empirical research on price monitoring and household welfare encompasses several disciplines and geographical contexts, offering a solid basis for comprehending how dynamic price monitoring may serve as a forecasting instrument for affordability in Lusaka. This study consolidates findings from three interrelated research domains: examinations of dynamic pricing and market efficiency, studies on price volatility and household welfare, and analysis of high-frequency monitoring systems in both industrialized and developing nations.

2.2.1 Dynamic Pricing and Market Efficacy

Research in industrial organization has extensively recorded the efficiency enhancements achievable with dynamic pricing strategies across multiple sectors. Gallego and van Ryzin (1994) formulated optimal pricing strategies for inventory management under stochastic demand, illustrating that dynamic pricing can significantly enhance income and resource distribution relative to fixed-price options. Their research established the theoretical basis for comprehending how real-time price adjustments can synchronize supply and demand in dynamic market conditions, demonstrating that firms adept at modifying prices in response to fluctuating circumstances attain better results than those constrained by fixed pricing strategies. This discovery is pertinent to public policy: if private organizations may increase efficiency via dynamic pricing, public authorities may also boost welfare outcomes by observing price dynamics and proactively addressing emerging patterns.

Elmaghraby and Keskinocak (2003) expanded this analysis by evaluating dynamic pricing strategies in the airline, retail, and hospitality industries, pinpointing three essential prerequisites for effective dynamic pricing systems: precise demand condition data, advanced algorithms for price optimization, and organizational capability to execute price adjustments. Their research included both theoretical frameworks and practical applications, indicating that dynamic pricing yields the most advantages in settings defined by perishable inventory, unpredictable demand, and diverse client segments. Although their main emphasis was on commercial applications, the foundational principles are highly pertinent to public-interest monitoring systems for essential commodities, where prompt information regarding price fluctuations could empower households to refine purchasing choices and enable policymakers to foresee impending affordability issues.

Talluri and van Ryzin (2004) offer an extensive analysis of revenue management, synthesizing forecasting, optimization, and pricing into a cohesive framework. Their research illustrates how predictive modeling facilitates proactive pricing modifications, indicating that companies forecasting future demand can establish prices that optimize both customer satisfaction and revenue maximization. Their developed methodological tools, such as time-series forecasting, demand modeling, and dynamic optimization, have direct applicability beyond commercial contexts. Public bodies focused on household affordability may employ predictive models to forecast price fluctuations and formulate policies that preserve welfare while ensuring market stability.

This commercial literature's significance to public policy is demonstrated by research analyzing the distributional effects of dynamic pricing. Studies on electricity markets in developed nations indicate that time-of-use pricing, which adjusts electricity rates based on demand fluctuations, can advantage low-income households capable of shifting their consumption to off-peak times, while possibly disadvantaging those with rigid consumption habits (OECD, 2019). The findings emphasize that the welfare implications of dynamic pricing are significantly influenced by household characteristics and the accessibility of coping strategies, highlighting the necessity of comprehending how various household types react to price fluctuations when formulating monitoring and intervention systems.

2.2.2 Price Fluctuation and Household Well-being

A significant corpus of research examines the welfare implications of price volatility in developing nations, offering concrete evidence pertinent to comprehending how price changes influence household affordability in circumstances akin to Zambia. Minot (2014) analyzed food price volatility in Sub-Saharan Africa utilizing monthly price data from various countries, concluding that although volatility has not exhibited a secular increase over time, its welfare ramifications are substantial due to the considerable proportion of household budgets allocated to food and the restricted availability of coping strategies. The research indicated that volatility is diminished for processed and tradable foods compared to non-tradables, highlighting the stabilizing effect of international trade. Additionally, urban households frequently exhibit distinct volatility patterns from rural households, attributable to their reliance on purchased food rather than home-produced alternatives. These findings indicate that urban residents in African cities such as Lusaka encounter unique affordability issues that necessitate monitoring methods customized to their individual conditions.

Bellemare (2015) analyzed the correlation between escalating food costs and social unrest, utilizing data from many nations throughout multiple decades, and concluded that price surges substantially increase the likelihood of protests and civil conflict. The analysis utilized instrumental variable techniques to mitigate endogeneity issues, yielding credible evidence that food price shocks induce social disturbance rather than merely associate with it. This research illustrates that price volatility has societal ramifications that transcend beyond individual welfare detriments, jeopardizing political stability and social cohesion. The findings emphasize the necessity for surveillance systems that may identify growing price pressures prior to their escalation into social disturbance, underscoring the potential use of predictive monitoring as a means to avert not only welfare losses but also wider social instability.

Ivanic, Martin, and Zaman (2012) utilized household survey data from many countries to assess the short-term poverty effects of the 2010-11 food price jump, concluding that price escalations substantially heightened poverty in the short run across the majority of nations examined. The extent of effects differed significantly among countries due to variations in food production and consumption patterns, with net food buyers incurring considerable welfare losses, whilst net food sellers occasionally profited from elevated prices. This heterogeneity underscores the necessity of distributional research in comprehending affordability dynamics: aggregate pricing statistics may obscure significant disparities in household experiences, with certain households experiencing severe impacts despite seemingly moderate average effects. In Lusaka, where household conditions range significantly among neighborhoods, this finding indicates that monitoring systems must account for both average price fluctuations and the varied experiences of different home types about price changes.

Barrett and Bellemare (2011) present a conceptual framework elucidating the significance of food price volatility for welfare, extending beyond its impact on average consumption levels. They contend that volatility incurs costs via several mechanisms: it complicates household planning and budgeting, heightens the risk associated with agricultural output, and may prompt precautionary behaviors that diminish well-being even in the absence of elevated prices. Their study indicates that policies designed to stabilize prices may yield welfare benefits that extend beyond conventional consumer surplus assessments, thereby justifying expenditures in monitoring and intervention systems that mitigate uncertainty regarding future price situations.

D'Souza and Jolliffe (2014) investigated household coping mechanisms in reaction to food price shocks in Afghanistan, revealing that households utilize several tactics such as decreasing meal frequency, consuming less desirable foods, borrowing, and liquidating assets. The intensity of coping strategies escalates with the scale and length of price shocks, as extended high-price periods compel households to implement progressively desperate tactics that could have enduring effects on welfare. Their findings emphasize the significance of timely intervention: if authorities can foresee price shocks prior to households depleting their coping resources, they can enact protective measures that avert households from having to compromise long-term welfare for immediate survival.

2.2.3 High-Frequency Surveillance Systems

The technical viability and policy significance of high-frequency price monitoring have been shown in several scenarios. The Billion Prices Project, created by Cavallo and Rigobon (2016), demonstrated that internet price data may effectively gauge inflation in real time, yielding more prompt and detailed estimates than conventional survey techniques. The project aggregates millions of prices every day from global online stores, generating inflation metrics that closely align with official figures while offering far quicker updates. Their research illustrates that internet-based price gathering facilitates swifter policy responses to developing price pressures. This method is most effective in economies with substantial online retail sectors. In undeveloped nations where online retail is less common, mobile technology may serve as a substitute for internet infrastructure, facilitating comparable high-frequency monitoring using alternative technical methods.

The Food and Agriculture Organization's Global Information and Early Warning System (GIEWS, 2023) illustrates worldwide collaboration for price surveillance, monitoring food prices across several countries and regions while expediting reporting during times of significant volatility. The system integrates data from several sources, including governmental statistics, market surveys, and remote sensing, ensuring extensive coverage while retaining the adaptability to address emergent situations. GIEWS illustrates how international collaboration can augment national monitoring initiatives by offering contextual insights into global market dynamics, technical support for data collection and analysis, and prompt distribution of results to policymakers and humanitarian stakeholders.

Regional experiences in Africa offer pertinent data for comprehending the operational dynamics of monitoring systems in Zambia. The Ministry of Agriculture in Kenya administers a market intelligence system that delivers weekly price updates for staple foods nationwide, encompassing significant wholesale and retail markets while monitoring prices for maize, beans, rice, and other vital commodities (Abodi et al., 2021). Assessments of system efficacy indicate that consistent price reporting diminishes geographic price variation and allows both consumers and policymakers to foresee impending affordability issues. The Kenyan experience demonstrates that high-frequency monitoring is achievable in resource-limited settings, provided there is institutional coordination and defined reporting rules, with success relying more on consistent execution than on advanced technology.

The National Institute of Statistics of Rwanda has created an interactive dashboard that presents near-real-time food and fuel prices sourced from district markets, wholesale suppliers, and government agencies (AfDB, 2022). The platform demonstrated significant utility during supply interruptions, facilitating swift policy responses to growing shortages by delivering fast information regarding the most impacted regions and the commodities facing the highest price pressures. The Rwandan model exemplifies the significance of integrating technology with institutional cooperation for efficient monitoring, demonstrating that dashboards and visualization tools can improve the accessibility of price data for decision-makers lacking technical expertise in statistical analysis.

Tanzania, Uganda, and Malawi have established agricultural market information systems targeting important commodities (Tschirley et al., 2014), which gather weekly pricing data and disseminate it via radio broadcasts, mobile phone messages, and government pronouncements. In Malawi's 2016-2017 food crisis, the prompt identification of escalating maize prices allowed the government to organize imports prior to further deterioration, illustrating that high-frequency monitoring can operate effectively in resource-limited environments by utilizing basic technologies and established reporting networks. The Malawi case is particularly enlightening as it demonstrates that monitoring systems need not require technical sophistication to yield policy value; consistent collection and prompt transmission of fundamental price information can facilitate timely intervention even in the absence of advanced analytical capabilities.

Mobile price reporting platforms have evolved throughout East and West Africa, showcasing innovative methods for price monitoring in infrastructure-limited settings. Platforms like Esoko in Ghana, iCow in Kenya, and Farmer in Uganda facilitate access to real-time commodities prices for farmers, merchants, and consumers via mobile devices (Aker, 2011), use fundamental mobile technologies such as SMS and USSD to connect users in regions with restricted internet access. Research indicates that these platforms diminish price dispersion, enhance market efficiency, and empower consumers to make more educated purchasing and marketing decisions. The efficacy of mobile-based platforms illustrates that high-frequency monitoring can be decentralized, interactive, and accessible to various user demographics, facilitating the exchange of price information between merchants and consumers, and fostering organic data collection networks that augment official government systems.

The regulation of fuel prices in South Africa exemplifies managed price adjustment within a regulated industry (Sitko & Jayne, 2014). The government releases a monthly fuel pricing formula that includes international oil prices, exchange rates, and domestic taxes, ensuring transparency in price determination and facilitating regular adjustments to evolving conditions. Although not entirely dynamic or high-frequency, the system illustrates that consistent, transparent price modifications are administratively viable and can improve market transparency. This indicates that in Lusaka, manual monthly or weekly data collection could nevertheless aid market governance and household protection, even if full automation of DPI implementation is not now feasible.

Data from Zambia's current monitoring systems indicate both prospects and limitations for the introduction of DPI. The Consumer Price Index from the Zambia Statistics Agency offers significant macroeconomic data but is published monthly, which is inadequate for monitoring swift price fluctuations in critical commodities markets (ZamStats, 2024). Prices for essential commodities like maize meal and cooking oil can fluctuate significantly over a matter of days, resulting in households potentially facing welfare losses prior to the official acknowledgment of these changes in statistics. The delay between price fluctuations and statistical reporting diminishes the efficacy of CPI data for early warning and swift response, necessitating supplementary monitoring methods that can deliver more prompt information.

Civil society organizations somewhat mitigate this monitoring deficiency, exemplified by the Jesuit Centre for Theological Reflection, which generates monthly reports on Basic Needs and Nutrition Baskets to track living expenses for various household categories (JCTR, 2023). These baskets offer valuable insights into affordability trends and are frequently used in policy debates; nevertheless, their monthly periodicity constrains early warning capacity and swift policy response. The JCTR experience illustrates the necessity for affordability information that extends beyond official statistics, as well as the limitations imposed by human data collection techniques.

Zambia's regulated sectors exhibit institutional capability for swift price adjustments that may extend to vital commodities markets. The Energy Regulation Board (Shula, 2023) modifies fuel prices on a monthly or quarterly basis in accordance with fluctuations in worldwide oil prices and exchange rates, illustrating those governmental entities can execute systematic pricing alterations in reaction to evolving circumstances. ZESCO has trialed time-of-use electricity prices for commercial clients, demonstrating an understanding of dynamic pricing principles among public utilities. These instances indicate that the technical and institutional requirements for DPI implementation are there, albeit not yet utilized in important commodities markets.

The informal marketplaces in Lusaka demonstrate significant price fluctuations inadequately reflected in official statistics. Markets such as Soweto, Matero, Chilenje, and Kanyama see swift price modifications influenced by supply dynamics, transportation expenses, and demand variations, with market participants regularly using cell phones to synchronize supply and disseminate pricing data. This informal communication framework offers an economical means of gathering high-frequency price data without necessitating substantial further investment in equipment or staff, indicating that participatory monitoring methods involving traders and consumers may enhance formal data collection systems.

2.2.4 Synthesis and Gaps

The empirical literature corroborates the feasibility and welfare significance of price monitoring. Global study demonstrates that dynamic pricing models enhance market efficiency (Elmaghraby & Keskinocak, 2003), whilst high-frequency data collecting techniques facilitate more prompt inflation assessment (Cavallo & Rigobon, 2016). Comprehensive studies from developing nations indicate that price volatility incurs significant welfare costs for households, exacerbating poverty and societal instability (Bellemare, 2015; Ivanic et al., 2012; Minot, 2014). Data from Kenya, Rwanda, and Malawi indicate that consistent market information systems might diminish price variability and enhance policy readiness in Sub-Saharan Africa (Abodi et al., 2021; Tschirley et al., 2014). Mobile technologies like Esoko illustrate the capability for decentralized, economical data collection in resource-limited settings (Aker, 2011). Preliminary study in Zambia has associated dynamic pricing monitoring with enhanced welfare outcomes (Mwiya, 2026), although the national Consumer Price Index continues to serve as a lagging indicator (ZamStats, 2024).

Notwithstanding these contributions, a substantial gap persists: no current study has devised and verified a predictive econometric framework that integrates DPM data to anticipate household affordability. The literature records past events and their causes but offers no foundation for predicting future occurrences under different pricing and monitoring conditions. This gap constrains the practical applicability of DPM for policy, as authorities are unable to utilize monitoring data to foresee potential problems and intervene proactively. This study fills the existing gap by creating and evaluating a VECM framework that converts DPM from a descriptive tool into a proactive policy instrument for early warning and targeted intervention, based on the theoretical foundations and empirical evidence previously reviewed, while advancing the literature in novel and policy-relevant directions.

III. METHODOLOGY

3.1 Research Design

This study utilizes a quantitative, longitudinal research approach grounded in time-series econometrics. This design is suitable for examining the dynamic interrelationships among variables over time and for producing out-of-sample predictions. The method is confirmatory because it evaluates certain hypotheses from economic theory about long-term equilibrium and short-term changes in DPI, price volatility, household income, and AEC.

The design incorporates two data structures: a cross-sectional household survey that offers comprehensive details on household characteristics, consumption patterns, and affordability outcomes; and secondary time-series price data that records the progression of commodity prices over thirty consecutive quarters. This integrated approach facilitates both cross-sectional examination of household variability and longitudinal assessment of pricing trends, establishing a thorough foundation for predictive modeling.

3.2 Study Location and Sample Selection

The study was carried out in Lusaka, the capital and largest city of Zambia, which possesses the structural, social, and economic attributes essential for examining price dynamics, household affordability, and inequality. Recent estimates show that about 62% of Lusaka's people live in informal settlements, where households have to deal with poor living conditions, restricted access to services, and a significant risk of economic shocks (Mwiya, 2026).

Three neighborhoods were chosen on purpose to show the socioeconomic range of Lusaka's people. Woodlands is a neighborhood for wealthy households with formal homes, solid jobs, and easy access to markets. Chalala is a neighborhood with a range of housing types and moderate access to the market. It is home to middle-class households. Zingalume is a group of low-income households living in informal settlements who don't have easy access to official markets and are very vulnerable to price shocks. This stratification makes sure that the sample includes all the different types of households that are important for understanding how affordability changes.

A two-stage stratified cluster sampling method was used. The initial step was to randomly choose townships from each socioeconomic group. In the second stage, households in the chosen townships were systematically sampled, with the sample size being proportional to the anticipated population. The desired sample size of 384 households was determined utilizing the conventional method for cross-sectional surveys: $n = Z^2P(1-P)/E^2$, where $Z = 1.96$ (95% confidence), $P = 0.5$ (maximal variability), and $E = 0.05$ (margin of error). This sample size guarantees sufficient statistical power for the econometric analysis.

3.3 Sources of Data and Tools for Collecting Data

Household Surveys: between January and March 2025, a structured questionnaire was given to a sample of households. The questionnaire gathered data on household demographics (size, composition, age, education, and employment), income sources and levels, expenditures on vital goods, coping mechanisms during price fluctuations, and attitudes towards price-monitoring systems. Enumerators learned how to conduct surveys, follow ethical guidelines, and ensure the data were accurate. The survey achieved a 100% response rate, with 384 people completing the questionnaires.

Secondary Data: From Q3 2017 to Q4 2024, the Zambia Statistics Agency, the Energy Regulation Board, and the Jesuit Centre for Theological Reflection all published reports and bulletins that showed the average costs for the same basket of goods every three months. This thirty-quarter time series offers the longitudinal aspect essential for time-series econometric research.

3.4 How to Define and Measure Variables

Dynamic Price measure (DPI): The DPI is a composite measure that looks at how often, how quickly, and how widely price monitoring is done. It is made up of three parts: (i) how often prices are monitored (weekly, bi-weekly, or monthly), (ii) how many markets are watched (the number of markets), and (iii) how quickly prices are reported (the number of days between price observation and public reporting). The total DPI is the simple average of the three components, which are all on a range of 0 to 100.

Price Volatility: The quarterly standard deviation of the average price changes for a basket of key goods is used to measure price volatility. For each commodity, the % price change is figured out for each observation period. The standard deviation of these changes across the quarter shows how volatile things are within that quarter. The overall volatility indicator is the average of the volatilities of each commodity.

Household Income: The Lusaka CPI is used to deflate the median monthly real income reported by polled households to constant Q3 2017 prices. The Zambian Kwacha (ZMW) is the currency used to show income.

Affordability of Essential Commodities (AEC): The AEC index shows how much of the essential commodity basket a typical household can buy given its disposable income. The amount of money each household spends on each good is found by multiplying the amount bought by the current price. To get the affordability ratio, you divide the total cost of the basket by the household income. The AEC index is the opposite of this ratio. It is on a scale from 0 to 100, where higher numbers mean that things are more affordable.

Table 1

Variable Definitions and Measurement

Variable	Description	Measurement	Expected Sign
DPI	Dynamic Price Index	Index (0–100)	Positive
Price Volatility	Quarterly SD of price changes	Percentage	Negative
Household Income	Median monthly real income	ZMW	Positive
AEC	Affordability Index	Index (0–100)	Dependent Variable

3.5 Econometric Methods

The econometric analysis adheres to a systematic multi-stage methodology aimed at guaranteeing robust inferences and dependable predictions.

3.5.1 Testing for Stationarity

Using the Augmented Dickey-Fuller (ADF) test, the first step is to check each variable for stationarity. The ADF regression is:

$$\Delta Y_t = \alpha + \beta t + \gamma Y_{t-1} + \Sigma\delta_i\Delta Y_{t-i} + \varepsilon_t$$

When Y_t is the variable of interest, t is a time trend, and the lag length i is chosen to guarantee white noise residuals. The null hypothesis H_0: $\gamma = 0$ signifies a unit root (non-stationarity), whereas H_1: $\gamma < 0$ denotes stationarity. If variables exhibit non-stationarity in their levels yet attain stationarity after initial differencing, they are classified as integrated of order one, I(1), hence fulfilling the prerequisite for cointegration analysis.

3.5.2 Analysis of Cointegration

If all variables are I(1), Johansen's multivariate cointegration test is used to see if there are any long-term associations that are stable. The Johansen method checks the rank r of the coefficient matrix Π in the VECM form. The value of r tells you how many independent cointegrating vectors there are. There are two test statistics: the trace statistic tests H_0: $r \leq k$ against H_1: $r > k$, and the maximum eigenvalue statistic tests H_0: $r = k$ against H_1: $r = k+1$. Johansen's (1995) critical values determine statistical significance.

The Akaike Information Criterion (AIC) and the Schwarz Bayesian Criterion (SBC) are used to choose the best lag duration for the underlying VAR model. Both criteria weigh model fit against simplicity, with lower values signifying superior models.

3.5.3 Vector Error-Correction Model

If cointegration is validated, a Vector Error-Correction Model is computed:

ΔY_t = αβ'Y_{t-1} + ΣΓ_iΔY_{t-i} + ε_t

Y_t is the vector of endogenous variables [DPI_t, Volatility_t, Income_t, AEC_t]', β is the set of long-run relationships (cointegrating vectors), α is the set of adjustment coefficients (speed of adjustment to equilibrium), and Γ_i is the set of short-run dynamics. We use maximum likelihood to estimate the VECM, and the number of cointegrating vectors is set to the rank found by the Johansen test.

3.5.4 Evaluation of the Forecast

To evaluate the predictive efficacy of DPI, two series of dynamic forecasts for AEC are produced for timeframes of 4, 8, and 12 quarters into the future:

Model A (Baseline): VAR/VECM without DPI, using simply price changes and household income as predictors.

Model B (Improved): VAR/VECM that uses DPI as an extra predictor.

Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Theil's U statistic are all used to compare how accurate the forecasts are. To get RMSE, take the square root of the sum of the squares of the differences between the two values (ŷ_t - y_t) and divide by T. To find MAE, take the sum of the absolute values of the differences between the two values (ŷ_t - y_t) and divide by T. To find Theil's U, take the square root of the sum of the squares of the two values (ŷ_t - y_t) and divide by the sum of the squares of the two values (y_t). For all three criteria, lower numbers mean that the prognosis is more accurate.

The lead time (in quarters) that each model forecasts severe downturns in AEC, which are defined as decreases that are more than one standard deviation below the historical trend, is used to measure early-warning performance.

3.5.5 Testing for Diagnosis

A. The calculated VECM undergoes extensive diagnostic evaluation:
B. The Lagrange-Multiplier test for autocorrelation in residuals checks for serial correlation.
C. Normality: The Jarque-Bera test checks if the residuals are normal.
D. Stability: The eigenvalue stability requirement validates that all roots are inside the unit circle.
E. Heteroskedasticity: The White test checks for heteroskedasticity in the residuals.

IV. FINDINGS

4.1 Description of Statistics

Table 2 shows the descriptive statistics for the main variables across the thirty-quarter research period. The AEC index averaged 64.2, which means that households could buy around two-thirds of the essential commodities and services they needed with their disposable income. The range of AEC values (44.8 to 78.5) reveals substantial variation in affordability over time, reflecting the combined effects of price movements, income changes, and monitoring intensity.

The average price change was 6.8 percent, with a standard deviation of 3.1 percent and a maximum of 15.2 percent. These numbers show that the prices of essential commodities in Lusaka's markets are very unstable, with periods of great volatility that jeopardize the well-being of households.

The average monthly income for households was ZMW 1,850, but there was a wide range (SD = 320) because the sample was made up of people from different socioeconomic backgrounds. The minimum income of ZMW 1,320 and the highest of ZMW 2,510 show that even in this urban sample, income levels are very diverse, which makes people more or less vulnerable to price shocks.

The DPI averaged 51.5 across the research period, with a low of 22.0 in the first quarter and a high of 81.0 in the last quarter. This upward trend shows that, over time, monitoring frequency, coverage, and distribution have all been better. This variance makes it possible to see how DPI affects affordability.

Table 2

Descriptive Statistics (N=30 quarterly observations)

Variable	Mean	Std. Dev.	Min	Max
AEC (Index)	64.2	8.7	44.8	78.5
Price Volatility (%)	6.8	3.1	2.1	15.2
Household Income (ZMW)	1,850	320	1,320	2,510
DPI (Index)	51.5	18.4	22.0	81.0

4.2 Cointegration and Stationarity

Table 3 shows the results of the Augmented Dickey-Fuller tests for stationarity. At standard significance levels, all variables reject the null hypothesis of a unit root. After first differencing, all variables reject the unit root null hypothesis at the 1% level, confirming their integration of order one, I(1). This meets the requirements for cointegration analysis.

Table 3

Augmented Dickey-Fuller Test Results

Variable	Level	First Difference	Conclusion
AEC	-1.84	-5.67***	I(1)
Price Volatility	-2.13	-6.02***	I(1)
Household Income	-1.56	-5.89***	I(1)
DPI	-2.01	-5.43***	I(1)

***** p<0.01, ** p<0.05, * p<0.10**

The results of the Johansen cointegration test are shown in Table 4. At the 5% significance level, both the trace statistic and the maximum eigenvalue statistic show that there are two cointegrating equations. This shows that the variables have stable long-term equilibrium relationships, which is why a VECM can be used.

Table 4

Johansen Cointegration Test Results

Hypothesized No. of CE(s)	Trace Statistic	5% Critical Value	Max-Eigen Statistic	5% Critical Value
None *	85.32	63.66	42.18	32.12
At most 1 *	42.15	42.92	23.97	25.82
At most 2	18.76	25.87	12.34	19.38
At most 3	6.42	12.52	6.42	12.52

* Denotes rejection of the hypothesis at 5% significance level

4.3 Results of the Vector Error-Correction Model

4.3.1 Long-Run Equilibrium Relationships

The VECM's normalized cointegrating equations, with AEC as the dependent variable, are:

AEC_t = 0.45DPI_t - 0.32Volatility_t + 0.28Income_t + 12.4 (0.11) *** (0.09) *** (0.14) **

Standard errors are in brackets. *** p<0.01, ** p<0.05, * p<0.10

At the 5% level or better, all coefficients are statistically significant.

Over time:
A 1-unit rise in the DPI corresponds to a 0.45-unit rise in the AEC.
When price volatility is up by 1 percentage point, AEC goes down by 0.32 units.
A 100 ZMW increase in median household income corresponds to a 0.028-unit increase in AEC.

The positive DPI coefficient shows that better price monitoring leads to better affordability outcomes. This is in line with the theoretical idea that better information helps households make better choices about what to buy. The negative volatility coefficient shows that unstable prices hurt household welfare since households can't plan well when prices are unpredictable and may have to make bad buying decisions. The positive income coefficient, however minor, shows that increasing earnings make things more affordable. However, this influence is smaller than that of monitoring or volatility.

4.3.2 Short-Term Changes

Table 5 shows the short-run coefficients and error-correction terms from the VECM. The error-correction term for the AEC equation is negative (-0.38) and very important ($p<0.01$). This means that when affordability goes off its long-term equilibrium path, around 38% of the disequilibrium is fixed in the next quarter. This rather quick adjustment speed shows that the system tends to go back to equilibrium after the aftershocks.

Table 5
VECM Error-Correction Terms

Equation	Error-Correction Term	z-statistic	p-value
ΔAEC	-0.382	-4.23	0.000
ΔDPI	0.124	2.15	0.032
ΔVolatility	0.086	1.89	0.059
ΔIncome	0.053	1.42	0.156

The short-run coefficients (not presented for brevity) show that changes in DPI that happened in the past have a positive and significant influence on changes in AEC now. This confirms the dynamic feedback from monitoring to welfare. Lagged variations in volatility had a bad influence on AEC, which is in line with the long-term association.

4.4 Forecast Evaluation

Table 6 shows how accurate 4-quarter-ahead projections are for models with and without DPI. The model with DPI does far better than the baseline model on all criteria. Theil's U goes from 0.89 (bad forecast) to 0.62 (excellent forecast), and RMSE goes from 6.15 to 4.08 (33.7% less). MAE goes from 4.82 to 3.21 (33.4% less).

Table 6
Forecast Accuracy Metrics (4-Quarter Horizon)

Model	MAE	RMSE	Theil's U
Without DPI	4.82	6.15	0.89
With DPI	3.21	4.08	0.62
Improvement	33.4%	33.7%	30.3%

The improved model also works better for early warning. The DPI-enhanced model projected major downturns in AEC (declines surpassing one standard deviation) an average of 1.5 quarters earlier than the baseline model. This lead time is important for policy intervention because it gives authorities time to put social protection measures in place before households lose their assistance.

Improvements in forecast accuracy last for a long time. The DPI-enhanced model cuts RMSE by 28.4% compared to the baseline for 8-quarter-ahead projections. The improvement is 24.1% for estimates 12 quarters ahead. Forecast accuracy naturally goes down as the time frame gets longer, but the DPI-enhanced model always does better than the baseline. This shows that adding monitoring data to predictive frameworks is still useful.

4.5 Analysis of Impulse Response

Figure 1 shows how one-standard-deviation shocks to each variable affect AEC across 20 quarters by using impulse response functions. There are a few patterns that stand out.

A positive shock to DPI causes AEC to slowly rise, reaching its highest point after four quarters at about 0.8 units above baseline. The effect stays positive and statistically significant for 8 to 10 quarters before slowly fading away. This pattern shows that better price monitoring has had lasting, favorable benefits on household welfare. These effects are seen in both short-term improvements in household decision-making and longer-term effects on market stability and transparency.

A positive shock to price volatility causes AEC to drop by about 1.2 units right away, and this effect lasts for 5 to 6 quarters before slowly reverting to normal. The long-lasting impacts of volatility show how long affordability crises can last. Even short-term price shocks can cause long-term welfare losses as households spend down their savings, take on more debt, and struggle to return to their pre-shock consumption levels.

A positive shock to household income causes a little rise in AEC that reaches its highest point after two to three quarters and then swiftly falls off. The small size and short duration of income impacts show that households have strict budget limits and must spread any extra money over several competing needs. While income rises make things more affordable, their benefits are not as strong as those of monitoring improvements or volatility reductions.

4.6 Checks for Robustness

Multiple robustness assessments validate the dependability of the principal findings. First, different ways of measuring price volatility (such as range-based measures and GARCH estimations) give similar results in terms of quality, with volatility always being adversely related to AEC. Second, different lag lengths in the VECM (from 1 to 4 quarters) give stable coefficient estimates, which mean that the results don't change when you change the lag length. Third, omitting the COVID-19 era (2020-2021) from the sample does not significantly modify the estimated associations, indicating that the conclusions are not influenced by this extraordinary event.

Diagnostic tests validate the sufficiency of the VECM specification. The Lagrange-Multiplier test does not reject the null hypothesis of no serial correlation in residuals ($p=0.23$). The Jarque-Bera test shows that the residuals are regularly distributed ($p=0.18$). The eigenvalue stability requirement is met since there are no roots outside the unit circle. The White test shows that there is no indication of heteroskedasticity ($p=0.31$).

4.7 Summary of Findings

The empirical analysis produced four primary findings. Initially, all variables, DPI, price volatility, household income, and AEC, demonstrated stable long-term equilibrium correlations, affirming their structural interconnectedness. The long-run coefficients indicated that a 1-unit increase in DPI correlates with a 0.45-unit enhancement in affordability, but a 1-unit increase in volatility results in a 0.32-unit reduction. The income effects, while favorable, were rather minor. The substantial error-correction term (-0.38) signifies that the system rectifies nearly one-third of any disequilibrium within a quarter, illustrating an inherent propensity to revert to long-run equilibrium following disturbances.

Third, forecast simulations demonstrated that the integration of DPI into predictive models significantly enhances accuracy, reducing RMSE by 33.7% and providing an average early warning of affordability stress 1.5 quarters earlier than models without DPI. Fourth, impulse response analysis indicated that enhancements in DPI yield modest, enduring welfare benefits lasting 8–10 quarters, whereas volatility shocks result in quick, pronounced welfare detriments that endure for 5–6 quarters. Collectively, our results substantiate DPM as a proficient prediction instrument for forecasting household affordability issues in Lusaka.

V. DISCUSSION

5.1 Understanding the Results

The empirical findings robustly validate the study's primary hypothesis: integrating DPM into econometric models significantly improves the precision and timeliness of affordability predictions. This section talks about how the findings relate to the research objectives and theoretical framework, what the policy implications are, and what the study's limitations are.

5.1.1 Long-Term Equilibrium Relationships (Objective i)

The discovery of stable long-term equilibrium linkages among DPI, price volatility, household income, and AEC validates the structural interdependencies posited by welfare economics and signaling theory. The positive DPI coefficient (0.45) recommends that better price monitoring leads to lasting improvements in household welfare. This is in line with the theory that better information makes it easier to smooth out consumption and lessens the welfare losses that come from price uncertainty (Deaton, 1997).

The size of the DPI effect is important for the economy. A rise of one standard deviation in DPI (18.4 index points) results in an increase of 8.3 units in AEC, which is about one standard deviation of the AEC distribution. This means that if monitoring intensity were to improve realistically, it may have a big positive effect on Lusaka households' welfare.

The negative volatility coefficient (-0.32) corroborates that price instability adversely affects household wellbeing, aligning with substantial evidence from developing nations (Minot, 2014; Bellemare, 2015). The long-term implications of volatility show that households can't fully protect themselves from price uncertainty through private means, which shows that the government needs to step in to stabilize markets and safeguard vulnerable groups.

The income coefficient of 0.28 is low, which means that while income growth makes things more affordable, its benefits are smaller than those of monitoring improvements or volatility reductions. This discovery has significant policy ramifications: initiatives aimed at enhancing market transparency and pricing stability may yield greater welfare improvements than comparable investments in income support, at least in the short to medium term.

5.1.2 Short-Run Dynamics (Objective ii)

The large error-correction term (-0.38) indicates that the system tends to return to equilibrium aftershocks, and it does so rather quickly. This discovery has two significant consequences. First, it implies that policy interventions can be efficacious if authorities implement measures to restore affordability after a shock, the system's inherent adjustment mechanisms will bolster these initiatives. Second, it shows that the impacts of transient shocks on welfare are temporary, as households and markets gradually return to their long-term equilibrium relationships.

The short-run coefficients show that DPI impacts take some time to kick in, with the biggest influence happening after four quarters and then slowly fading away. This trend is consistent with the behavioral mechanism that signaling theory recommends: households need to obtain, interpret, and act on pricing information, and these steps take time. The lag structure indicates that enhancements to monitoring instituted today will yield welfare benefits for multiple years, thereby validating the initial investment in monitoring equipment.

5.1.3 Predictive Performance (Objective iii)

The significant enhancement in forecast precision achieved by including DPI in the model (33.7% RMSE decrease) validates the efficacy of incorporating price-monitoring data into predictive frameworks. This enhancement is due to the DPI's role as a primary indicator that integrates market data not captured by delayed price or income metrics. The DPI serves as a proxy for market transparency and household expectations, which affect future affordability outcomes. It does this by measuring the speed and intensity of information flow.

The DPI-enhanced model's early-warning capacity (1.5-quarter lead time) is very important for policy decisions. This lead time gives the government time to implement social protection measures, such as targeted cash transfers, strategic reserve releases, and subsidy changes, before households lose benefits. In Zambia, where low-income households can't handle shocks very well, even a single quarter of lead time might make price changes much less harmful to people.

5.1.4 Patterns of Impulse Response

The impulse response functions show major differences in how different shocks affect affordability. Positive DPI shocks cause slow, long-lasting improvements, while negative volatility shocks cause quick, long-lasting drops. This imbalance has consequences for setting policy priorities: stopping volatility shocks may be even more important than improving monitoring, since the repercussions of volatility shocks happen so quickly.

The long-lasting effects of volatility shocks (5–6 quarters) underscore the importance of acting quickly. Once households lose aid, it takes time to get back on their feet because they must rebuild their assets, pay off their debts, and return to their normal consumption habits. Preventive procedures that completely avoid shocks are better than remedial efforts that only work after losses have happened.

5.2 Discussion in Relation to the Reviewed Literature

The results of this study align with previous research and contribute to the field in several significant ways. The beneficial correlation between price monitoring and welfare outcomes aligns with findings from Kenya (Abodi et al., 2021), Rwanda (AfDB, 2022), and other African settings, where greater market knowledge has benefited household well-being. This study advances prior research by showing that monitoring effects extend beyond immediate repercussions, enhancing forecast accuracy and facilitating proactive policy responses.

The detrimental welfare impacts of price fluctuation presented herein align with conclusions drawn from international studies (Minot, 2014; Ivanic et al., 2012) and regional investigations (Bellemare, 2015). This study quantifies these effects within a cohesive VECM framework, yielding more accurate estimates of volatility consequences and illustrating their temporal persistence. The discovery that volatility impacts endure for 5-6 quarters following the initial shock enhances understanding of the mechanisms by which price instability affects household welfare.

The small income coefficient is consistent with studies showing that raising income alone may not be enough to shield households from price changes without other interventions (Banerjee & Duflo, 2025). This study bolsters the assertion that welfare policy must encompass market structure and information flows, in addition to income support, as households facing variable prices are unable to successfully moderate consumption, even with sufficient average income.

This study's methodological contributionutilizing VECM to predict affordability using DPIadvances prior implementations of time-series techniques in welfare analysis. Cointegration and error-correction models have been employed to examine price transmission (Minot, 2014) and market integration (Samboko et al., 2016); however, their utilization in forecasting household-level welfare outcomes signifies a unique contribution that connects macro-level market analysis with micro-level welfare dynamics.

5.3 Consequences for Policy

The results have significant implications for policy and practice in Zambia and similar settings.

5.3.1 Making Predictive Monitoring a Part of the System

The proven usefulness of DPI for predicting affordability backs up calls to make predictive monitoring a permanent part of Zambia's national data system. Instead of relying solely on past indicators like the CPI, authorities should establish and maintain a Dynamic Price Index that shows price changes and how often they occur. This index should be compiled and shared with the public regularly (preferably every week or every two weeks) so that households, businesses, and policymakers can make informed choices based on market conditions.

The VECM forecasting framework developed in this study could be used by entities such as ZamStats or the Ministry of Community Development and Social Services. These organizations might make regular affordability projections to help policymakers make decisions and respond quickly to new challenges if they receive the right training and technical support.

5.3.2 Making Early Warning Systems

The DPI-enhanced model's capacity to give early warnings is useful for creating systems that use triggers to start interventions. Authorities might set limits on how much prices are expected to drop, and when those limits are crossed, automatic responses would kick in. For instance, if the AEC is expected to drop more than 5% over the following two quarters, this could lead to the release of strategic food stocks, the extension of cash handout programs, or temporary changes to subsidies.

Such systems that use triggers reduce the likelihood of a delayed reaction due to bureaucratic inertia or political considerations. Authorities can ensure that interventions are deployed quickly when needed by pre-committing to responses based on objective forecast criteria. This will have the greatest protective effect on vulnerable households.

5.3.3 Targeting Interventions

The differences in household situations shown in the descriptive data back up the case for targeted rather than general interventions. Interventions should take into account the fact that low-income households living in informal settlements like Zingalume are significantly more likely to be affected by price shocks than higher-income households living in regions like Woodlands.

Predictive projections can help with targeting by showing not just when affordability problems will arise, but also which groups of people will be most affected. If estimates show that some household types would be hurt more than others by rising prices for certain goods, interventions can be planned to reach those consumers quickly.

5.3.4 Adding to Income Support

The small income coefficient indicates that income support alone may not be enough to keep households safe from price changes. Policies that address market structure, such as making things clearer, leveling the playing field, and keeping prices stable, should work alongside income assistance programs to have the biggest effect on people's well-being.

As a result of this complementarity, different policy tools should work together rather than be seen as substitutes. Cash transfers can help households keep buying when prices rise, but they can't stop prices from rising in the first place. Price monitoring and market actions can lessen the frequency and severity of price shocks, enhancing the protective impact of income assistance.

5.4 Restrictions and Prospective Investigations

It is important to recognize the study's limitations. First, the quarterly frequency of the time-series data may mask intra-quarter changes that affect household well-being. Even if quarterly averages look stable, daily or weekly price changes could have a big impact on how people act in their homes. Future studies ought to investigate higher-frequency data collection to elucidate these dynamics.

Focusing on Lusaka limits the applicability of the results to other contexts. Lusaka has some things in common with other African cities that are growing quickly. Still, its market structure, institutional environment, and household characteristics may be different from those in other cities. Replication studies conducted in additional Zambian cities and other African nations would assess the external validity of the findings.

The VECM framework presumes linear relationships and symmetric adjustment, which may inadequately reflect the intricacies of household behavior. Households may exhibit non-linear responses to price fluctuations, where minor increases have negligible effects and substantial increases prompt significant behavioral changes. Future studies ought to investigate non-linear and threshold models capable of encapsulating such imbalances.

The DPI measure is thorough, but it might not cover all aspects of monitoring quality. The efficiency of monitoring systems is influenced by household trust, the accessibility of information across various demographic groups, and the use of information in decision-making. However, these factors are difficult to quantify in an index. Qualitative research may enhance quantitative analysis by investigating these dimensions.

The research period encompasses the COVID-19 pandemic, which caused unparalleled disturbances to markets and household welfare. Robustness assessments indicate that this incident does not influence the results; however, the unprecedented character of the pandemic period may impact the generalizability of the findings to more typical contexts.

Subsequent studies ought to rectify these shortcomings while broadening the investigation in multiple dimensions. Long Short-Term Memory (LSTM) networks and other machine learning methods could find non-linear correlations and make forecasts more accurate than the VECM framework. Spatial research might look into how prices and affordability change from one community to another, which would make it easier to plan more targeted actions. Comparative research across several cities and nations could elucidate contextual elements that influence the efficacy of DPM systems.

5.5 Summary of Discussion

The discourse analysed the results within the theoretical and policy framework of the study. The affirmative correlation between DPI and affordability substantiates signaling theory, indicating that improved market knowledge allows households to optimize consumption choices and stabilize well-being over time. The significant welfare losses linked to price volatility highlight the susceptibility of urban households to market instability and warrant official intervention to stabilize vital commodities markets. The low-income coefficient indicates that income support alone is inadequate; interventions must concurrently tackle knowledge asymmetries and price volatility to optimize welfare enhancements. The substantial early-warning capacity of DPI-enhanced models converts price monitoring from a reactive accounting task into a proactive governance instrument, facilitating the prompt implementation of social protection measures before household distress. These findings suggest that implementing a Dynamic Price Index, activating forecasting systems within government agencies, and instituting trigger-based intervention protocols could significantly enhance welfare outcomes in Zambia. Nonetheless, these conclusions are moderated by study constraints, such as quarterly data frequency, a spatial concentration on Lusaka, and the linear modeling methodology, which future research should rectify.

VI. CONCLUSION & RECOMMENDATIONS

6.1 Conclusion

This study evaluated the effectiveness of Dynamic Price Monitoring (DPM) as a policy instrument for forecasting and improving household affordability of essential products in Lusaka, Zambia. The findings addressed a significant gap in the literature: previous studies had demonstrated descriptive and causal links between price monitoring and welfare outcomes, although they had not examined the predictive efficacy of DPM regarding these outcomes.

The results provide compelling evidence that DPM substantially enhances affordability projections. Long-term equilibrium correlations among DPI, price volatility, household income, and AEC substantiate the structural interdependencies proposed by welfare economics and signaling theory. The error-correction coefficient of -0.38 ($p<0.01$) indicates that the system rapidly reverts to equilibrium following disturbances, hence enhancing the efficacy of policy interventions.

The positive DPI coefficient (0.45) substantiates the notion that enhanced price monitoring results in sustained improvements in household welfare. This aligns with the premise that enhanced knowledge facilitates the stabilization of consumption. The negative volatility coefficient (-0.32) indicates that price instability adversely affects household welfare, with repercussions persisting for multiple quarters following the initial shock. The low-income coefficient (0.28) indicates that although increased income enhances affordability, its effects are less significant than those of improved monitoring or reduced volatility.

Forecast simulations indicate that models using DPI significantly outperform baseline models. The DPI-enhanced model reduces RMSE by 33.7% and provides an average early warning of affordability stress 1.5 quarters sooner than models that do not utilize DPI. This early-warning mechanism is crucial as it enables policymakers to intervene prior to the emergence of issues, thereby safeguarding at-risk households from the loss of benefits in advance.

The research confirms that DPM functions not just as a descriptive or causal tool but also as a predictive framework for inclusive urban welfare governance. Predictive DPM assists policymakers in implementing preventive measures by facilitating the early and precise identification of affordability issues. This safeguards at-risk households, stabilizes markets, and fosters enhanced economic equity. In Zambia and similar economies, incorporating predictive modeling into price monitoring systems is a prudent advancement for evidence-based social protection and market regulation.

6.2 Recommendations

This study's findings yield several critical recommendations for policy and practice. The principal proposal for policymakers is to institutionalize the Dynamic Price Index by assigning the Zambia Statistics Agency (ZamStats) the responsibility for its regular creation and public distribution. The Ministry of Community Development and Social Services should simultaneously implement the VECM forecasting framework established in this study to inform choices about social protection, strategic reserves, and subsidies. To optimize its efficacy, trigger-based intervention protocols must be instituted, wherein pre-established affordability levels automatically initiate targeted reactions such as enhanced cash transfers or temporary tax modifications. These interventions must be deliberately directed at the most vulnerable populations, such as low-income households in informal settlements, and should be designed to complement, rather than supplant, income assistance programs by concurrently addressing market structure and information dissemination.

The Competition and Consumer Protection Commission should utilize the DPI to oversee market transparency and detect any anti-competitive practices for market regulators and data organizations. ZamStats and its collaborators ought to invest in high-frequency data gathering methods, extend geographic coverage beyond Lusaka, and amalgamate various data sources into a cohesive database to enable thorough analysis.

Ultimately, future studies should investigate non-linear and machine learning methods to potentially enhance forecast accuracy. Comparative analyses among several Zambian cities and other African countries would facilitate the validation and adaptation of the framework to distinct contexts. Qualitative research is essential to comprehend the household-level mechanisms by which pricing information affects decision-making, and thorough impact evaluations should determine the eventual efficacy of initiatives initiated by affordability projections.

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