

## Feasibility of constructing a dynamic price index to monitor essential commodity markets in Lusaka, Zambia

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### ABSTRACT

Urban households in low-income developing economies are significantly susceptible to variations in the cost of vital goods, especially in environments marked by structural poverty, stark income disparity, and disjointed market systems. In Zambia, where a significant percentage of urban households dedicate a considerable portion of their income to food, electricity, and other essentials, even brief price surges might result in rapid welfare detriments. Notwithstanding this susceptibility, current price monitoring tools, particularly the Consumer Price Index (CPI), are primarily intended for macroeconomic inflation assessment and are constrained by monthly reporting intervals that mask intra-period price fluctuations. Consequently, swift price fluctuations in vital commodity markets frequently remain unnoticed in real time, limiting the ability of policymakers and families to respond promptly to affordability crises. This study evaluates the technological, economic, institutional, and welfare viability of developing a dynamic price index (DPI) specifically for vital commodity markets in Lusaka, Zambia. Anchored in a cohesive theoretical framework that merges signalling theory with the theory of income inequality, the research defines the DPI as both an informational infrastructure and a policy instrument attuned to distributional considerations. A mixed-methods sequential explanatory methodology is utilised, incorporating high-frequency market price data from both formal and informal markets, cross-sectional household survey data from various income groups, and a documentary study of current regulatory and statistical frameworks. Descriptive analysis indicates significant intra-period price volatility among staple commodities, characterised by weekly swings overlooked by standard monthly reporting methods. Econometric estimations, such as Ordinary Least Squares (OLS), Difference-in-Differences (DiD), and Vector Error Correction Models (VECM), reveal statistically significant correlations between dynamic price fluctuations and household affordability outcomes, as indicated by the Affordability of Essential Commodities (AEC) Index. Data from a pilot price information initiative suggests that enhanced access to high-frequency price signals improves household affordability and diminishes dependence on detrimental coping techniques, especially among economically vulnerable groups. An institutional assessment verifies the presence of essential capacities for dynamic monitoring within Zambia's statistics agencies, regulatory entities, and digital infrastructure, characterised by extensive mobile penetration and developed sector-specific pricing systems. Nonetheless, the heterogeneity of data governance and coordinating methods constitutes a significant operational issue. The results combined demonstrate that the establishment of a dynamic price index for Lusaka is technically feasible, econometrically sound, institutionally practical, and economically warranted. The study suggests that shifting from retroactive inflation assessment to prospective affordability monitoring will improve market transparency, increase policy responsiveness, and help mitigate inequalities in access to basic goods. It advocates for the implementation of a multi-source DPI platform with coordinated institutional supervision, integration with social protection systems, and the creation of a transparent dissemination strategy to optimise household welfare benefits.

**Keywords:** Affordability of Essential Commodities, Dynamic Price Monitoring, Household Welfare, Lusaka, Price Volatility, Price Index Construction

### I. INTRODUCTION

Through the transmission of information about scarcity, the direction of production and consumption decisions, and the creation of public policy responses, prices play a crucial coordinating function in market economies (Stiglitz, 1989). Because food, electricity, hygiene products, and other needs account for a significant amount of household income in economies with high levels of poverty and inequality, like Zambia, changes in the cost of vital commodities have a direct impact on household welfare outcomes. According to the World Bank (2023), even slight price rises can result in rapid welfare losses, especially for low-income households whose purchasing power is already limited. These dynamics become more intense with urbanization. Essential commodity markets in Lusaka are influenced by spatial price dispersion, disjointed supply chains, informal trading networks, and a lack of real-time regulatory control

(ZamStats, 2024). Official data frequently fall short of lived economic reality in these situations, leaving people vulnerable to unexpected shocks to affordability and restricting the ability of policymakers to act quickly. Although traditional monitoring instruments, such as the Consumer Price Index, are still essential for macroeconomic management, they are structurally built for measuring inflation every month rather than providing welfare protection in real time.

Globally, Dynamic Price Monitoring (DPM) has become a popular alternative paradigm that emphasizes real-time analytics, high-frequency data collecting, and predictive policy capabilities (Li et al., 2016). In contrast to commercial dynamic pricing systems that optimize income, DPM is envisioned as a public-interest information infrastructure that aims to protect vulnerable consumers, improve transparency, and lessen information asymmetry. In light of this, the current study explores the viability of building a dynamic price index based on real-time monitoring of the prices of vital commodities within the institutional, technological, and economic framework of Lusaka. The ongoing socioeconomic problems in Zambia highlight the need for this kind of research. Most urban households live on thin margins, with a national poverty rate of over 60% and a Gini value of 0.53 indicating extreme economic inequality (United Nations, 2022).

Low-income budgets are disproportionately consumed by essential commodities, which are defined here as things needed for fundamental household functioning and showing generally inelastic demand. Therefore, price volatility directly affects nutritional outcomes, food security, and the continuation of poverty cycles (Banerjee & Duflo, 2011). Vulnerable households have already absorbed welfare losses through decreased consumption, debt accumulation, or asset depletion by the time price spikes are publicly documented, resulting from the official statistics' current monthly or quarterly reporting cycle. This research systematically assesses the viability of a dynamic price index for Lusaka, adding to the conversation in academia and policy. It goes beyond theoretical propositions to empirical evaluation, looking at institutional readiness through monitoring frameworks already in place, econometric validity through modelled price-affordability relationships, welfare justification through household coping behavior analysis, and technical viability through observed price volatility patterns. The results offer a thorough body of information for decision-makers who are thinking about implementing real-time monitoring systems as tools to improve market transparency, stabilize household welfare, and advance economic equality.

### 1.1 Statement of the Problem

The welfare of households in Zambia's cities is extremely susceptible to changes in the cost of necessities. Low-income households' financial vulnerability is increased, nutritious intake is decreased, and consumption stability is disrupted by abrupt price rises for cooking energy, hygiene items, and staple foods (Jatta, 2013). However, these processes cannot be captured in real time by the monitoring mechanisms now in place. Price fluctuations and policy knowledge are delayed by survey-based reporting, and variation among income categories and residential locations is obscured by aggregated national metrics. As a result, policymakers do not have the timely evidence needed for early response, and affordability shocks are still mostly unchecked. Corrections, if any, are applied after households have already experienced welfare losses due to the temporal lag in monthly CPI data. Furthermore, it is more difficult to focus interventions like short-term subsidies, social cash transfers, or strategic reserve releases to the particular neighborhoods or commodities that are most volatile when there is no spatially disaggregated, high-frequency index available.

Economic inequality is strengthened by this monitoring gap. Price shocks can be absorbed more easily by higher-income households, while low-income households are compelled to utilize harmful coping mechanisms, such as cutting back on meal portions, switching to inferior products, taking money away from healthcare or education, or taking on high-interest loans (Mwiya, 2026). These tactics have long-term effects on the persistence of poverty and the development of human capital.

Therefore, the primary research issues this article addresses are the lack of empirical and operational evidence about whether it is feasible to build and institutionalize a dynamic price index that can offer real-time, detailed insights into the price movements of essential commodities within Lusaka's unique market and governance ecosystem to improve affordability protection and lessen welfare disparities.

### 1.2 Research Objective

To examine the feasibility of developing a Dynamic Price Index to enhance household affordability of essential commodities in Lusaka.

## II. LITERATURE REVIEW

### 2.1 Theoretical Review

#### 2.1.1 Signalling Theory

Signalling Theory explains how economic actors communicate credible information in situations characterized by information asymmetry. Spence (1973) originally developed the theory to explain how individuals convey private information in labour markets. In such contexts, signals—such as educational qualifications—help reduce uncertainty by providing observable indicators of underlying characteristics.

In commodity markets, prices often function as signals that convey information about scarcity, production conditions, and demand fluctuations. In ideal market conditions with perfect information, price signals guide production and consumption decisions efficiently. However, real-world markets rarely operate under such conditions. In many developing economies, information is unevenly distributed among market actors due to fragmented supply chains, infrastructure limitations, and weak information dissemination systems (Thomsen, 2002).

In Lusaka's essential commodity markets, informational advantages tend to increase along the supply chain. Wholesalers and large traders often possess more comprehensive information about supply conditions, including harvest projections, import schedules, transportation costs, and inventory levels (Reardon et al., 2021). Retail traders receive partial information from upstream suppliers but may lack broader knowledge of supply dynamics. Households, particularly those with limited income and education, are typically the least informed actors and often observe price signals only at the point of purchase.

Under these conditions, households may struggle to distinguish between temporary price fluctuations and sustained market changes. As a result, they may reduce consumption unnecessarily during short-term price increases or fail to adjust behaviour during long-term price rises (Li & Zhang, 2025). Such informational constraints can lead to inefficient consumption decisions and increased vulnerability to price volatility.

Dynamic Price Monitoring (DPM) systems aim to address these challenges by systematically collecting and disseminating price information across markets. Through standardized data collection and validation processes, DPM systems aggregate dispersed market information and translate it into signals accessible to households, traders, and policymakers (Dutta & Mitra, 2017). Dissemination through mobile platforms, radio broadcasts, or digital dashboards can further improve accessibility and timeliness of price information (Yusof, 2025).

The Dynamic Price Index (DPI) represents a quantitative summary of these price signals. By consolidating price trends across markets, the DPI provides a clear indicator that enables households and policymakers to interpret market changes more easily and respond appropriately (IMF & UNCTAD, 2011). When signals are credible and accessible, households may adjust purchasing behaviour, substitute commodities in response to relative price changes, and allocate limited budgets more efficiently.

Empirical studies in Sub-Saharan Africa support the relevance of price information systems. For example, Kirimi et al. (2011) found that Kenya's market information system reduced spatial price dispersion and improved market participation among farmers and traders. Similarly, Tschirley, Snyder, and Dolislager (2013) showed that food price monitoring systems in Malawi and neighbouring countries enabled earlier policy responses to price surges during food crises.

Despite its usefulness, Signalling Theory has limitations when applied to affordability analysis. The theory assumes that recipients of information can interpret and respond to signals effectively. In practice, literacy constraints, limited access to communication technologies, and behavioural biases may restrict households' ability to use price information efficiently (Basu, Narayan, & Ravallion, 2001; Gigerenzer, 2018). Moreover, the theory focuses primarily on information flows and does not fully account for structural constraints such as poverty, infrastructure limitations, or weak market regulation that may prevent households from responding even when information is available (Yasar, Martin, & Kiessling, 2021).

These limitations highlight the importance of complementing Signalling Theory with structural perspectives that consider inequality and household vulnerability.

#### 2.1.2 Theory of Income Inequality

The Theory of Income Inequality emphasizes how disparities in income and resource distribution shape welfare outcomes and economic resilience. Major contributions by Sen (1999), Stiglitz (2012), and Piketty (2014) highlight the structural conditions that influence households' ability to cope with economic shocks.

Sen's capability approach reframes development as the expansion of human freedoms rather than simply increases in income. From this perspective, affordability depends not only on prices but also on households' capabilities—such as income stability, asset ownership, social protection, and access to markets—that allow them to secure essential consumption sustainably.

Income inequality influences affordability through several channels. First, poorer households allocate a larger share of their income to food and basic necessities than wealthier households, consistent with Engel's Law (Olufemi-

Phillips, 2024). Consequently, price increases in essential goods generate disproportionately larger welfare losses for lower-income households.

Second, coping capacity differs across income groups. Higher-income households typically possess buffers such as savings, credit access, or diversified consumption options that allow them to absorb price increases without significantly reducing essential consumption (Roll et al., 2019). In contrast, low-income households often respond by reducing food consumption, substituting cheaper foods, or diverting resources away from healthcare and education.

Third, inequality interacts with spatial market conditions. Urban households in informal settlements frequently face higher effective prices due to transportation costs, limited storage capacity requiring frequent small purchases, and weaker bargaining power with vendors (Olufemi-Phillips, 2024). These conditions amplify the cost-of-living disparities between income groups.

Empirical evidence supports these theoretical expectations. The World Bank (2023) reports that food price shocks in Sub-Saharan Africa raise poverty rates more sharply than in higher-income regions because poorer households allocate a larger proportion of their income to food. Similarly, Ivanic, Martin, and Zaman (2012) estimate that the 2007–2008 global food crisis pushed nearly 100 million people into poverty.

Evidence from Zambia confirms these dynamics. Jatta (2013) found that households in Lusaka's informal settlements reduced consumption significantly during periods of maize price volatility. The Jesuit Centre for Theological Reflection (JCTR, 2023) also reports that the cost of meeting basic living standards frequently exceeds the income of many urban households.

While Income Inequality Theory explains structural vulnerability to price shocks, it provides limited explanation of how households respond to information or how improved information systems might influence welfare outcomes (Kochar, 1995; Mendola, 2007). Consequently, integrating inequality perspectives with signalling mechanisms provides a more comprehensive framework for understanding affordability dynamics.

## 2.2 Conceptual Review

The conceptual framework guiding this study integrates insights from Signalling Theory and Income Inequality Theory to explain how dynamic price monitoring systems influence household affordability outcomes.

Policy interventions provide the institutional environment that enables effective monitoring systems. Regulatory frameworks establish rules for price data collection and dissemination, while institutional arrangements determine which agencies are responsible for monitoring, analysis, and communication of price information (Dorrer, 2024). Adequate funding and technical resources are necessary to maintain system reliability and sustainability (Khan & Nencioni, 2023). Complementary policy measures such as targeted subsidies, social protection programs, and competition regulation may further enhance households' ability to respond to price information (Liu & Zhang, 2024).

The Dynamic Price Monitoring (DPM) system constitutes the operational core of the framework. It involves high-frequency price data collection from formal and informal markets, standardized validation procedures, analytical tools that transform raw data into interpretable indicators, and dissemination channels that communicate information to households and policymakers (Li et al., 2025). The Dynamic Price Index (DPI) represents the measurable output of this system, summarizing price movements and improving market transparency.

Market dynamics provide the broader environment within which monitoring operates. Supply conditions—including production cycles, import dependence, distribution efficiency, and transportation costs—influence price formation (Seba, 2024). Demand conditions are shaped by income levels, demographic characteristics, and seasonal consumption patterns. External shocks such as fuel price fluctuations, exchange rate movements, and climatic events may further increase price volatility.

Household characteristics influence how price signals translate into welfare outcomes. Income levels affect the share of expenditure devoted to essential commodities, while household size and composition determine consumption needs. Employment type influences income stability, and education levels affect households' ability to interpret price information (Seba, 2024). Access to savings, credit, and social networks also determines the capacity to cope with price fluctuations.

Affordability outcomes are measured through the Affordability of Essential Commodities (AEC) Index, which represents the proportion of household income required to purchase a standard basket of essential goods (Nathaniel, 2023). Distributional outcomes are further captured through an Economic Equality Index (EEI) and behavioural indicators such as substitution, borrowing, or reductions in consumption (Bhasker et al., 2024).

Feedback mechanisms connect welfare outcomes to policy responses. Declining affordability may trigger interventions such as targeted subsidies, enhanced market oversight, or strategic reserve releases. Over time, improved access to price information may also strengthen households' capacity to adapt to market volatility.

## 2.3 Empirical Review

International research on dynamic pricing demonstrates the technical feasibility of high-frequency price monitoring. Early work in revenue management shows how dynamic pricing algorithms can optimize resource

allocation under uncertain demand conditions (Gallego & van Ryzin, 1994). Subsequent studies document applications across industries such as airlines, hospitality, and retail, where continuous data collection and predictive analytics enable real-time price adjustments (Elmaghraby & Keskinocak, 2003; Talluri & van Ryzin, 2004).

However, efficiency gains do not automatically translate into improved welfare outcomes. Price discrimination may disadvantage price-sensitive consumers, particularly lower-income households, during periods of high demand (Phillips, 2005; Stiglitz, 2012). These concerns highlight the importance of considering distributional impacts when applying dynamic pricing principles to essential commodity markets.

Technological innovations have further expanded monitoring possibilities. The Billion Prices Project demonstrates that automated data collection can generate high-frequency price indicators by gathering millions of online prices daily (Cavallo & Rigobon, 2016). Such approaches illustrate how digital technologies can overcome limitations of traditional price statistics.

In Sub-Saharan Africa, research has focused largely on agricultural market information systems. Evidence suggests that regular price reporting improves market transparency and reduces spatial price disparities. For example, Kenya's market information system improved market participation and reduced price dispersion among markets (Kirimi et al., 2011). Cross-country analyses also show that timely monitoring enabled earlier detection of food price surges and facilitated policy interventions during crises (Tschirley et al., 2013).

Mobile technologies have further expanded opportunities for decentralized price monitoring. Platforms using SMS, USSD, and mobile applications enable farmers, traders, and consumers to share market price information at relatively low cost (GSMA, 2023). These systems demonstrate that effective monitoring can be implemented even in infrastructure-constrained environments.

In Zambia, existing price monitoring systems operate primarily at monthly frequency. The Consumer Price Index produced by the Zambia Statistics Agency supports macroeconomic management but does not capture rapid price changes affecting household purchasing power (ZamStats, 2024). Civil society initiatives such as the Basic Needs and Nutrition Basket provide complementary information on the cost of living but are also limited by monthly reporting cycles (JCTR, 2023). Urban markets in Lusaka frequently experience rapid price fluctuations influenced by transportation costs, seasonal supply conditions, exchange rate movements, and fuel prices. Studies show that such volatility significantly affects household consumption patterns, particularly among low-income households in informal settlements (FAO, 2023; Jatta, 2013). Despite the presence of several monitoring initiatives, Zambia lacks an integrated system combining high-frequency market price data with household socioeconomic information. Without such integration, policymakers cannot fully assess how price fluctuations affect affordability across different household groups.

### III. METHODOLOGY

#### 3.1 Approach

To fully examine feasibility, this study uses a mixed-methods sequential explanatory design that combines qualitative evaluation of institutional frameworks with quantitative analysis of pricing and household data (Creswell & Plano Clark, 2017). The research philosophy is grounded on positivism, using an empirical epistemology that depends on methodical observation and econometric verification, and acting under the ontological premise that price dynamics and welfare results are objective, quantifiable realities.

#### 3.2 Data Structure and Sources

Three related datasets form the foundation of the analysis: High-frequency Price Information: For 30 consecutive quarters (Q3 2017–Q4 2024), secondary data on the retail prices of 15 key commodities (such as maize meal, wheat meal, beans, cooking oil, charcoal, sugar, and bathing soap) were gathered from a stratified sample of Lusaka marketplaces. The markets were chosen to ensure typological and spatial representation by representing official retail (e.g., supermarkets), big informal markets (e.g., Soweto, City Market), and neighborhood retail businesses.

Cross-Sectional Household Survey Data: Three purposefully chosen residential areas in Lusaka, Chalala (planned, mid-income), Woodlands (established, higher-income), and Zingalume (informal, low-income) were the sites of 384 families who completed a structured questionnaire. Representation throughout the socioeconomic spectrum was guaranteed by this stratification. Among the information gathered were household demographics, sources of income, specific spending on necessities, price shock coping mechanisms, and opinions toward price monitoring. Policy and Institutional Data: To map current data infrastructure, regulatory frameworks, and monitoring capacities, a documentary analysis was carried out on reports from JCTR, ERB, ZESCO, ZamStats, and pertinent ministries.

### 3.3 Variable Index Construction and Operationalization

Dynamic Price Index (DPI): The relevant independent variable. Price relative is computed for each commodity  $i$  in period  $t$ . Next, an index of the Laspeyres type is created often (weekly):

$$DPI_t = \sum_{i=1}^n w_{i,0} \left( \frac{P_{i,t}}{P_{i,0}} \right)$$

Where  $P_{i,t}$  and  $P_{i,0}$  represent the current and base period prices, respectively, and  $w_{i,0}$  is the budget share of commodity  $i$  in a base period as determined by household survey data. Both the overall basket and its sub-indices (such as food and energy) are used to calculate the DPI. The principal dependent welfare variable is the Affordability of Essential Commodities (AEC) Index. The AEC is determined for every home  $h$  as follows:

$$AEC_h = \frac{\text{Actual Expenditure on Essential Commodities Basket}}{\text{Household Income}}$$

Greater affordability is indicated by a lower AEC ratio. In order to facilitate cross-income comparability, the index is also calculated for standardized baskets. In econometric models, control variables are used to separate the impact of price fluctuations. These include the size of the household, the monthly income cluster, the type of work, the residential region, and the availability of credit or alternative sources of revenue.

### 3.4 Econometric Models and Analytical Framework

An analytical procedure with multiple stages was used to determine feasibility: Descriptive and Technical Analysis: Intra-period price volatility was visualized and quantified using time-series plots and dispersion metrics (coefficient of variation, rolling standard deviation), which directly informed technical viability.

Institutional Analysis: To assess institutional capability, data interoperability, and possible governance models for a DPI, a SWOT (strengths, weaknesses, opportunities, and threats) framework was used. Econometric Modeling: Some models were estimated to assess the viability of econometrics. To determine the baseline link between the DPI and the AEC index, ordinary least squares (OLS) regression is used (Lukáš & Jan, 2011).

$$AEC_h = \beta_0 + \beta_1 DPI_t + \beta_2 X_h + \epsilon_h$$

Where  $X_h$  is a home control vector. The purpose of ordered logistic regression is to examine the factors that influence household coping mechanisms (ordinal outcome: "no change," "substitute," and "reduce consumption") in response to price changes that are recorded by the DPI. Difference-in-Differences (DiD) with Lasso Selection: A prototype market information SMS service was gradually implemented in a few zones as a "treatment" in a quasi-experimental setting. In order to evaluate the Average Treatment Effect (ATE) of improved price information on affordability, Lasso regression was utilized for robust variable selection in a high-dimensional scenario.

$$ATE = E[Y(1) - Y(0) | D = 1]$$

Where  $D$  represents treatment status and  $Y(1)$  and  $Y(0)$  represent possible affordability outcomes with and without treatment. In order to analyze the dynamic temporal correlations between the DPI, aggregate AEC, and more general macroeconomic indicators such as fuel prices, Vector Autoregression (VAR) and Vector Error Correction Model (VECM) are used. This analysis offers insights into long-run equilibrium and lead-lag structures. Diagnostic Checks: To verify robustness, all models underwent diagnostic checks for multicollinearity (VIF), heteroskedasticity (Breusch-Pagan test), autocorrelation (Durbin-Watson), and stationarity (Augmented Dickey-Fuller test).

## IV. FINDINGS & DISCUSSION

### 4.1 Findings

#### 4.1.1 Characteristics of Socioeconomic and Price Volatility

This section presents the empirical results of the mixed-methods investigation into the feasibility of constructing a Dynamic Price Index for essential goods marketplaces in Lusaka. The results are organized to encompass all four feasibility dimensions outlined in the research objectives. Initially, descriptive data establishes the socioeconomic context for the sampled households and illustrates the extent of price variation among key items regularly. This promptly informs the evaluation of technical feasibility. Secondly, analyzing household coping strategies reveals the welfare transmission mechanisms that necessitate a dynamic monitoring approach.

The econometric findings, such as OLS regression, Difference-in-Differences estimation, and Vector Error Correction modeling provide robust evidence of the statistical relationships between price fluctuations and their affordability for families, demonstrating the feasibility of econometrics. Finally, an institutional analysis examines the existing governance frameworks, technical competencies, and coordination shortcomings that will influence the efficacy of a Dynamic Price Index in Lusaka.

The socioeconomic profile of the sampled families (Table 1) reveals a significant disparity that underscores the necessity for a Dynamic Price Index. Households in the informal community of Zingalume exhibit heightened sensitivity to price fluctuations. They possess the lowest average salaries (ZMW 1,450), the largest family sizes (6.2 members), the greatest dependence on informal employment (78%), and allocate the highest amount of their income (72%) to essential commodities. Conversely, families in Woodlands, a more affluent and established suburb, earn over five times as much and allocate merely 35% of their income to essential requirements. This fundamental disparity indicates that any increase in prices will disproportionately affect the urban poor compared to the broader population.

**Table 1**  
*Selected Household Characteristics by Residential Area*

| Characteristic            | Chalala (Planned) | Woodlands (Established) | Zingalume (Informal) |
|---------------------------|-------------------|-------------------------|----------------------|
| Avg. Monthly Income (ZMW) | 3,200             | 7,500                   | 1,450                |
| % Informal Employment     | 45%               | 22%                     | 78%                  |
| Avg. Household Size       | 4.8               | 3.5                     | 6.2                  |
| % Income on Essentials    | 58%               | 35%                     | 72%                  |

The socioeconomic disparity across the research sites is glaringly evident in Table 1. Families in Zingalume, the informal settlement, spend more than 70% of their income on necessities, have the greatest household sizes, the lowest earnings, and the most reliance on informal work. A strong welfare case for enhanced monitoring is presented by this profile, which emphasizes extreme price shock susceptibility.

**Table 2**  
*Price Volatility Metrics for Selected Commodities (Weekly Data, 2023-2024)*

| Commodity         | Average Price (ZMW) | Coefficient of Variation (CV) | Max. Weekly % Change |
|-------------------|---------------------|-------------------------------|----------------------|
| Maize Meal (25kg) | 185                 | 0.18                          | +12.4%               |
| Cooking Oil (1L)  | 45                  | 0.15                          | +9.8%                |
| Charcoal (50kg)   | 120                 | 0.25                          | +18.2%               |
| Sugar (2kg)       | 32                  | 0.10                          | +6.5%                |

The results in Table 2 clearly suggest technical feasibility. With coefficients of variation ranging from 0.10 to 0.25, essential commodities show significantly high-frequency volatility. The price of charcoal is quite volatile. Monthly CPI reporting would completely overlook the large intra-month shocks represented by the documented maximum weekly changes (e.g., 18.2% for charcoal). This volatility is not random noise; rather, it frequently exhibits predictable patterns associated with seasonal shortages, transportation difficulties, or fluctuations in fuel prices, demonstrating the ability of a high-frequency DPI to pick up on important market signals.

#### 4.1.2 Household Coping Strategies and Perceived Price Monitoring

The welfare transmission process is explained in Table 3. The majority of low-income households utilize erosive tactics, such as cutting back on purchases, switching to other foods, or skipping meals, which directly affect the quantity and quality of consumption. Financial coping strategies, such as borrowing or saving, are more prevalent among middle-income households. Households with high incomes are generally shielded. This gradient supports the necessity for a monitoring tool that can initiate targeted support by confirming that the burden of price volatility is unequally distributed. Importantly, more than 85% of families polled said they lacked fast, trustworthy price information before shopping and that this knowledge would affect their choices. This reveals a dormant desire for the transparency that a DPI might offer.

**Table 3***Prevalence of Coping Strategies during Price Spikes, by Income Cluster*

| Coping Strategy               | Low-Income Cluster | Middle-Income Cluster | High-Income Cluster |
|-------------------------------|--------------------|-----------------------|---------------------|
| Reduce Quantity Purchased     | 78%                | 45%                   | 12%                 |
| Substitute with Inferior Good | 65%                | 30%                   | 5%                  |
| Skip Meals / Reduce Meals     | 42%                | 10%                   | 0%                  |
| Use Savings or Borrow         | 38%                | 55%                   | 20%                 |
| No Major Change               | 5%                 | 25%                   | 83%                 |

**4.1.3 Econometric Support for Price-Affordability Associations**

To set up the welfare framework for dynamic price monitoring, the study first looked at the socioeconomic traits of households in the chosen residential areas and the price changes of basic goods. To figure out how vulnerable people are to price shocks and how useful a Dynamic Price Index (DPI) can be as a protective monitoring tool, it's important to know about differences in income, job structure, and spending obligations.

**Table 4***OLS Regression Results – Determinants of Affordability (AEC Index)*

| Dependent Variable: AEC Index (Lower = More Affordable) | Coefficient | Std. Error | p-value |
|---|-------------|------------|---------|
| Log(Dynamic Price Index), DPI                           | 0.317***    | 0.045      | 0.000   |
| Household Income (Log)                                  | -0.408***   | 0.038      | 0.000   |
| Household Size  | 0.095***    | 0.018      | 0.000   |
| Informal Employment (Dummy)                             | 0.062**     | 0.025      | 0.014   |
| Residence: Informal Area (Dummy)                        | 0.121***    | 0.031      | 0.000   |
| Constant  | 1.842***    | 0.210      | 0.000   |
| Observations  | 384         |            |         |
| R-squared   | 0.67        |            |         |

\*\*\*p&lt;0.01, \*\*p&lt;0.05

Econometric feasibility is strongly supported by the fundamental OLS model (Table 4). As predicted, affordability is considerably worsened (increases the AEC index) when the DPI rises (price increases). A substantial association is indicated by the highly significant (p<0.01) coefficient of 0.317. The control factors act as predicted: greater household size puts more strain on affordability, higher income increases affordability, and informal work and housing are linked to higher affordability stress.

**Table 5***Difference-in-Differences (DiD) Results – Impact of Price Information Pilot*

| Outcome: AEC Index                | Coefficient (ATE) | Std. Error | p-value |
|-----------------------------------|-------------------|------------|---------|
| Treatment Effect (Post x Treated) | -0.187***         | 0.056      | 0.001   |
| Pre-Treatment Mean (Control)      | 1.987             | 0.008      | -       |
| Post-Treatment Adjusted Mean      | 1.812             | 0.057      | -       |
| Lasso-Selected Controls Included  | Yes               |            |         |

\*\*\*p&lt;0.01

The viability of DPM as an intervention is supported by causal evidence provided by the DiD analysis (Table 5). In comparison to the control group, households that got the pilot SMS pricing information (the treatment group) saw a statistically significant improvement in affordability (a 0.187-point drop in the AEC index). This implies that simply giving customers access to timely price information can enable them to search for better deals, make more informed purchases, and ultimately lessen their financial burden. A parsimonious model that controlled for important confounders was guaranteed by the application of Lasso regression.

**Table 6***VECM Long-Run Equilibrium Relationship*

| Cointegrating Equation | Coefficient        | Std. Error |
|------------------------|--------------------|------------|
| DPI                    | 1.000 (normalized) | -          |
| Aggregate AEC          | 0.891***           | 0.102      |
| Fuel Price Index       | 0.457***           | 0.085      |
| Constant               | -1.234             | -          |

\*\*\*p&lt;0.01

A steady long-term equilibrium link between the DPI, overall affordability (AEC), and fuel prices is shown by the VECM data (Table 6). The cointegrating equation's significant positive coefficient for AEC (0.891) attests to the systematic relationship between long-term changes in the DPI and changes in affordability. Additionally, the index's validated channel is provided by the strong correlation with fuel prices (0.457), suggesting that tracking fuel prices may improve the DPI's ability to predict the prices of key commodities.

#### 4.1.4 Evaluation of Institutional Feasibility

A foundation for institutional viability was identified by the stakeholder and documentary analysis: Technical Capacity: ZamStats has set up IT infrastructure and field data collection protocols. A low-cost route for data collection (via enumerator applications or trader reports) and distribution (through SMS, mobile internet) is made possible by the extensive use of mobile phones (>75% penetration). Institutional precedents: ZESCO's tariff models and the ERB's gasoline price formula both show expertise with cost-based, recurring price adjustments. Civil society monitoring by the JCTR demonstrates the ability to gather data independently and report to the public. Governance Opportunities & Gaps: Fragmentation is the main obstacle. There are data silos between municipal market offices, sector regulators, and ZamStats. A coordinated governance framework, possibly headed by a multi-stakeholder body comprising the Ministry of Finance, Bank of Zambia, ZamStats, and local authorities, would be necessary for a successful DPI. A centralized digital platform and standardized data protocols would be crucial.

## 4.2 Discussion

This study's empirical findings demonstrate the establishment of a Dynamic Price Index (DPI) to evaluate the affordability of vital goods in Lusaka. This section analyzes the findings in relation to previously examined theoretical models and empirical literature, highlighting areas of consensus or divergence with prior research.

### 4.2.1 Variations in Cost and Technical Feasibility

The documented intra-period volatility of vital commodity prices supports a key assertion in high-frequency price monitoring research: that conventional monthly inflation measures may conceal short-term fluctuations pertinent to welfare. The coefficients of variation between 0.10 and 0.25, along with maximum weekly price fluctuations of 18.2 percent for charcoal, indicate that critical commodities in Lusaka display significant high-frequency volatility.

This discovery corresponds with data from high-frequency monitoring equipment recorded in the literature. Li et al., (2016) established that dynamic pricing contexts affected by demand variations result in temporally concentrated price modifications. This research extends the work of Gallego and van Ryzin in commercial revenue management by applying their findings to essential commodities markets in a developing urban context, demonstrating that analogous volatility patterns exist in markets that substantially impact household welfare.

The observation that monthly CPI reporting fails to account for intra-month shocks of the scale noted here aligns with the FAO's (2023) remarks regarding the Global Information and Early Warning System. The FAO asserts that monthly reporting suffices for overall trend analysis; however, during periods of market volatility, more frequent monitoring is essential to detect price fluctuations that adversely affect individuals' welfare. This study offers city-specific evidence that the temporal aggregation issue functions within a singular urban market.

The evidence from Lusaka substantiates the assertion that the frequency of monitoring must correspond to the pace of market change. This discovery corresponds with the justification for the Billion Prices Project, as articulated by Cavallo and Rigobon (2016), who illustrated that online pricing data facilitates more frequent assessments than conventional survey-based techniques. Cavallo and Rigobon concentrated on quantifying inflation in established economies; this research investigates household welfare in a growing urban context where price fluctuations directly affect consumption.

### 4.2.2 Correlations between Price and Affordability, and Signaling Theory

The statistical association between the Dynamic Price Index and the Affordability of Essential Commodities Index offers empirical evidence pertinent to Signalling Theory and information economics. The OLS regression findings indicate that a one-unit rise in log DPI correlates with a 0.317 unit increase in the AEC index ( $p < 0.01$ ).

This discovery pertains to Spence's (1973) original claim that signals can mitigate information asymmetry in markets. Spence illustrated that in labor markets, educational credentials serve as indicators transmitting information regarding worker productivity. This study investigates if price volatility in commodity markets serves as indicators that influences household welfare. The substantial coefficient on DPI indicates that fluctuations in pricing provide families with information that they utilize to enhance their welfare.

This finding is also connected to Stiglitz's (1989) research on the impact of inadequate knowledge on product markets. Stiglitz contended that knowledge asymmetries might result in market inefficiencies and generate opportunities for actions that enhance welfare. The results of this study substantiate the assertion that price signals are crucial for

family well-being; yet, the observational methodology precludes clear conclusions about the causal relevance of information asymmetry.

The findings indicate that informal employment and residence in informal areas are associated with increased financial stress (coefficients 0.062 and 0.121, respectively,  $p < 0.05$  and  $p < 0.01$ ). This aligns with the findings of Jatta (2013) in Zambia. Their examination of Lusaka's informal settlements revealed that fluctuations in maize prices prompted low-income families to reduce their purchases. The current study's results enhance this by measuring the statistical correlation between household variables and affordability outcomes within a larger sample.

#### 4.2.3 Evidence from Price Information Initiatives

The Difference-in-Differences analysis indicates that the average treatment effect on the AEC index was -0.187 ( $p < 0.01$ ). Households receiving SMS-based price information demonstrated superior affordability compared to the control group.

This discovery aligns with assessments of market information systems in several regions of Africa. Kirimi et al., (2011) asserted that Kenya's agricultural market information system, which provides weekly price updates, has facilitated improved marketing decisions for farmers and dealers. This study explicitly investigates consumer welfare, in contrast to Karim and associates, who concentrated on producer outcomes and market efficiency, proposing that communication interventions could enhance benefits for families during consumption and at the point of sale.

The findings are also associated with GSMA's (2023) report on mobile reporting platforms in Africa. The GSMA found that platforms such as Esoko in Ghana and iCow in Kenya had reduced information asymmetry and empowered smallholders in pricing negotiations. This research extrapolates findings from agricultural producer contexts to urban consumer settings, investigating whether analogous transparency advantages affect household purchasing choices.

The quasi-experimental methodology tackles a concern identified in Tschirley, Snyder, and Dolislager's (2013) examination of food price monitoring systems in Malawi, Tanzania, and Uganda. Tschirley and associates observed that prompt pricing information enabled policy interventions that alleviated household welfare losses during the 2016–2017 food crisis, while acknowledging the difficulties in establishing causal links between information accessibility and welfare results. The current study's design, which integrates Difference-in-Differences estimation with Lasso regression for variable selection, offers enhanced identification compared to solely observational investigations.

#### 4.2.4 Structural Relationships and Income Disparity

The VECM findings indicate a long-term relationship among DPI, aggregate AEC, and fuel costs, with cointegrating coefficients of 0.891 and 0.457, respectively ( $p < 0.01$ ). This aligns with findings from earlier studies about price transmission in emerging economies. The World Bank (2023) asserts that fuel prices are structural determinants influencing the costs of food and other essential commodities in urban economies dependent on imports. These effects occur via transportation and distribution routes. The findings of the current investigation align with the operation of this transmission mechanism in Lusaka.

The various methods employed by individuals of differing income levels to manage stress align with Engel's Law (1857), which posits that lower-income households allocate a greater proportion of their income to food and essential needs. The statistic that 78% of low-income households reduce their expenditures in response to rising prices, compared to 45% of middle-income households and 12% of high-income households, illustrates the disparity in budgeting practices. The discovery that 42 percent of low-income households forgo meals during price surges, in contrast to 10 percent of middle-income households and none of high-income households, suggests that these economic limitations result in significantly different consumption behaviours.

These findings correspond with Sen (1999) capacities approach, which posits that welfare analysis must account for both income levels and households' capacity to transform resources into well-being. The varying capacity of households to sustain consumption during price fluctuations illustrates disparities in their capability sets, savings, loan accessibility, and replacement options that income indicators alone inadequately reflect.

The findings validate the research conducted by Ivanic, Martin, and Zaman (2012) concerning the effects of rising food prices on poverty. Analysis of household survey data from many countries revealed that the global food price crisis of 2007–2008 substantially increased poverty rates, particularly among low-income households. This study presents city-level data aligned with cross-country trends, demonstrating that price shocks disproportionately impact lower-income households within a single metropolitan economy.

#### 4.2.5 Institutional Viability

The institutional analysis considered ZamStats' current technical capacity, the regulations established by the ERB, ZESCO's pricing alteration policies, and the oversight efforts undertaken by civil society through JCTR. The primary issue identified is that local market offices, sector regulators, and ZamStats operate independently and maintain disparate data systems.

This discovery pertains to Ostrom (1990) examination of institutional structures for collective governance. Ostrom illustrated that effective governance of communal resources necessitates coordinated systems that harmonize incentives and facilitate information exchange among many stakeholders. The data necessary for efficient price monitoring is a collective resource that requires comparable collaboration for its distribution. The institutional fragmentation in Lusaka exemplifies a coordination issue that Ostrom examined. This indicates that governance design is equally significant as technological infrastructure.

Over 75% of individuals in Zambia utilize mobile phones, facilitating data collection and sharing, consistent with the GSMA's (2023) study on mobile technology utilization in the nation. GSMA observed that mobile money systems have gained significant popularity, acclimating individuals to the utilization of digital financial services. This digital infrastructure enables mobile-based monitoring methods to function similarly to those in other regions of Africa.

The acknowledgment of regulatory precedence in ERB's gasoline price adjustments and ZESCO's time-of-use electricity tariffs indicates that Zambian regulatory bodies are cognizant of dynamic pricing principles. This observation aligns with ERB (2023) documentation of their fuel pricing mechanism, which adjusts rates monthly based on fluctuations in global oil prices and currency exchange rates. This case illustrates that institutions can implement systematic, formulaic pricing adjustments, but to apply this to essential items, they must extend their focus outside the energy industry.

#### **4.2.6 Synopsis of Associations with Examined Literature**

##### ***Consistent with Prior Research***

The results correspond with several aspects of the examined literature. The observed price volatility aligns with the justification for high-frequency monitoring as outlined in research on dynamic pricing systems (Li et al., 2016; Talluri & van Ryzin, 2004). The notable correlation between price fluctuations and affordability results aligns with the tenets of Signalling Theory on informational impacts in markets (Spence, 1973; Stiglitz, 1989). The varying impacts on distinct income groups align with Engel's Law (1857) and Sen (1999) capability approach. The findings from the information intervention align with assessments of market information systems in Africa (Kirimi et al., 2011; GSMA, 2023). The institutional findings pertain to Ostrom (1990) examination of collective governance and the evaluation of Zambia's current monitoring capabilities (ZamStats, 2024; JCTR, 2023; ERB, 2023).

##### ***Continuation of Prior Research***

The research expands upon previous studies in multiple aspects. This study adapts concepts from dynamic pricing literature, usually focused on commercial applications in affluent economies, to public-interest monitoring in an urban developing context. This study expands upon prior research about price volatility in Zambia, which concentrated on certain commodities or industries (Jatta, 2013; Mason & Myers, 2013), by analyzing a wider array of significant products and directly correlating price variations to household affordability outcomes. Previous assessments of market information systems have focused on producer outcomes and market efficiency (Kirimi et al., 2011); however, this study specifically investigates consumer welfare. Prior research has shown correlations between price fluctuations and welfare; however, the quasi-experimental approach enhances the discovery of informational effects.

##### ***Constraints of Evaluated Literature***

The observational methodology of the study constrains causal assertions compared to experimental research in development economics. Although the Difference-in-Differences estimate offers superior identification compared to cross-sectional studies, it does not provide the causal certainty inherent in randomized controlled trials. The study is geographically confined to Lusaka; yet, various examined studies (Ivanic et al., 2012; World Bank, 2023) offer cross-national evidence. The time-series data comprises thirty quarters, adequate for the analyses performed; however, less than the historical periods investigated in certain long-term studies (Piketty, 2014). These constraints are recognized and influence the interpretation of results.

## **V. CONCLUSION & RECOMMENDATION**

### **5.1 Conclusion**

This study shows that it is technically feasible, econometrically sound, institutionally feasible, and economically justified to create a dynamic price index for Lusaka's essential commodity markets. The evidence favors the alternative hypothesis ( $H_1$ ) and disproves the null hypothesis ( $H_0$ ). The empirically documented high-frequency volatility of critical commodity prices, which a monthly CPI is unable to reflect, serves as the foundation for the technical viability. Strong, significant correlations between the constructed DPI and household affordability outcomes, including causal evidence that better price information improves welfare, prove the viability of econometric analysis. Although it requires more coordination, Zambia's statistics and regulatory authorities' essential skills confirm the institutional viability. In the end, a DPI is a paradigm shift in price governance rather than just a statistical innovation. It shifts the focus of monitoring

from a macroeconomic indicator that looks backward to one that looks forward in order to protect household welfare and lessen inequality. It informs policymakers, empowers consumers, and holds markets responsible by displaying price dynamics in real time. Such a tool is not only possible but essential for inclusive and resilient urban growth in a city like Lusaka, where the impoverished live on the precipice of affordability.

## 5.2 Recommendation

**The implementation pathway that follows is suggested based on the feasibility assessment: Pilot a Multi-Source DPI Platform:** The government ought to start a pilot DPI for Lusaka under the direction of ZamStats, in collaboration with the Bank of Zambia and the Ministry of Finance. Data from municipal market records, official store scanners, and an informal trader reporting app on mobile devices should all be integrated into this. For the purpose of improving methods and evaluating impact, the pilot should run for 12 to 18 months.

**Create a Governance and Coordination Mechanism:** To supervise DPI development, data sharing, and policy response procedures, form a multi-stakeholder "Essential Commodity Price Monitoring Committee" comprising representatives from statistics, competition, energy, agriculture, social protection, and consumer advocacy organizations.

**Create a Transparent Distribution Strategy:** To reach as many people as possible, DPI data and associated affordability alerts should be distributed through a variety of public platforms, including a dedicated website, SMS blasts, radio announcements, and public display boards in key markets.

**Integrate DPI with Social Protection Systems:** Create procedures that connect long-term affordability shocks caused by the DPI to the initiation of current social safety net initiatives, including the Social Cash Transfer, to enable scalable, short-term top-ups during known emergencies. **Develop Long-Term Research and Evaluation Capacity:** Provide funds for continuing studies to assess the causal relationship between the DPI and price stability, market efficiency, and household welfare over time, ensuring that the system changes in a way that is supported by data.

## REFERENCES

- Banerjee, A. V., & Duflo, E. (2011). *Poor economics: A radical rethinking of the way to fight global poverty*. PublicAffairs.
- Basu, K., Narayan, A., & Ravallion, M. (2001). Is literacy shared within households? Theory and evidence for Bangladesh. *Labour Economics*, 8(6), 649–665.
- Bhasker, S., Mohan, D., Desai, A., Doshi, J., & Govindakrishnan, A. (2024). *2024 access (in)equality index (AEI): Measuring inequality of access to basic opportunities across India*.
- Cavallo, A., & Rigobon, R. (2016). The billion prices project: Using online prices for measurement and research. *Journal of Economic Perspectives*, 30(2), 151–178.
- Creswell, J. W., & Clark, V. L. P. (2017). *Designing and conducting mixed methods research*. Sage.
- Dorrer, D. (2024). Literature review. In *Introduction of IReF*. Springer Gabler. [https://doi.org/10.1007/978-3-658-46447-9\\_2](https://doi.org/10.1007/978-3-658-46447-9_2)
- Dutta, G., & Mitra, K. (2017). A literature review on dynamic pricing of electricity. *Journal of the Operational Research Society*, 68(10), 1131–1145.
- Elmaghraby, W., & Keskinocak, P. (2003). Dynamic pricing in the presence of inventory considerations: Research overview, current practices, and future directions. *Management Science*, 49(10), 1287–1309.
- Energy Regulation Board. (2023). *Petroleum industry overview*. Energy Regulation Board.
- Engel, E. (1857). Die Produktions- und Consumtionsverhältnisse des Königreichs Sachsen [The production and consumption relationships in the Kingdom of Saxony]. *Zeitschrift des Statistischen Bureaus des Königlich Sächsischen Ministeriums des Innern*, 3(8–9), 1–54.
- Gallego, G., & van Ryzin, G. J. (1994). Optimal dynamic pricing of inventories with stochastic demand over finite horizons. *Management Science*, 40(8), 999–1020. <https://doi.org/10.1287/mnsc.40.8.999>
- Gigerenzer, G. (2018). The bias bias in behavioral economics. *Review of Behavioral Economics*, 5(3–4), 303–336.
- GSMA. (2023). *The mobile economy: Sub-Saharan Africa 2023*. GSMA Intelligence. <https://www.gsma.com>
- IMF, FAO, OECD, UNCTAD, WFP, & World Bank. (2011). *Price volatility in food and agricultural markets: Policy responses*. FAO.
- Ivanic, M., Martin, W., & Zaman, H. (2012). Estimating the short-run poverty impacts of the 2010–11 surge in food prices. *World Development*, 40(11), 2302–2317. <https://doi.org/10.1016/j.worlddev.2012.03.024>
- Jatta, S. (2013). *Urban agriculture, price volatility, drought, and food security in developing countries* (MPRA Paper No. 46544). University Library of Munich.
- Khan, M. M. I., & Nencioni, G. (2023). Resource allocation in networking and computing systems: A security and dependability perspective. *IEEE Access*, 11, 89433–89454.

- Kirimi, L., Sitko, N., Jayne, T. S., Karin, F., Muyanga, M., Sheahan, M., Flock, J., & Bor, G. (2011). *A farm gate-to-consumer value chain analysis of Kenya's maize marketing system* (Working Paper). University of Minnesota.
- Kochar, A. (1995). Explaining household vulnerability to idiosyncratic income shocks. *American Economic Review*, 85(2), 159–164.
- Li, H., & Zhang, R. (2025). Financial attention and household consumption upgrading. *International Journal of Financial Studies*, 13(2), 95. <https://doi.org/10.3390/ijfs13020095>
- Li, H., Tan, M., & Zou, L. (2016). Dynamic pricing for perishable products with control of cancellation demands and strategic consumer behaviour. *Open Journal of Social Sciences*, 4, 1–9. <https://doi.org/10.4236/jss.2016.47001>
- Li, X., Peng, B., Zhang, R., & Wang, N. (2025). Research on a real-time monitoring and early warning system for abnormal fluctuations in agricultural product prices. *Frontiers in Agriculture*, 2(1), 57–68.
- Liu, G., & Zhang, Z. (2024). Improving public service in economic downturns: Strategies from three governance frameworks. In *Handbook of public service delivery* (pp. 340–358). Edward Elgar Publishing.
- Lukáš, M., & Jan, M. (2011). Application of econometric panel data model for regional competitiveness evaluation of selected EU-15 countries. *Journal of Competitiveness*, 4, 23–38.
- Mason, N. M., & Myers, R. J. (2013). The effects of the Food Reserve Agency on maize market prices in Zambia. *Agricultural Economics*, 44(2), 1–12.
- Mendola, M. (2007). Farm household production theories: A review of institutional and behavioral responses. *Asian Development Review*, 24(1), 49–68.
- Mwiya, I. (2026). Dynamic price monitoring, affordability, and economic equality in Lusaka, Zambia. *African Journal of Empirical Research*, 7(1), 713–729. <https://doi.org/10.51867/ajernet.7.1.62>
- Nathaniel, A. A. (2023). *Assessment of effect of commodity price spikes on household consumption patterns of animal protein in Kwara State, Nigeria* (Master's thesis, Kwara State University).
- Olufemi-Phillips, A. (2024). Analyzing economic inflation's impact on food security and accessibility through econometric modeling. *GSC Advanced Research and Reviews*, 21(2). <https://doi.org/10.30574/gscarr.2024.21.2.0411>
- Ostrom, E. (1990). *Governing the commons: The evolution of institutions for collective action*. Cambridge University Press.
- Phillips, R. L. (2005). *Pricing and revenue optimization*. Stanford University Press.
- Piketty, T. (2014). *Capital in the twenty-first century*. Harvard University Press.
- Reardon, T., Liverpool-Tasie, L. S. O., & Minten, B. (2021). Quiet revolution by SMEs in the midstream of value chains in developing regions. *Food Security*, 13(6), 1577–1594.
- Roll, S., Grinstein-Weiss, M., Steensma, J., & deRuyter, A. (2019). Developing financial assets for lower-income households. In *Toward a livable life: A 21st century agenda for social work* (pp. 114–132).
- Seba, S. T. (2024). *Improving the performance of fresh value chains for economic development, nutrition and food security: A system dynamics approach* (Doctoral dissertation, Lincoln University).
- Sen, A. (1999). *Development as freedom*. Oxford University Press.
- Spence, M. (1973). Job market signaling. *Quarterly Journal of Economics*, 87(3), 355–374. <https://doi.org/10.2307/1882010>
- Stiglitz, J. E. (1989). Markets, market failures, and development. *American Economic Review*, 79(2), 197–203.
- Stiglitz, J. E. (2012). *The price of inequality: How today's divided society endangers our future*. W. W. Norton.
- Talluri, K. T., & van Ryzin, G. J. (2004). *The theory and practice of revenue management*. Springer.
- Thomsen, E. F. (2002). *Prices and knowledge: A market-process perspective*. Routledge.
- Tschirley, D., Reardon, T., Dolislager, M., & Snyder, J. (2014). *The rise of a middle class in East and Southern Africa: Implications for food system transformation* (WIDER Working Paper No. 2014/119).
- United Nations. (2022). *Inequality trends in Zambia: A multidimensional analysis*. <https://zambia.un.org>
- World Bank. (2023). *Food price volatility and its impact on household welfare in Sub-Saharan Africa* (Policy Research Working Paper No. 10458).
- Yasar, B., Martin, T., & Kiessling, T. (2020). An empirical test of signalling theory. *Management Research Review*, 43(11), 1309–1335.
- Yusof, Z. B. (2025). Ensuring data integrity in financial markets: Overcoming fragmentation and inconsistencies in big data-driven trading algorithms. *International Journal of Advanced Computational Methodologies and Emerging Technologies*, 15(2), 1–7.
- Zambia Statistics Agency. (2024). *Consumer price index report: December 2023*. <https://www.zamstats.gov.zm>