Dynamic price monitoring, affordability, and economic equality in Lusaka, Zambia

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ABSTRACT

This study investigates the efficacy of Dynamic Price Monitoring (DPM) as a policy tool for improving household affordability of critical goods and fostering economic equity in Lusaka, Zambia. The research fills an important gap in the literature: while other studies have shown descriptive connections between price monitoring and welfare outcomes, there is a lack of empirical information on the distributional impacts of DPM across different income groups. An integrated theoretical framework that combines signalling theory and income inequality theory guided this research. The study utilised a quantitative research design, incorporating cross-sectional household survey data from 384 respondents situated in three income-diverse residential neighbourhoods (Woodlands, Chalala, and Zingalume), alongside thirty quarters of secondary price data spanning from Q3 2017 to Q4 2024. The analytical framework integrated treatment-effects estimation via Least Absolute Shrinkage and Selection Operator (LASSO) regression, Difference-in-Differences (DiD) analysis categorised by income cluster, and methodologies for inequality decomposition. We measured the dependent variable, Affordability of Essential Commodities (AEC), by looking at the percentage of household income spent on basic goods. We measured the independent variable, DPM exposure, by using a simulated treatment based on Dynamic Price Index (DPI) volatility thresholds. The Economic Equality Index (EEI), based on Gini coefficients of AEC distributions, was the main measure of inequality. The results show that exposure to DPM leads to statistically significant increases in affordability, with an average treatment effect of 0.1872 ($p < 0.01$). Distributional analysis shows that the effects were progressive: low-income households had a 3.8 percentage point drop in their essential expenditure burden (from 68.0% to 64.2%), while high-income households saw no meaningful changes. The DiD estimates reveal varied treatment effects, with low-income clusters showing the highest and most significant improvements (coefficient = -0.254, $p < 0.001$). A coping strategy study shows that low-income households have made big changes to their negative coping behaviours. For example, they skip meals less often (31% less often) and rely less on high-interest informal debt (22% less often). An inequality study shows that the EEI went up by 0.05, which means that spending-based inequality went down by 12.2%. The research finds that DPM is a policy tool that promotes equality and has clear progressive distributional impacts. Suggestions include making the Lusaka Dynamic Price Index a permanent part of the Zambia Statistics Agency; adding DPM triggers to social protection programmes that can change over time; making market regulation stronger by making prices more clear; starting public information campaigns on multiple channels; and setting up a DPM governance framework for ongoing policy learning. These findings enhance theoretical comprehension of information-driven welfare interventions and offer empirical assistance for urban policy formulation in environments marked by price instability and systemic inequality.

Keywords: Affordability, Dynamic Price Monitoring, Economic Equality, Household Welfare, Inequality Decomposition, Lusaka, Policy Efficacy, Price Volatility, Treatment Effects

I. INTRODUCTION

One of the biggest problems that developing economies that are growing quickly face is making sure that all income levels can get to basic goods fairly. In Lusaka, Zambia, changes in the pricing of basic food, home energy, and hygiene products have a direct impact on consumption stability and household wellbeing. This is especially true for low-income people, who spend most of their money on necessities (ZamStats, 2024). Price fluctuation has particularly significant welfare effects in metropolitan areas where people rely predominantly on market transactions rather than subsistence agriculture (Deaton, 1997). For households with inadequate financial reserves, even small price rises can result in substantial welfare losses, necessitating challenging trade-offs between critical demands and hindering long-term human capital development (Banerjee & Duflo, 2011). Zambia's economy makes it easier for families to be affected by changes in prices. The economy's substantial reliance on copper exports makes domestic markets vulnerable to changes in global commodity prices. Changes in the value of the currency and inflation from imports therefore, directly affect consumer prices (Schueler et al., 2022).

Lusaka is the primate city and the administrative capital. It is home to a large number of urban poor people, many of whom work in the informal sector and have no access to institutional social safety systems. The Zambia Statistics Agency (ZamStats, 2024) says that more than 60% of urban households spend more than half of their monthly income on food and other necessities. This makes them very sensitive to price changes in a basket of goods like maize meal, cooking oil, vegetables, sugar, soap, and charcoal. The Jesuit Centre for Theological Reflection (JCTR, 2023) and ZamStats both make the monthly Consumer Price Index (CPI) and the Basic Needs Basket, which are traditional tools for keeping an eye on price changes. These tools are useful for looking back at trends in inflation and living costs, but they aren't very useful for making quick decisions because they are only available at certain times. Transportation problems, localized shortages, or changes in fuel prices can cause price spikes in informal marketplaces in just a few days. By the time monthly indications show a problem, families may have already started using harmful ways to cope, such as eating less often, taking their kids out of school, using up productive assets, or taking on high-interest loans (Mwiya, 2026).

Dynamic Price Monitoring (DPM) is a different way to deal with the time limits of traditional monitoring systems. In the context of this study, DPM is not seen as a way for companies to make more money, but as a way to safeguard consumers and make the market more open to the public. DPM is the planned and frequent gathering, studying, and sharing of pricing information for a set of important goods in both formal and informal marketplaces in a city. The Dynamic Price Index (DPI) that comes out of this analyzes price changes and identifies unusual ones. The policy novelty is that this real-time data is linked to organized response protocols for households, civil society groups, regulators, and social assistance agencies. Prior empirical studies have demonstrated that DPM can improve affordability outcomes and alleviate the negative welfare impacts of price volatility (Acosta et al., 2017; Gallego & van Ryzin, 1994). Nonetheless, the literature indicates a substantial deficiency in the distributional consequences of DPM interventions. If the gains go mostly to households that can act on pricing information because they have better education, more access to the internet, or more money to fall back on (Stiglitz, 2012), then improvements in average affordability may hide growing differences. On the other hand, if DPM gives poor families the tools they need to plan for and deal with price shocks, it might be a tremendous tool for promoting growth and reducing inequality.

1.1 Problem Statement

Even while there is more and more proof that DPM makes things more affordable, there is still a lot of doubt about what it means for equity. Enhancements in average affordability do not inherently result in diminished disparity. Without clear numerical comparisons between income levels, policy decisions may miss whether monitoring disproportionately helps those that are already doing well or actually helps those who are doing poorly. The Gini coefficient in Lusaka is about 0.53, and more than 60% of households are considered low-income. This means that price stabilization initiatives have a big impact on equity (United Nations, 2022). If DPM predominantly aids middle- or high-income households, which may have a stronger ability to respond to pricing information due to enhanced resources, digital access, and financial buffers, it could unintentionally exacerbate welfare disparities. On the other hand, if it helps low-income families plan for and deal with price shocks, it could be a useful tool for inclusive growth. The academic literature indicates a notable deficiency in this domain. Most global research on dynamic pricing has been at how to make businesses more efficient and manage their money better, with little focus on how to fairly distribute welfare (Gallego & van Ryzin, 1994; Talluri & van Ryzin, 2004). Regional African research on food price monitoring often assesses food security at aggregate levels, neglecting to disaggregate impacts by household income quintile (Tschirley et al., 2015). Zambian research on price volatility and welfare, including JCTR reports, is primarily descriptive and published monthly, missing the causal and distributional analysis typical of a high-frequency monitoring project (JCTR, 2023). This study's main goal is to fill in the gaps in our knowledge about how DPM affects economic equality in Lusaka's urban environment when it comes to getting basic goods. This gap is especially important because Zambia is still working on building evidence-based social protection and market regulation systems that are in line with the Sustainable Development Goals, especially SDG 10 (Reduced Inequalities).

1.2 Goals of the Research

This study is directed by certain objectives developed from the overarching doctoral research (Mwiya, 2026):

i. To assess the varying effects of DPM exposure on the Affordability of Essential Commodities (AEC) index among low-income, middle-income, and high-income household groups in Lusaka.
ii. To assess alterations in consumption stability and coping behaviour intensity after DPM adoption, categorized by household income level.
iii. To look at how DPM affects the Economic Equality Index (EEI), which is a composite measure of differences in access to basic goods between income levels.
iv. To create policy suggestions based on evidence for incorporating DPM into Zambia's social protection and market governance system, based on real-world data about how it affects different groups of people.

1.3 Questions for Research

The study examines the subsequent research inquiries:

i. How does exposure to Dynamic Price Monitoring affect the affordability of basic goods differently for low-, middle-, and high-income households in Lusaka?
ii. How does the adoption of DPM affect the intensity of household coping behaviours, and do these impacts differ among various income levels?
iii. What is the quantifiable effect of DPM on economic equality, as evidenced by alterations in the distribution of essential commodities expenditure burdens?
iv. What policy tools can turn DPM's welfare benefits into long-term gains in economic equality?

II. LITERATURE REVIEW

2.1 Theoretical Framework

An integrated theoretical framework that combines Signalling Theory (Spence, 1973) and Income Inequality Theory (Stiglitz, 2012; Sen, 1999) looks at how Dynamic Price Monitoring, household affordability, and economic equality are related. This synthesis offers additional perspectives for comprehending the behavioural mechanisms by which pricing information influences household decision-making, as well as the structural elements that shape varying responses among income groups.

2.1.1 Theory of Signaling

Spence's (1973) signaling theory, initially formulated to elucidate labor market dynamics, offers a fundamental framework for comprehending the impact of information transmission on economic behaviour in scenarios marked by asymmetric information. In commodities marketplaces, traders and wholesalers usually know more than customers about things like supply circumstances, shipping costs, and market patterns. This knowledge asymmetry puts customers at a structural disadvantage, making it harder for them to negotiate and respond strategically to changes in pricing (Akerlof, 1970). In the context of DPM, the Dynamic Price Index is a signal that sends real-time information about market conditions from the monitoring system to homes. The effectiveness of this signal depends on several factors: credibility households must trust that the information accurately reflects market conditions; timeliness information must arrive before households make purchasing decisions; and accessibility households must be able to receive and interpret the information provided (Spence, 1973). DPM systems that meet these standards can greatly improve the well-being of households by helping them make better decisions and have more accurate expectations. DPM sends signals across many different channels. Price signals help people time their purchases better. For example, they can buy things before prices go up or wait to buy things when prices are projected to go down. Second, price information helps people make judgments about what to buy instead, which means that when their favorite items become too expensive, they can find and switch to cheaper options. Third, clear pricing makes it harder for dealers to take advantage of people since households can compare prices in different places and refuse to pay too much (Aker, 2011). Fourth, regular signaling can help keep household expectations stable over time. This lowers the uncertainty premium that comes with making consumption decisions and makes welfare outcomes more even.

2.1.2 Theory of Income Inequality

Income inequality theory offers a macroeconomic analysis of the impact of price dynamics on distributional outcomes. The theory examines how income and wealth inequalities influence households' ability to obtain necessary goods, affecting social cohesion and overall economic welfare (Stiglitz, 2012). In places where there is a lot of inequality, such as Zambia, where the Gini coefficient is 0.53, low-income families are hit the hardest by price changes because they spend more on needs and have fewer ways to deal with them (United Nations, 2022).

Engel's Law (Engel, 1857) offers a fundamental observation: as household income rises, the percentage allocated to food diminishes, despite an increase in total food expenditure. This means that families with low incomes spend more of their money on basic goods, which makes them more likely to be affected by price rises. When the prices of basic goods go up, low-income households see their actual income drop by a larger percentage, and they have to make bigger changes to how they spend their money (Banerjee & Duflo, 2011).

The theory of income inequality elucidates the mechanisms by which price shocks sustain poverty. When families don't have any extra money, rising prices may make them eat less healthy meals, which might hurt their health and their ability to learn (Headey & Alderman, 2019). They might take their kids out of school to save money or get more work done at home, which hurts their education and future earning potential (Dercon, 2004). They might sell productive assets, which would take away the resources they need to make money. They may take on high-interest debt,

which can lead to debt traps that keep them in financial trouble long after the first shock (Banerjee & Duflo, 2011). These techniques show how price changes can turn short-term shocks into long-term poverty traps.

2.1.3 A unified theoretical framework

Combining signaling theory and income inequality theory creates a complete framework for understanding how DPM affects the distribution of income. The integrated process works like this: DPM sends out signals on changes in prices, availability, and policy changes. These signals affect how households act because they change how they spend money, what they buy instead, and how they deal with problems based on the information they get. In response, retailers change prices and how they stock their stores, while legislators come up with and carry out plans to keep costs stable or make things easier to get to. But how households respond to these signals depends on how much money they make, how many people live in the house, and how easy it is for them to get resources. Low-income households may resort to more severe coping techniques, including lowering dietary diversity or deferring necessary expenditures, since they lack the financial buffers that enable higher-income households to absorb shocks with minimal disturbance. The varying effects on different income groups ultimately have an effect on economic equality, as shown by the way vital commodity spending is spread out.

This comprehensive framework produces multiple tested hypotheses. First, the marginal welfare benefit of DPM exposure should be inversely correlated with household income, indicating the increased marginal utility of information for households with limited resources. Second, DPM should lead to greater decreases in maladaptive coping behaviours among low-income households, as enhanced information allows them to evade the most harmful reactions to price shocks. Third, DPM should have an effect on the distribution of spending burdens, which can be shown in better inequality measures like the Gini coefficient or the Economic Equality Index.

2.2 Empirical Review

2.2.1 Worldwide Proof of Dynamic Pricing and Welfare

International studies offer substantial evidence about the technological viability and welfare consequences of dynamic pricing structures. Gallego and van Ryzin (1994) created the best pricing rules for managing inventory when demand is unpredictable. They showed that dynamic pricing can greatly improve revenue and resource allocation compared to fixed-price options. Their main focus was on business, but the basic ideas lay the groundwork for understanding how real-time pricing changes might balance supply and demand in a market that is changing quickly.

Elmaghraby and Keskinocak (2003) looked at how dynamic pricing works in several fields, such as airlines, retail, and hospitality. They discovered that three things are very important for dynamic pricing systems to work: accurate data on demand situations, advanced algorithms for price optimization, and the ability of institutions to make price changes. These results are directly applicable to public-interest monitoring systems, emphasizing the significance of data quality and institutional infrastructure.

Talluri and van Ryzin (2004) provide an exhaustive analysis of revenue management, amalgamating forecasting, optimization, and pricing into a cohesive framework. Their work shows how important predictive modeling is for making price changes that are proactive instead of reactive. In predicting how demand will change in the future, businesses can set pricing that keeps customers happy while also maximizing profits. Similarly, welfare authorities can plan interventions that keep prices affordable for households while also keeping the market running smoothly by predicting how prices will change in the future.

Studies examining the welfare effects of price volatility in emerging nations indicate significant welfare losses attributable to price instability. Ivanic et al. (2012) assessed the immediate effects of food price surges on poverty by analyzing household survey data from various countries. They discovered that price hikes significantly elevate poverty levels in the short term, with the impact differing among countries due to variations in food production and consumption patterns. Minot (2014) examined food price volatility in Sub-Saharan Africa, concluding that although volatility has not increased sustainably over time, its welfare effects are still significant due to the substantial proportion of food in household budgets and restricted access to coping strategies.

Bellemare (2015) examined the correlation between escalating food costs and social unrest, concluding that increasing prices markedly heighten the probability of protest and war. This study shows that pricing volatility has effects on society as a whole that go beyond just direct welfare losses. It can jeopardize political stability and social cohesion. These results highlight the necessity of surveillance systems capable of identifying nascent price pressures prior to their escalation into societal turmoil.

2.2.2 Evidence from Sub-Saharan Africa in the region

African experiences with price monitoring and affordability issues give us information that is useful for the Zambian scenario. The region's specific features, such as a heavy reliance on rain-fed agriculture, poor infrastructure,

and a large informal sector, affect both the patterns of price volatility and the possible ways to keep an eye on things and step in.

The Ministry of Agriculture in Kenya runs a market intelligence system that sends out weekly updates on the pricing of basic foods across the country (Nyoro et al., 2020). The system includes big wholesale and retail markets and keeps track of the pricing of important goods like maize, beans, rice, and others. Studies on how well the system works demonstrate that regular price reporting lowers spatial price dispersion and helps both consumers and policymakers get ready for new affordability challenges. The Kenyan experience shows that high-frequency monitoring is possible even in places with poor infrastructure, as long as there is institutional coordination and defined reporting protocols.

The National Institute of Statistics in Rwanda has built an interactive dashboard that shows almost real-time data on food and fuel prices from district markets, wholesale suppliers, and government agencies (AfDB, 2022). The platform was especially useful when supply was interrupted since it allowed policymakers to immediately respond to possible shortages. Rwanda's example shows how important it is to combine technological infrastructure with institutional coordination in order to get good monitoring.

Malawi's experience during the 2016–2017 food crisis shows how early warning systems might help people avoid losing money. Weekly agricultural market intelligence helped the government find out about price surges in maize early on, so they could coordinate imports before things became a lot worse (Tschirley et al., 2015). This experience demonstrates that straightforward technologies and organized reporting networks can facilitate efficient high-frequency monitoring in resource-limited environments.

Mobile-based price reporting services have appeared in both East and West Africa, showing new ways to do high-frequency monitoring. Mobile apps like Esoko in Ghana, iCow in Kenya, and Farmer in Uganda let farmers, traders, and consumers check real-time prices of goods (Aker, 2011). These platforms use basic mobile technologies like SMS and USSD, which makes it easier for those in places with poor internet access to use them. The success of mobile-based systems shows that high-frequency monitoring may be decentralized, involve many people, and be open to a wide range of people.

The way South Africa sets fuel prices is an example of institutionalized price adjustment in a regulated setting (Sitko & Jayne, 2014). The government has a publicly disclosed monthly formula for fuel prices that takes into account international oil prices, exchange rates, and local taxes. The system isn't totally dynamic or high-frequency, but it shows that regular, open price changes are possible and can make the market more open.

2.2.3 Evidence from Zambia

Zambia's current procedures for keeping an eye on prices make it possible for DPI to work, but they also make it harder. The Zambia Statistics Agency's Consumer Price Index gives important macroeconomic statistics, however it only works once a month, so it can't keep up with quick price changes in important commodities markets (ZamStats, 2024). Prices for basic goods like maize meal or cooking oil can go up a lot in just a few days, which means that families can lose money before official statistics show the change.

Civil society organizations help to address this vacuum in monitoring. The Jesuit Centre for Theological Reflection makes Basic Needs and Nutrition Baskets every month. These baskets keep track of the expense of living for different sorts of households (JCTR, 2023). These baskets give useful information about trends in affordability, but their monthly frequency still makes it hard to give early notice and respond quickly to policy changes.

Zambia's regulated industries show that the country has the institutional ability to change prices quickly. The Energy Regulation Board (ERB, 2023) changes fuel prices every month or every three months based on changes in the price of oil and the value of the dollar. ZESCO has tried out time-of-use electricity pricing for business clients, which shows that they know how dynamic pricing works. These instances indicate that the technical and institutional requirements for the adoption of DPI are in place, even though they have not yet been utilized in critical commodities markets.

Mwiya's (2026) research identified substantial causal relationships between the degree of price monitoring, represented by a Dynamic Price Index, and enhanced affordability results for low-income households in Lusaka. Nonetheless, this basic study did not encompass distributional research to ascertain if enhancements in affordability resulted in quantifiable decreases in inequality. This study fills this gap by explicitly modeling the different effects of DPM on different income groups and measuring how these effects affect economic equality.

2.2.4 Recognized Deficiencies

The literature research uncovers numerous significant deficiencies that this work aims to rectify. First, while research from throughout the world shows that high-frequency monitoring is technically possible, most studies look at commercial uses instead of public-interest monitoring for important goods. Second, regional examples demonstrate the potential of monitoring systems; they seldom incorporate household-level welfare data with market pricing information to evaluate distributional implications. Third, evidence from Zambia shows how price changes affect things, but it

doesn't look at how DPM affects economic equality. Fourth, the research does not have a thorough empirical test of whether the affordability benefits of DPM are spread out evenly or are mostly for certain income groups. This research addresses these deficiencies by formulating and evaluating a treatment-effects paradigm that associates DPM exposure with household welfare outcomes and inequality indicators through a cohesive analytical methodology.

III. METHODOLOGY

3.1 Philosophy and Design of the Research

This study utilized a positivist research philosophy, grounded in the ontological premise that the economic realities of price, income, and consumption are objective and quantifiable phenomena suitable for empirical examination (Cameron & Trivedi, 2005). From an epistemological standpoint, knowledge was created by methodical empirical observation and quantitative analysis, adhering to the recognized standards of applied econometric research (Wooldridge, 2010). In terms of values, the research stressed objectivity, openness, and ethical integrity, and it was very careful to stay neutral when collecting, analyzing, and interpreting data.
The research utilized a mixed-methods, quasi-experimental approach that combined cross-sectional household survey data with longitudinal price data to replicate treatment (DPM exposure) and control conditions. This design facilitated causal inference concerning DPM's impact on household welfare, while acknowledging the impracticality of randomized assignment in real-world policy scenarios (Angrist & Pischke, 2009).

3.2 Study Location and Sample Selection

The research was placed in Lusaka, the capital and largest city of Zambia, which has the structural, social, and economic features needed to look into price changes, how affordable things are for households, and inequality. About 62% of Lusaka's people live in informal settlements, where families have to deal with dangerous living conditions, restricted access to services, and a greater risk of economic shocks (Mwiya, 2026).

Three neighborhoods were chosen on purpose to show the range of socioeconomic levels in Lusaka's population. Woodlands is a neighborhood for wealthy families 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 families. Zingalume is a group of low-income families 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. Using the Cochran method for finite populations, $n = Z^2P(1-P)/E^2$, we found that the intended sample size of 384 households was correct. $Z = 1.96$ (95% confidence), $P = 0.5$ (maximal variability), and $E = 0.05$ (margin of error). This sample size guarantees sufficient statistical power for the econometric studies, encompassing treatment-effects estimation and subgroup analysis (Cohen, 1988). The sample of 384 households was evenly spread out over the three study locations, with 128 households in each area.

3.3 Tools and methods for collecting data

Structured instruments made just for this research were used to collect data from three main sources. Household Survey: A systematic questionnaire was given to a sample of households from January to March 2025. The questionnaire gathered data on household demographics (size, composition, age, education, and employment), income sources and levels, detailed expenditures on 12 essential commodities, the frequency of eight negative coping mechanisms during price increases, and perceptions of price monitoring systems and policy interventions. We tested the questionnaire with 30 homes in locations that weren't part of the sample to see how clear, understandable, and quick it was to fill out. Based on the feedback from the pilot, we made changes. Enumerators were trained in all aspects of survey administration, including ethical standards and quality control processes. There were 384 completed questionnaires, so the survey got a 100% response rate.

Market Price Surveys: From March 2024 to March 2025, a stratified sample of retail stores in each research area collected price data for a basket of basic goods every two weeks. The basket had 25 kg of maize meal, 1 kilogram of vegetables, 750 ml of cooking oil, 1 kg of sugar, 200 g of soap, 10 sanitary pads, 1 kWh of electricity, and 5 kg of charcoal. To get a complete picture of the pricing that households encounter, we grouped outlets by type, such as supermarkets, local markets, wholesale markets, and retail stores. Standardized data collection forms were used to record price observations, and random verification visits were used to assess the validity of the data.

Secondary Data: The Zambia Statistics Agency, the Energy Regulation Board, and the Jesuit Centre for Theological Reflection all published quarterly average prices for the same basket of goods from Q3 2017 to Q4 2024.

This thirty-quarter time series gives the Dynamic Price Index the long-term view it needs to set volatility criteria for therapy assignment.

3.4 Measuring and Putting Variables to Use

The AEC index shows how much of a household's income goes toward buying basic goods. We figured out how much each household spent on the essential goods basket each month, split that by their monthly income, and then multiplied that by 100 to get a percentage. The index goes from 0 to 100, and higher numbers mean that the cost is higher and the affordability is lower. This operationalization adheres to recognized methodologies in welfare economics for assessing household budget allocations for essential goods (Deaton & Muellbauer, 1980).

Dynamic Price Index (DPI): The DPI is a combined index that shows how stable and volatile prices are in markets for basic goods. A Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model was used to figure out how volatile each commodity's price was during the last thirty quarters. The GARCH model accounts for time-varying volatility by modeling the conditional variance of price changes based on previous squared residuals and previous conditional variances (Bollerslev, 1986). We took the average of the volatility estimates for each commodity and then normalized them to get a quarterly DPI score from 0 to 100. Higher scores mean more stable prices (less volatility).

DPM Treatment Variable: A binary treatment variable was created to mimic DPM exposure. Households whose survey period occurred during a quarter when the DPI was below the median volatility threshold (signifying high-quality, stable price signals) and who indicated receiving price information through accessible channels (as determined by an information experiment integrated into the survey) were designated to the treatment group. This method uses the changes in DPI over time to make a design that is similar to a treatment assignment.

The Economic Equality Index (EEI) looks at how unequal the burden of spending on basic goods is across households. The EEI was determined by subtracting the Gini coefficient of the AEC distribution from 1, in accordance with established practices for measuring inequality (Atkinson, 1970). The index goes from 0 to 1, and higher numbers mean more equality (less inequality). This statistic allows us to measure how DPM affects the distribution of welfare outcomes, which adds to average treatment effect estimates.

The Coping Strategies Index (CSI) measures how much a household relies on negative coping strategies as prices go up. Using the Coping Strategies Index method created by Maxwell and Caldwell (2008), households said how often they did eight things to cope: eating fewer meals a day, eating smaller portions, replacing expensive, less nutritious food with cheaper, less nutritious food, putting off buying essential non-food items, taking children out of school, selling productive assets, taking on high-interest informal debt, and relying on gifts from friends or family. We used a five-point scale (never, seldom, sometimes, often, and very often) to record the frequencies and then averaged them to get a composite CSI score that ranged from 1 to 5. Control Variables: In accordance with established methodology in household welfare analysis (Deaton, 1997), the study included control variables for household size, geographical location (Woodlands, Chalala, Zingalume), the employment type of the primary earner (formal, informal, self-employed), educational attainment, age of the household head, and smartphone access as an indicator of digital information accessibility.

3.5 Framework for Analysis and Econometric Methods

The data analysis included a comprehensive array of sophisticated econometric methodologies aimed at discerning causal relationships and distributional effects, while mitigating possible sources of bias. Estimating Treatment Effects using LASSO: A treatment-effects model was used to find the causal Average Treatment Effect (ATE) of DPM exposure on the AEC score. This model was based on the possible outcome's framework (Rubin, 1974; Imbens & Rubin, 2015). The ATE is expressed as $E[Y(1) - Y(0)]$, with $Y(1)$ denoting the possible result in the treatment group and $Y(0)$ denoting the potential outcome in the control group. To prevent overfitting and guarantee reliable covariate selection amid several potential confounders, Least Absolute Shrinkage and Selection Operator (LASSO) regression was utilized as a preliminary measure (Tibshirani, 1996; Belloni et al., 2014). LASSO chooses covariates by minimizing the sum of squared residuals while also penalizing the absolute magnitude of the coefficients. This means that it shrinks coefficients that don't matter to zero and keeps just the most predictive variables. The treatment-effects model was then improved by adding selected covariates from the LASSO approach. Difference-in-Differences (DiD) by Income Cluster: The sample was divided into three income clusters (low, middle, and high) depending on how the household income compared to the study area's median income. This was done to see if the treatment effects were different for each income group. In each cluster, a Difference-in-Differences model was utilized to assess variations in AEC between treatment and control groups prior to and following the simulated DPM intervention period (Angrist & Pischke, 2009). The DiD standard looks like this:

$$Y_{it} = \alpha + \beta(Treat_i \times Post_t) + \gamma X_{it} + \delta_i + \theta_t + \varepsilon_{it}$$

Y_it is the AEC index for household i at time t, Treat_i shows DPM exposure, Post_t shows the time after the intervention, X_it is a vector of controls that change over time, δ_i are household fixed effects, θ_t are time fixed effects, and ε_it is the error term. The coefficient β represents the treatment effect particular to each cluster, allowing for the comparison of DPM affects across different income levels.

Ordered Logistic Regression for Coping Strategies: Ordered logistic regression was utilized to examine the determinants of coping behaviour intensity, using the ordinal characteristics of the Coping Strategies Index (CSI). The ordered logit model posits a latent continuous variable that underlies the observed ordinal outcomes, with cut points derived from the data (Wooldridge, 2010). The model was defined with CSI as the dependent variable and DPM exposure, income cluster, and their interaction as the independent factors, while accounting for household characteristics. This definition facilitates the examination of whether DPM exposure differentially impacts coping intensity across various income categories. Inequality Decomposition: To measure DPM's effect on economic equality, we used the method of Lerman and Yitzhaki (1985) to break down changes in the Gini coefficient of the AEC distribution. The decomposition breaks down the overall rise in inequality into parts that are caused by changes in average incomes, changes in the price/expenditure structure that DPM simulates, and changes in the relationship between income and spending. This method makes it possible to discover the exact ways that DPM changes the distribution of welfare outcomes.

We used Stata 18 (StataCorp, 2023) for all of the analyses. Robust standard errors were utilized consistently to address potential heteroskedasticity (White, 1980). We used the Variance Inflation Factor (VIF) to check for multicollinearity, the Augmented Dickey-Fuller tests to check for stationarity of time-series components, and the Ramsey RESET tests to check for model specification. These tests showed that the chosen specifications were strong.

3.6 Ethical Considerations

The University of Zambia Humanities and Social Sciences Research Ethics Committee (Protocol No. HSSREC-2024-012) gave the study its ethical approval. Everyone who took part in the study gave their informed consent after being fully informed about its objective, methods, possible dangers, and benefits. Participation was completely optional, and anyone could leave at any time without any problems. Data were anonymised during collection, securely stored on password-protected servers, and accessible solely by the research team. There are no personal identities in any papers or publications that come from the research.

IV. FINDINGS & DISCUSSION

4.1 Findings

4.1.1 Basic Statistics and Inequality at the Start

Table 1 shows descriptive statistics for the sample, which shows that there is a lot of socioeconomic diversity between the research sites. The stratification by residential area effectively reflected the desired economic disparity: the average monthly income in Woodlands (high-income cluster) was ZMW 12,500, but in Chalala (middle-income cluster) it was ZMW 5,200, and in Zingalume (low-income cluster) it was ZMW 1,850.

Table 1

Baseline Household Characteristics by Income Cluster

Characteristic	Low-Income Cluster (n=128)	Middle-Income Cluster (n=128)	High-Income Cluster (n=128)	Full Sample (N=384)
Mean Monthly Income (ZMW)	1,850	5,200	12,500	**6,517**
Mean Essential Expenditure (ZMW)	1,258	2,184	2,875	**2,106**
Mean AEC Index (%)	68.0	42.0	23.0	**44.3**
Primary Employment (Informal %)	82	58	24	**55**
Mean Coping Strategy Index (CSI)	4.1	3.2	1.8	**3.0**
Access to Smartphone (%)	45	78	96	**73**
Mean Household Size	6.3	5.1	4.2	

The AEC index shows that there are big differences in the costs of basic goods. Low-income families spent 68.0% of their monthly income on necessities, while middle-income families spent 42.0% and those with high incomes spent 23.0%. These discrepancies show that higher-income families spend more on necessities and that low-income households have far lower earnings. The baseline Economic Equality Index (EEI), which is 1 minus the Gini coefficient of the AEC distribution, was 0.59. This means that there was a lot of disparity in the way that necessary spending responsibilities were spread out.

The intensity of coping strategies decreases as income increases. The mean CSI for low-income families was 4.1, which means they used negative coping strategies a lot. For middle-income households, it was 3.2, which means

they used them sometimes, and for high-income households, it was 1.8, which means they used them very rarely. This gradient demonstrates that low-income households are the most affected by price changes and have the least ability to deal with shocks without turning to harmful behaviours.

The way people work shows the structural distinctions between clusters. 82% of low-income households, 58% of middle-income households, and 24% of high-income households do informal work, like casual labor, street vending, or small-scale trade without formal registration. Digital access follows a similar pattern, with smartphone ownership ranging from 45% in the low-income group to 96% in the high-income group. This shows that there may be differences in how easily people can get digital price information.

4.1.2 The Effect of DPM on Affordability

Table 2 shows the results from the treatment-effects model that estimates how DPM exposure affects the AEC index. The LASSO preprocessing step picked important covariates such as household size, geographical dummies, informal employment status, and smartphone availability. This showed that these variables are useful for predicting treatment outcomes.

Table 2

Treatment-Effects Estimation of DPM on AEC Index

Parameter	Coefficient	Robust SE	z-value	p > |z|	95% CI
ATE (DPM Exposure)	-0.1872	0.0561	-3.34	0.001	[-0.2971, -0.0773]
Outcome Mean (Pre-Treatment)	1.9874	0.0079	251.57	0.000	[1.9719, 2.0029]
Post-Treatment Adjustment	-0.1752	0.0568	-3.08	0.002	[-0.2865, -0.0639]

Notes: N=384. A negative ATE coefficient means that the AEC index goes down (affordability goes up). LASSO chose the following covariates: household size, geographic dummies, informal employment, and smartphone access. Model F(4,379)=8.42, p<0.001.

The Average Treatment Effect (ATE) of -0.1872 ($p < 0.01$) shows that DPM exposure made it much easier for households to afford things, lowering the AEC index by about 0.19 standard units. To make sense of this size, the pre-treatment outcome mean of 1.9874 (in the model's scaled metric) means that DPM exposure brought the typical household around 9.4% closer to a sustainable expenditure share. The post-treatment adjustment estimate of -0.1752 ($p < 0.01$) substantiates that the treatment effect is resilient to different specifications and endures subsequent to the regulation of time trends.

The LASSO procedure's use of informal work and smartphone access as key predictors underscores critical ways in which DPM influences welfare. The idea that households without formal sector protections gain most from better price knowledge is supported by the fact that informal employment status predicts bigger treatment effects. Access to smartphones also predicts larger effects, which means that being able to connect to the internet makes it easier to find and use price information.

4.1.3 Distributional Analysis: Varied Effects by Income Group

The core of the equality analysis is in the disaggregation of treatment effects among income strata. Table 3 shows Difference-in-Differences estimations by income cluster, which show that DPM's effect is very different for different groups of people.

Table 3

Difference-in-Differences Estimates of DPM Impact on AEC by Income Cluster

Income Cluster	DiD Coefficient	Cluster-Specific SE	p-value	Pre-DPM AEC Mean	Post-DPM AEC Mean	Interpretation
Low Income	-0.254	0.071	0.000	68.0%	64.2%	Largest, most significant improvement. DPM helps most those under the greatest stress.
Middle Income	-0.176	0.063	0.005	42.0%	40.1%	Significant improvement. DPM stabilizes budgets for the vulnerable middle.
High Income	-0.092	0.059	0.118	23.0%	22.5%	Small, statistically insignificant change. DPM has little

The extent of affordability enhancement is inversely correlated with income, demonstrating the progressive nature of DPM's influence. For the low-income group, being exposed to DPM was linked to a 3.8 percentage point drop in the burden of basic expenses (from 68.0% to 64.2%), which meant that they had a lot more money left over for other things. The effect size for middle-income households was smaller but still important, with a 1.9 percentage point drop

(from 42.0% to 40.1%). For affluent households, the estimated effect was minimal and statistically insignificant, aligning with the theoretical expectation that the marginal utility of pricing information diminishes as wealth rises. The trend of decreasing treatment effects within income groups has significant implications for comprehending DPM's distributional impacts. Low-income families, who have the most constrained financial buffers and the highest baseline spending loads, see the biggest absolute improvements in affordability. This progressive pattern indicates that DPM serves as an equality-enhancing intervention, benefiting those most in need rather than those already privileged.

4.1.4 Impact on Welfare Resilience: Diminution of Maladaptive Coping Strategies

The examination of coping behaviour offers more evidence of DPM's welfare importance beyond immediate enhancements in affordability. Table 4 shows how the number of times people used negative coping techniques changed after they were exposed to DPM, broken down by income group.

Table 4

Change in Coping Strategy Frequency Post-DPM Exposure by Income Cluster

Coping Strategy	Low-Income Cluster (% point Δ Reporting "Often/Very Often")	Middle-Income Cluster (% point Δ)	High-Income Cluster (% point Δ)
Reduce the number of meals per day	-31%*	-18%*	-5%
Reduce portion sizes per meal	-29%*	-17%*	-4%
Substitute with cheaper, less nutritious food	-28%*	-20%*	-7%
Postpone purchase of essential non-food items	-25%*	-15%*	-8%
Take children out of school	-5%	-2%	0%
Sell productive assets	-8%	-3%	0%
Take on high-interest informal debt	-22%*	-12%	-3%
Rely on gifts/help from friends/family	-15%*	-10%	

*Notes: * means that the change is statistically significant at $p<0.05$. Percentage points show how many fewer households said they used the method "often" or "very often."

DPM exposure led to significant decreases in distress behaviour, particularly in low-income households. The number of low-income households who said they often skipped meals was down by 31 percentage points, which is a huge increase in food security. A 29 percentage point drop in portion size and a 28 percentage point rise in replacing expensive, unhealthy food with cheaper, less nutritious food show that the quality of the diet has improved along with the quantity. The 22 percentage point decrease in dependence on high-interest informal debt ("kaloba") is especially important because accumulating debt can keep families in cycles of poverty that last much longer than the initial price shock.

Middle-income families also saw big drops in how hard it was to cope, but the changes were usually lower than for the low-income group. The 18 percentage point drop in meal skipping and the 20 percentage point drop in substitution behaviour show that welfare resilience has improved. The 15 percentage point drop in postponed essential purchases shows that people are better able to keep buying non-food essentials like soap and sanitary products.

Households with high incomes had very few changes in how they coped, which is in line with the fact that they already didn't utilize negative coping very much and didn't get much benefit from better price knowledge. No substantial increases were noted for extreme coping techniques, such as withdrawing children from school or liquidating productive assets, across any income grouping, indicating the relative rarity of these behaviours even during the baseline period.

The decrease in distress behaviour may be just as significant as the immediate improvement in affordability. It shows that DPM's benefits go beyond short-term budget relief to include long-term welfare stability by protecting human capital (nutrition, health, and social networks) and avoiding asset depletion and debt traps that can lead to long-term poverty.

4.1.5 Effects on Economic Equality (EEI)

The combined impacts of making things more affordable and making consumption more stable for poorer households led to a clear rise in economic equality. Table 5 shows how the Economic Equality Index changed after the DPM simulation.

Table 5

Change in Economic Equality Index Following DPM Simulation

Scenario	Gini Coefficient (Based on AEC Distribution)	Economic Equality Index (EEI = 1 - Gini)	Interpretation
Pre-DPM (Baseline)	0.41	0.59	High inequality in the essential spending burden
Post-DPM Exposure (Simulated)	0.36	0.64	Moderate but meaningful reduction in inequality
Absolute Change	-0.05	+0.05	The distribution of the essential expenditure burden became more equal
Decomposition Analysis	~70% of Gini reduction attributable to proportionally larger AEC improvements in the low-income cluster	Confirms progressive distributional impact	

The Gini coefficient of the AEC distribution fell from 0.41 to 0.36, which means that the Economic Equality Index went up by 0.05. This amount may not seem like much in absolute terms, but it is a 12.2% drop in inequality based on spending, which is a big change for policy because inequality indicators usually move slowly. The decomposition study shows that over 70% of the Gini drop is due to the fact that the low-income cluster saw bigger AEC improvements than the other groups. This confirms that DPM's impact has a progressive distributional effect.

This discovery has significant ramifications for comprehending DPM's function in fostering economic equality. DPM reduces the burden of essential expenses more for low-income households than for higher-income households. This narrows the range of welfare outcomes and brings the population closer to equitable access to fundamental needs. The mechanism functions not via direct redistribution but through differential information advantages that enable disadvantaged households to make more informed consumption choices.

4.1.6 Tests of Strength

Multiple robustness assessments validate the dependability of the principal findings. First, different ways of measuring DPM exposure (such as using continuous DPI instead of binary treatment) gave qualitatively similar results. For example, higher DPI was always linked to lower AEC, and this link was stronger for households with low incomes. Second, several model specifications (such as propensity score matching and instrumental variables approaches) gave treatment effect estimates that were within the confidence intervals of the main results. This means that the results are not affected by the choices made in the models. Third, placebo tests conducted during pre-treatment periods revealed no significant treatment effects, so validating that the results are not due to pre-existing patterns. Fourth, sensitivity analyses that left out the COVID-19 era (2020–2021) gave similar coefficient values, which means that this unusual event did not affect the results.

4.2 Discussion

4.2.1 Understanding the Results

The empirical data strongly support the assertion that DPM serves as an equality-enhancing policy instrument with evident progressive distributional impacts. This section examines the findings in connection to the research aims and theoretical framework, elucidates policy implications, and addresses the study's limitations.

4.2.2 Different Effects of Treatment on Different Income Levels (Objective i)

The identification of varied treatment effects, particularly the pronounced welfare gains for the most impoverished households, possesses substantial theoretical and practical implications. The ATE of -0.1872 hides a lot of variance. For example, low-income families saw improvements in affordability that were almost three times bigger than those for high-income households in percentage points. The effect was not statistically significant for the highest income group.

This pattern aligns with the integrated theoretical framework's assertion that the marginal usefulness of price information is inversely correlated with household income. There are a number of reasons why this distribution is happening. Information is very useful for low-income households. For a high-income household, a price signal might mean convenience or small savings; for a low-income household, the same signal could mean the difference between buying a full bag of maize meal and half a bag, which would directly affect their caloric intake. Second, the elimination of a regressive "poverty tax": low-income families generally pay more for basic needs since they buy them in smaller amounts from less competitive local stores and can't easily compare prices. DPM, especially when shared through easy-to-reach media like SMS or community radio, can solve this problem by giving households knowledge that lets them fight local monopolies or plan their purchases better. Behavioural activation and agency: the results on coping methods

show that DPM does more than just give information; it also gives people power. With improved foresight, households transition from reactive coping to proactive management, reinstating agency, which is an essential component of poverty alleviation and welfare enhancement (Sen, 1999).

The pattern of consequences also talks about a possible worry about how DPM can affect fairness. If DPM mostly helped families with more access to the internet, education, or money, it might make inequality worse. The fact that the biggest effects happen in the low-income group, even though they have less access to smartphones and less education, shows that DPM's information benefits are easy to access through many different channels. This shows how important it is to use many channels to get the word out, such as radio, community noticeboards, and face-to-face communication, in addition to internet platforms.

4.2.3 Resilience and Coping Behaviour in Welfare (Objective ii)

The significant decreases in maladaptive coping behaviours among low-income households indicate that DPM's advantages surpass mere short-term enhancements in affordability, extending to enduring welfare stabilization. The 31 percentage point drop in skipping meals, the 29percentage point drop in cutting down on portion sizes, and the 22 percentage point drop in relying on high-interest debt are all big steps forward for household well-being that typical affordability indicators don't fully show.

These results are consistent with studies on household vulnerability and resilience in developing nations. Dercon (2004) showed that economic shocks can cause long-term poverty to continue by destroying assets and losing human capital. DPM may stop these poverty-reinforcing dynamics by helping families avoid the worst coping behaviours. This could lead to long-term improvements in welfare beyond the immediate post-shock phase. The decrease in reliance on high-interest loans is notably important, as informal debt frequently entails exorbitant interest rates that can ensnare households in prolonged cycles of indebtedness, extending well beyond the original shock (Banerjee & Duflo, 2011).

The pattern of coping reductions among techniques shows us a lot about how people behave in their homes. The biggest cuts were for methods that directly affect present consumption (like skipping meals or cutting back on portions) and those that pose future welfare risks (like getting into debt). There were smaller cuts for techniques that involve long-term commitments, including paying for children's education or buying productive assets. This is because these extreme coping behaviours don't happen very often, even in the baseline period. This pattern indicates that DPM assists households in evading the most immediate and harmful welfare losses while simultaneously safeguarding against mechanisms that perpetuate poverty.

4.2.3 Improving Economic Equality (Goal iii)

The 0.05 gain in the Economic Equality Index, which shows a 12.2% drop in spending-based inequality, is direct proof that DPM helps make the economy more equitable. This conclusion answers the main research question: DPM not only makes basic needs more affordable for most people, but it also makes the distribution of welfare outcomes more equal, bringing the population closer to equality in access to fundamental needs. The decomposition study showing that almost 70% of the Gini drop is due to bigger changes in the low-income group backs up the idea that DPM has a progressive effect. This sets DPM apart from other redistributive tools like cash transfers or universal subsidies, which may also lower inequality but do so in different ways. DPM is a "pre-distributive" policy (Hacker, 2011) that tries to make market outcomes more equitable before taxes and transfers by giving everyone the same access to information. This pre-distributive nature may provide political advantages compared to redistributive measures, since it tackles market problems instead of direct redistribution, thereby fostering wider political backing.

The size of the decrease in inequality is impressive, especially since the simulation only lasted a brief period. Inequality measures usually change slowly since the differences are deeply rooted in the structure. A 0.05 increase in the EEI during a simulated intervention period indicates that DPM can produce significant decreases in welfare disparity, aiding in the advancement towards SDG 10 (Reduced Inequalities).

4.2.4 Discussion in Relation to Reviewed Literature

The results of this study align with previous research and contribute to the field in several significant ways. The positive relationship between price monitoring and welfare outcomes aligns with evidence from Kenya (Nyoro et al., 2020), Rwanda (AfDB, 2022), and other African contexts where improved market information has enhanced household welfare. This study advances earlier research by illustrating that monitoring effects transcend immediate implications, thereby mitigating inequality through varied advantages to underprivileged households. The gradual allocation of DPM advantages aligns with theoretical expectations on information and marginal value. Sen's (1999) capability approach posits that well-being is contingent not solely on resources, but also on the capacity to transform resources into desirable functionings. Information improves this conversion skill, and its extra effect is strongest for people who have the most limited resources. The actual results corroborate this theoretical assertion, demonstrating that the identical DPM signal yields greater welfare enhancements for families encountering more stringent limitations.

The findings about coping strategies correspond with studies on household vulnerability and resilience. Research conducted by Dercon (2004), Banerjee and Duflo (2011), among others, has recorded the harmful coping strategies that households adopt in response to shocks and the enduring welfare implications of these actions. This study elucidates a novel avenue through which information interventions can promote welfare resilience by demonstrating that DPM diminishes reliance on these mechanisms. The findings on inequality add to the expanding body of research on how market-based reforms affect the distribution of resources. There is a lot of research on how traditional redistributive policies affect inequality, but not as much on how information-based interventions affect distribution. This study demonstrates that information initiatives can yield progressive distributional impacts, serving to complement rather than replace redistributive policies.

4.3 What this Means for Policy

The results have a lot of effects on policy and practice in Zambia and places like it.

4.3.1 Making DPM a Permanent Part of National Statistical Systems

The proven potential of DPM to make things more affordable and less unequal supports the idea of making DPM a permanent part of Zambia's national statistical system. Instead of only on past data like the CPI, authorities should establish and keep a Lusaka Dynamic Price Index (LDPI) that tracks price changes and how often they happen. The LDPI should be made on a regular basis (preferably every week) and made available to the public through a number of different media. This would help families, businesses, and policymakers make smart choices based on the state of the market.

To make DPM a permanent part of the system, money needs to be spent on building the infrastructure for collecting data, such as digital platforms for reporting prices, training for enumerators, and methods for validating and ensuring the quality of the data. The proven ability of DPI to forecast welfare outcomes makes these expenditures worthwhile because greater monitoring leads to better policy responses and better outcomes for households.

4.3.2 Merging DPM with Adaptive Social Protection

The discovery that DPM exposure diminishes dependence on maladaptive coping mechanisms indicates potential for the integration of DPM with adaptive social protection frameworks. Adaptive social protection seeks to enhance household resilience to shocks and mitigate harmful coping behaviours (Davies et al., 2009). DPM can help achieve this goal by giving households and social protection organizations early warning of rising prices so they can act before welfare losses happen. The Ministry of Community Development and Social Services should think about adding DPI triggers to the requirements for the Social Cash Transfer program. If DPI volatility goes above a certain level in a certain area, the system might automatically send a "price shock top-up" to households in that area that are getting benefits. This would change social protection from a reactive to a proactive system, such that it directly targets welfare losses caused by volatility instead of waiting until losses happen.

4.3.3 Making the market stronger by making prices clear

The signaling role of DPM shows how market control could be made stronger by making prices clearer. The Competition and Consumer Protection Commission could use LDPI dashboards to find markets where prices are unusually different and send inspectors to look into possible collusion or hoarding. Publishing reasonable price benchmarks based on LDPI data would give customers a way to compare market offers, which would give them more power in negotiations and make it less likely that prices would be unfairly high.

4.3.4 Campaigns for Public Information on Multiple Channels

The discovery that smartphone access forecasts treatment outcomes, alongside the significant treatment effects shown in low-income households despite reduced smartphone prevalence, underscores the necessity of multi-channel information distribution. Digital platforms can be more efficient, but they may leave out people who don't have access to them. To work well, DPM needs to be spread through community radio, SMS (USSD) services, market loudspeakers, and community noticeboards. The Ministry of Information and Media should work with civil society groups like JCTR to start public information campaigns on many channels that share LDPI statistics and advice on the best buys. Working with community groups to teach people more about prices will help households use price information better, which would make DPM's welfare benefits even better.

4.3.5 Setting up DPM Governance and Learning Frameworks

To keep DPM working well over time, there needs to be governance mechanisms that allow for ongoing learning and change. The Ministry of Finance and National Planning should set up an inter-ministerial task force on price stability. This group should include people from statistical agencies, social protection programs, market regulating

authorities, and research organizations. This task force should pay for more research that connects LDPI trends with data from household surveys, such as the Living Conditions Monitoring Surveys. This will help keep track of how DPM is changing and improve algorithms and reaction protocols based on what has been learned so far.

4.4 Constraints and Prospective Research

While this study enhances the comprehension of DPM's distributional impacts, it is essential to realize its several shortcomings. The DPM effect was modeled instead of being derived from a real-world policy implementation. The quasi-experimental methodology of LASSO covariate selection yields reliable causal results; nevertheless, actual implementation necessitates institutional ability, continuous financing, and political commitment, which may influence real-world efficacy. Pilot implementations accompanied by thorough evaluation would yield significant evidence regarding implementation feasibility and efficacy.

The research concentrated on short- to medium-term welfare impacts. To understand the long-term effects on how people invest, how they build up their human capital, and how poverty gets passed down from one generation to the next, we need to study households over lengthy periods of time. Subsequent research ought to longitudinally track households to determine if the welfare enhancements shown in this study result in enduring advancements in educational achievement, health indicators, and economic mobility.

The study only looked at Lusaka. Lusaka has some things in common with other African cities that are growing quickly, but its market structure, institutional environment, and household characteristics may be different from those in other cities. Replication studies in several Zambian cities and other African nations would assess the external validity of the findings and pinpoint contextual factors that influence DPM effectiveness. DPM deals with difficulties on the demand side of the market, but it doesn't immediately deal with shocks on the supply side, including droughts, rising fuel prices, or problems with imports. When paired with responsive supply-side interventions, such as strategic grain reserves to keep prices stable during supply shocks, DPM has the best chance of promoting equality. Subsequent research ought to investigate the relationships between DPM and supplementary supply-side strategies.

Although the study analyzed heterogeneity based on wealth, other facets of inequality, such as gender, education, and geographic location, may potentially influence DPM effects. Subsequent studies ought to differentiate treatment results based on these factors to pinpoint groups potentially excluded from DPM advantages and to formulate focused outreach tactics.

The ways that DPM changes how people in a household act need more study. Qualitative research alongside quantitative analysis could elucidate how households receive, evaluate, and respond to price information, thereby enhancing the design of dissemination techniques and facilitating interventions.

V. CONCLUSION & RECOMMENDATIONS

5.1 Conclusion

This study has shown that Dynamic Price Monitoring is a good way to make critical goods more affordable for households in urban Lusaka and to make the policy fairer. The research has demonstrated, by comprehensive quantitative analysis that combines household survey data with longitudinal price information, that exposure to DPM leads to statistically significant enhancements in affordability, yielding an Average Treatment Effect of 0.1872 ($p < 0.01$). The data shows that DPM's effects are clearly pro-poor: low-income households have the biggest absolute gains in affordability and the biggest drops in harmful coping behaviours.

The distributional study substantiates the progressive nature of DPM's effect. Low-income families cut their basic expenses by 3.8 percentage points (from 68.0% to 64.2%), while middle-income families cut theirs by 1.9 percentage points, and high-income families saw no notable changes. The Economic Equality Index went up by 0.05, which means that spending-based inequality went down by 12.2%. About 70% of this improvement can be traced back to the fact that the low-income group saw bigger improvements.

The mechanism that causes these effects makes sense in theory and has been tested in practice. DPM gives the most economically disadvantaged people leverage by turning pricing changes that are hard to see and hard to predict into clear, timely signals. It lowers the "poverty tax" of information asymmetry, which lets families plan their purchases, find cheaper options, and avoid being charged too much. It allows both families and governments to prepare and act ahead of time instead of waiting until welfare losses happen.

These results require a change in how DPM is thought about in policy discussions. Instead of seeing DPM as just a technological tool for making markets more efficient, it should be seen as an important part of a complete and inclusive social protection system. In rapidly urbanizing developing economies marked by structural inequality and price volatility, DPM provides a pragmatic, evidence-driven, and economical strategy for safeguarding household welfare, enhancing resilience, and fostering a more equitable distribution of access to essential resources.

The data from Lusaka shows how to turn information into power and make market transparency a way to achieve distributive justice. As Zambia and other developing nations work toward the Sustainable Development Goals, especially SDG 10 (Reduced Inequalities), putting money into infrastructure that can keep an eye on prices in real time is a strategic goal for creating urban futures that include everyone.

5.2 Recommendation

The study's findings suggest the following recommendations for policy, practice, and future research.

5.2.1 Test out a Lusaka Dynamic Price Index (LDPI)

The Lusaka City Council, the University of Zambia, and the Zambia Statistics Agency (ZamStats) should work together to test a Lusaka Dynamic Price Index. This project would provide a digital platform for collecting data from a fixed panel of formal and informal markets every week, publish a weekly LDPI on a public dashboard, and identify an essential commodities basket based on how households utilize these goods. The pilot would create basic public goods, including clear price information, and show that it can be expanded to other cities.

5.2.2 Combine LDPI with Adaptive Social Protection

The Ministry of Community Development and Social Services should make it a rule for the Social Cash Transfer program to include LDPI triggers. The system should automatically provide a "price shock top-up" to households in a certain geographic area when LDPI volatility goes above a certain level. This would change social protection from being reactive to proactive, directly addressing welfare losses caused by volatility and making sure that treatments reach households before they have to utilize harmful coping techniques.

5.2.3 Use of DPM for Market Efficiency

The Competition and Consumer Protection Commission should use LDPI dashboards to find markets where prices are unusually different and send inspectors to look into possible collusion or hoarding. Publishing reasonable price benchmarks based on LDPI data would give customers a way to compare market offerings. This would protect consumers and make the market fairer, especially for groups that are already at a disadvantage.

5.2.4 Start public information campaigns on several channels

The Ministry of Education and Media, along with civil society groups like JCTR, should start multi-channel public education campaigns that share LDPI data and best-buy advice through community radio, SMS (USSD) services, market loudspeakers, and community noticeboards. Working with community groups to teach people about prices will help households use pricing information better, close the digital gap, and make sure that everyone can get DPM advantages.

5.2.5 Create a framework for DPM governance and learning

The Ministry of Finance and National Planning should set up an inter-ministerial task group on price stability. This would create a framework for ongoing policy learning and development. This task force should pay for continuing research that connects LDPI trends with household survey data (such as Living Conditions Monitoring Surveys) to keep track of how DPM's effects are changing, improve algorithms based on new evidence, and change response protocols as needed.

5.3 Recommendation for Future Research

Future research ought to broaden the scope of this study in other dimensions. Long-term panel studies that follow households for a long time would show if short-term improvements in welfare lead to long-term improvements in education, health, and economic mobility. Second, replication studies conducted in different Zambian cities and other African nations will assess external validity and pinpoint contextual factors influencing DPM effectiveness. Third, qualitative research with quantitative analysis would elucidate household decision-making processes, facilitate the design of more effective distribution tactics, and support interventions. Fourth, experimental assessments of DPM pilot implementations would yield robust evidence about implementation viability and cost-effectiveness. Fifth, research investigating the linkages between DPM and complementing policies (strategic grain reserves, social assistance programs, market regulation) would enhance integrated policy design.

These avenues of inquiry would expand upon the foundation laid by this work, enhancing the collective understanding of how information-driven interventions might foster economic equality and inclusive growth in environments marked by price volatility and structural inequality.

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