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Effects of COVID-19 Measures on the Changes in Food Consumption Patterns for Urban Low-Income Households in Kenya

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Abstract

The COVID-19 pandemic has disrupted food chains worldwide. The Kenyan government-initiated measures to curb the spread of the novel disease. Some measures include lockdown, a ban on social gatherings, and the closure of institutions like school restaurants and eateries, potentially changing households' food consumption patterns. This study aimed to determine COVID-19 measures' effect on food consumption patterns for low-income urban households. The study was conducted in the Nakuru-west sub-county using a quantitative research design through a cross-sectional survey with a sample size of 246 household respondents. The study used the Multinomial Endogenous Switching Regression Model (MESRM) to control for possible bias resulting from non-observable traits. The results revealed that factors including the household food decision-maker age, changes in food prices, income changes, changes in the person in charge of food before COVID-19, fruits and vegetables shopping frequency, and the ban on social gatherings significantly affected the decrease in food consumption patterns. In contrast, money spent on food and movement restrictions significantly affected an increase in food consumption patterns. These findings suggest that the combined effects of these factors are likely to reduce household food consumption, impliying the need for subsidies on staple foods during crises, educational programs, effective communication of proposed measures, and the promotion of local production and sourcing to sustain the local economy.

Keywords: COVID-19 pandemic, Multinomial Endogenous Switching Regression, Nakuru-west sub-county, Food Consumption Patterns, Low-income Households

Introduction

Supply chains enable efficient movement of agricultural commodities from regions of surplus to areas of demand, thereby supporting food security. By connecting producers, processors, distributors, and retailers worldwide, supply chains ensure that diverse food products are available to consumers year-round, regardless of local [1, 2]. However, posits that the complexity and interdependence inherent in these systems make them susceptible to various disruptions, which can have cascading effects on food availability and affordability [3].

One of the most significant disruptions to supply chains in recent history was caused by the COVID-19 pandemic, which triggered severe economic crises worldwide, comparable in scale to the aftermath of World War II [4, 5]. The implementation of lockdowns, travel restrictions, and social distancing measures impeded the transportation and distribution of essential goods, leading to delays and shortages in food, medical supplies, and consumer products. Additionally, massive job losses and declining household incomes further eroded purchasing power, disproportionately affecting low-income populations and exacerbating food insecurity [6]. Trade disruptions and production declines led to price volatility, making food increasingly unaffordable for vulnerable households, particularly in developing nations like Kenya as they were already entering a recession by late 2019 (UNCTAD, 2020). These economic shocks underscored the fragility of supply chains and the urgent need for more resilient and adaptive food systems.

The pandemic caused profound changes in food systems, altering how people access, purchase, and consume food. According to Noah et al. (2020), pandemic-related control measures restricted access to diverse and nutritious food sources, compelling consumers to modify their food choices and spending habits argue that lockdowns, curfews, and market closures disrupted food production, processing, and retail, generating uncertainty in demand and supply chains. More so, logistical bottlenecks delayed food distribution, leading to increased food waste while simultaneously driving up food prices, particularly in low-income countries [7, 8, 4]. In April 2020, the World Food Program (2020) projected that the number of acutely food-insecure individuals could double by the end of the year without immediate intervention. This prediction highlighted the disproportionate impact of the crisis on vulnerable urban populations, many of whom rely on informal employment for sustenance.

Movement restrictions had an immediate adverse effect on food prices, limiting transportation and reducing market accessibility [9]. The closure of informal markets where a significant portion of low-income household's purchase food further restricted food availability and affordability. In addition to production and processing disruptions, food consumption patterns were negatively affected by declining purchasing power. As employment rates fell, many households shifted from nutrient-rich diets to more affordable but less nutritious alternatives.

Urban low-income households were particularly vulnerable to food insecurity due to rising food prices, declining incomes, and changes in food consumption patterns. Across different regions, economic hardships forced vulnerable populations to substitute nutritious foods with cheaper alternatives. For instance, in India, many low-income households replaced protein-rich foods with calorie-dense staples as a survival strategy [10]. Similarly, in Latin America, movement restrictions hindered street vendors and informal food markets, reducing access to affordable food [11]. In Kenya, the impact was severe in urban areas where informal employment plays a crucial role in household income. A nationwide telephone survey revealed that 30% of respondents were absent from work due to temporary layoffs or economic downturns (KNBS, 2020). In response to economic pressures, Nairobi households reduced their consumption of meat and sugar while increasing their intake of cereals and fruits as a coping mechanism [12]. Furthermore, the disruption of local food supply chains led to food price surges, making essential goods even more inaccessible for low-income families.

Several studies have examined the impact of COVID-19 on food consumption patterns, highlighting disruptions in food supply chains and economic hardships [9, 11]. While these studies provide valuable insights, much of the existing research has primarily focused on national food security trends or rural agricultural disruptions leaving gaps in understanding how urban low-income households were affected. Studies by Mbijiwe et al. (2020) and Mahajan and Tomar (2021) analyzed food consumption shifts in cities but lacked localized data on specific urban areas like Nakuru City, where informal employment and market access play a crucial role in food security. Moreover, these studies utilized various data analysis models, including Ordinary Least Squares (OLS) regression, Propensity Score Matching (PSM), Chi-square tests, and Difference-in-Differences (DiD) to evaluate the impact of COVID-19 on food security [9, 10, 12].

While these models provide important findings, they often assume homogeneity in treatment effects and fail to account for selection bias in household decision-making regarding food consumption. This research aims to fill these gaps by applying the Multinomial Endogenous Switching Regression Model (MESRM), which effectively controls for selection bias and unobserved heterogeneity in household food consumption behavior. The findings will offer evidence-based recommendations for policymakers to enhance food security strategies in urban settings, particularly during crises.

Materials and Methods

Study Area and Sampling

The study was conducted in Kaptembwa Ward, Kapkures ward, and Rhonda ward Nakuru West sub-county, Nakuru County. Nakuru County extends between longitude 36° 01′ and 37 ° 15′ east and latitude 0° 17′ and 1° 20′ south. The county occupies an area of 7,510 KM2 and has a population of approximately 616,046 households, with an average of 3-4 household members (KNBS, 2019). Nakuru, the newest fourth city in Kenya, has a vibrant and growing population. Nakuru west sub-county was selected for its higher number of wards and a distinct high population density (KNBS,2019). The three wards were purposively settled on since they mainly host low-income households in the urban area [13].

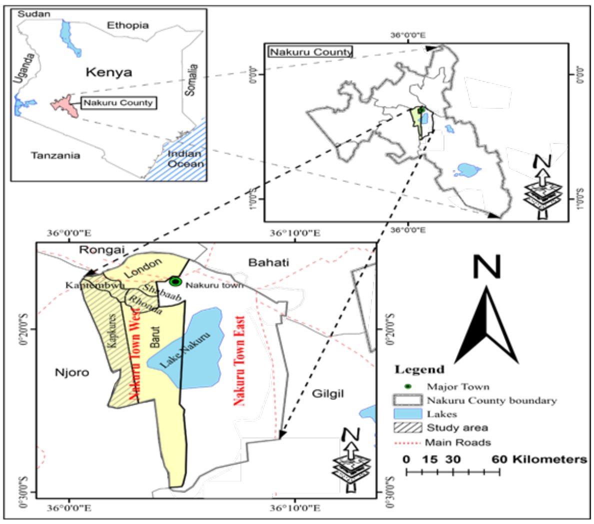

Figure 1: Map of Nakuru-West Sub-County

Research Design
This study used a quantitative research design through a cross-sectional survey. Results from quantitative research can be extrapolated to a larger population. Researchers can make judgements about the attitudes, actions, and opinions of the population being researched by using a sizable and diverse sample. Compared to other research approaches, cross-sectional surveys often have a greater sample size. This makes it possible to discover subtler variations between groups or variables and to increase statistical power.

The sample unit for this study consisted of household members from Nakuru West sub-County, Nakuru City. The selection of respondents followed a multi-stage sampling strategy. In the first stage, Nakuru county was chosen because it was among the most severely affected areas by the COVID-19 virus. It was subsequently classified as a high-risk area by the Kenyan government. This was attributed to the vibrant, growing population (MOH-Kenya, 2020). In stage two, the Nakuru West sub-county was used for its higher number of wards. In stage three, Kaptembwa, Kapkures, and Rhonda wards were selected for their high population densities, which are low-income households [13].

In the last stage, systematic random sampling was used to select the household respondent according to Table 3.1. The first household was selected randomly in the three study areas, and from which every 5th household was interviewed till the desired sample size per ward was achieved. Marek et al. (2017) noted that using a 5-point interval for sampling is a practical way to improve the effectiveness and representativeness of research investigations. The determination of the required sample size was through the probability sampling technique by way of a simple random sampling procedure to identify the households to be interviewed. The required sample size was determined by proportionate to the size sampling methodology (Anderson et al., 2007).

$$n = \frac{pqZ^2}{E^2} \quad \text{.........} \quad (1)$$

$$n = \frac{0.8 \times 0.2 \times 1.96^2}{0.05^2} = 245.9 \approx 246$$

Where n = Sample size; Z = confidence level (α=0.05); p = proportion of the population containing the significant interest, q=1-p, and E = allowable error. It was assumed that p= 0.8 since a majority, more than 80% of the population, meet the desired attributes according to the census report (KNBS, 2019). Therefore, q=1-0.8=0.2, Z= 1.96, and E = 0.05 (acceptable error term). This resulted in a sample of 246 respondents that were interviewed. Table 1 shows the distribution of the respondents in the three wards proportionate to the number of households in the ward.

Table 1: Sample Size Per Ward

Wards	No. of Households	Proportion	Sample size
Kapkures	12,099	8.56%	21
Rhonda	33,381	23.63%	58
Kaptembwa	95,811	67.81%	167
Total	141,291	100%	246

The study used primary data collected using a structured questionnaire. The instrument had multiple-choice answers to explore the respondents' feedback on several questions about their food consumption patterns before and after the implementation of COVID-19 measures. To determine changes in food consumption patterns, the household respondents were asked to report how often they consumed eleven categories of fresh, non-fresh, convenience, and snack food during and before the pandemic. Then, respondents were interviewed on their behaviour before and during COVID-19 on food purchase and consumption behaviour for factors like price change experiences, food availability, packaging and storage, stockpiling, panic purchasing, homemade meals, and food waste during the COVID-19 pandemic.

Respondents were further asked whether they had experienced specific changes due to COVID-19, including changes in household income and the closure of their physical workplace. Data was collected using the open data kit (ODK), and cleaning through SPSS and analysis was undertaken using STATA version 16.

Before the actual data collection, a pre-test was carried out in the Naivasha sub-county, Viwandani ward in Karagita town since it has similar attributes to the study area (NAIVAWASCO, 2022). Thirty household respondents were interviewed; this was at least 10% of the study's required sample size. These pilot study results were used in correcting and adjusting the final questionnaires administered for the study.

Empirical Strategy
The response variables for change in consumption patterns were collected as a dummy variable (1 if household FCP was affected by COVID-19 measures. 0 otherwise). In addition, households may have been affected by a different combination of COVID-19 measures. Some were affected by one, two, or three in their consumption patterns determined by observable and non-observable factors. What they consume may have innate characteristics that correlate with one or more COVID-19 measures. To control for possible bias resulting from non-observable traits like perception, the study used the Multinomial Endogenous Switching Regression Model (MESRM).

The model further determined the significant effects of COVID-19 measures on consumption patterns. Sample population responses were estimated, that is, the responses by household heads before and after the COVID-19 measures. The model corrects for both observable and non-observable biases that may result from providing unbiased estimates of the effects of FCP. This model was suitable since it estimates the average treatment effect (ATE) of COVID-19 measures on the outcome change in consumption patterns. It assumes that households aim to maximize food consumption under the different COVID-19 measures.

A maximum likelihood function was used to estimate the latent variable parameters. Three categories were formed: the first category is positive change H=1, the second base category is no change H = 0, and the third is negative change H= −1. Hence the likely outcome equation for all categories was given as follows;

$$\begin{cases} \text{Category one: } Q_{h1} = J_h\,\alpha_1 + \mu_{\eta 1} \text{ if } H=1 \\ \text{category two: } Q_{h1} = J_h\,\alpha_1 + \mu_{\eta 1} \text{ if } H = 0 \\ \text{category three: } Q_{h1} = J_h\,\alpha_1 + \mu_{\eta 1} \text{ if } H= -1 \end{cases} \quad \text{.......... (4)}$$

Positive food consumption change was measured as an increase in food consumption in terms of an increase in the number of meals, and a snack per day, increased shopping frequency, increased visits to restaurants/ eateries, increased income/ reduced price, and increased food availability. No change will be measured by a no increase or no decrease in the factors mentioned above, and negative change will be measured with a decrease in the same elements.

The multinomial endogenous switching model further assumed linearity assumptions, as shown in equation 5

$$E=(U_{hg} \mid \epsilon_{h1}\ldots\epsilon_{hg}) = \sigma_g \sum_{k\neq g}^{g} rg\,(\epsilon_{hk} - E(\epsilon_{hk}). \quad \text{.......... (5)}$$

With $\sum_h$=1rg=0 (meaning the correlations between U's and W's sum to zero). Hence following this assumption in the above three equations were summarized as shown below:

$$\begin{cases} \text{Category one: } Q_{h1} = J_h\,\alpha_1 + \sigma_h\lambda_1 + \omega_{h1} \text{ if } H=1 \\ \text{category two: } Q_{h1} = J_h\,\alpha_1 + \sigma_h\lambda_1 + \omega_{h1} \text{ if } H = 0 \\ \text{category three: } Q_{h1} = J_h\,\alpha_1 + \sigma_h\lambda_1 + \omega_{h1} \text{ if } H= -1 \end{cases} \quad \text{.......... (6)}$$

Where ω's are error terms with zero expected values, α_h is the covariance between Us and Cs, and ʎ is the inverse mills' ratio (IMR) which was computed from probabilities in equation 7

$$\lambda_g = \sum_{k\neq h}^{h} ph \left(\frac{p_{hk} Ln(p_{hk})}{1- p_{hk}} + \ln(p_{hg}) \right) \text{.......... (7)}$$

Where p is the correlation coefficient, the U's and ω's are error terms with an expected value of zero. The multinomial endogenous switching model further examined the average treatment effect on the treated by comparing the expected outcomes of each alternative COVID-19 measure.

According to Di Falco and Veronesi (2013), ATT is computed in the actual and counterfactual scenarios as follows:

For the substantial change in FCP in the sample, the outcome estimation model is given as

$$\begin{cases} E(Q_{h1} \mid H = 1 = J_h\,\alpha_1 + \sigma_1\lambda_1 \ldots a \\ E(Q_{h0} \mid H = 0 = J_h\,\alpha_0 + \sigma_0\lambda_0 \ldots b \\ E(Q_{h\text{-}1} \mid H = \text{-}1 = J_h\,\alpha_{\text{-}1} + \sigma_{\text{-}1}\lambda_{\text{-}1} \ldots c \end{cases} \quad \text{.......... (8)}$$

If households were not affected by COVID-19 measures, the counterfactual would be;

$$\begin{cases} E(Q_{h1} \mid H=1= J_h\,\alpha_2 + \sigma_2\lambda_2 \ldots a \\ E(Q_{h0} \mid H=0= J_h\,\alpha_0 + \sigma_0\lambda_0 \ldots b \\ E(Q_{h\text{-}1} \mid H=\text{-}1= J_h\,\alpha_{\text{-}2} + \sigma_{\text{-}2}\lambda_{\text{-}2} \ldots c \end{cases} \quad \text{.......... (9)}$$

The above-estimated values helped derive unbiased estimates of the average treatment effects on treated (ATT), which were the difference between equations 9a and 8a.

$$ATT = E\,[Q_{i2} \mid I = 2] - E\,[\,Q_{i1} \mid I=2] = Z_i\,(\alpha_2 - \alpha_1) + ʎ_i\,(\sigma_2 - \sigma_1) \quad \text{.......... (10)}$$

The first term on the right-hand side of Equation 10 represents the expected change in Household consumption patterns due to COVID-19 measures. The second term (λ) is the selection term that captures all potential effects of difference in unobserved variable.

As shown in table 2 the various explanatory variables used were adopted from previous related studie [14-17]. These variables include; age, sex, education level, closure of restaurants and eateries, closure of workplaces, Income loss due to pandemic measures, changes in food availability during the pandemic, changes in food shopping frequency, eating frequency in terms of the number of daily meals before and during the pandemic, changes in the price of commodities due to pandemic measure.

Table 2: Description and Expected Signs of the Variables used in the Multinomial Endogenous Switching Regression Model

List of Variables	Descriptions	Measurements	Expected signs
Age	Age of household head	Number of years	+/-
Gen	Gender	Dummy 1=male, 0=female	+/-
Edu	Education level	Number of years	+
HhSz	Household size	Number of individuals-	+/-
ClosRest	Closure of restaurants and eateries	Dummy 1=yes, 0=no	+
Closwork	Closure of workplaces	Dummy 1=yes, 0=no	+
Incloss	Income loss due to pandemic measures	Dummy 1=yes, 0=no	+
FoodAva	Changes in food availability during the pandemic	Continuous variable: 5-point interval-scale	+/-
ShopFreq	Changes in food shopping frequency	Continuous variable: 5-point interval-scale	+
EatFreq	Eating frequency in terms of the number of daily meals before and during the pandemic	Continuous variable: 5-point interval-scale	+
Prichan	Changes in the price of commodities due to pandemic measure	Continuous variable: 5-point interval-scale	+/-

Results and Discussions

Alternative Combinations of COVID-19 Measures

The study considered the effects of three different interrelated COVID-19 measures: movement restrictions(M), closure of institutions (C), and a ban on social gatherings (B). The effects of these measures were measured as a categorical variable: 1 for positive effect, 0 for no effect, and -1 for negative effect. Joint probability estimation was conducted to establish the interrelationship across the three COVID-19 measures, generating eight possible COVID-19 combined effects. This was based on the configurational joint effects theory, which focuses on how the specific combination or configuration of the COVID-19 measures produced a distinct joint effect on food consumption patterns. The resulting combinations had an estimated joint probability reflecting the interrelationships between the measures. Through examining the most probable combinations, the joint analysis gave a more complete picture than the individual analysis of each measure, which quantified the likelihood of households experiencing those specific joint effect configurations. Therefore, combinations provided insights into the predominant interrelated effects of imposing the COVID-19 measures.

As indicated in Table 3, out of the sampled 246 households, more than half (63.01%) were affected negatively by the three COVID-19 measures (MnCnBn). About 7.32% experienced no effect following the combination of all three COVID-19 measures (MoCoBo), while 6.10% experienced positive effects from the COVID-19 measure (MpCpBp).

During the COVID-19 pandemic, the majority of households experienced negative effects as a result of alternative measures combinations. Due to movement restrictions, there was less trade and transportation of goods within and outside the country. This had a direct negative effect on the income sources of individuals in the country as well as food supply chains, resulting in food unavailability and price increases. The government's designation of certain areas as high-risk worsened the situation, as curfews and quarantines were enforced in those areas. These restrictions on movement made it difficult for households to access and obtain food.

Similar findings were documented by Kodish et al. (2019) and Ouko et al. (2020), who argued that with the rise in COVID-19, containment measures implemented across the country had negative consequences for households, including the movement of food along supply chains leading to spoilage of highly perishable goods, income losses due to institution closures and bans on social gatherings, and nutritional insecurity. While containment measures reduced virus spread, the country also suffered significant economic losses, including foreign exchange earnings from the tourism and hospitality industries, due to movement restrictions.

Nonetheless, the containment measures had some positive effects, which were felt by only 6% of the total interviewed respondents. The benefits accrued from various interventions by the Kenyan government and various stakeholders were among the positive effects of the COVID-19 measures. Among these initiatives are the COVID-19 cash transfer programs, given directly, which targeted low-income households, the elderly, and the most vulnerable (Wangari et al., 2021). Income tax reduction from 30% to 25%, 100% tax exemption for individuals earning less than KES 24000, and VAT reduction from 16% to 14% (Wanjala, 2020) were some of the positive effects of the Kenyan government's COVID-19 measures.

Table 3: Alternative combinations of COVID-19 measures (n=246 households)

COVID-19 Measures Combinations		Frequencies	Percentages(%)
0	MoCoBo	18	7.32
1	MnCoBn	11	4.47
2	MnCnBn	155	63.01
3	MnCnBo	19	7.72
4	MnCoBo	16	6.5
5	MpCpBp	15	6.1
6	MoCnBo	7	2.85
7	MoCnBn	5	2.03

Note: COVID-19 Measure combination represents the eight possible combinations of closure of institutions (C), Ban on social gathering (B), and movement restrictions (M) measures

Determinants of Exposure to Effects of Alternative Combinations of COVID-19 Measures

Before conducting the analysis for objective three, a variance inflation factor (VIF) was applied to assess multicollinearity among the independent variables. The results of the multicollinearity tests revealed that the VIF for all independent variables was below 2.00, with an overall mean of 1.33. This indicated absence/low multicollinearity.

To determine the determinants of exposure to the effects of alternative combinations of COVID-19 measures,a multinomial regression was conducted and the results are presented in Table 4, with their corresponding marginal effects displayed in Table 5. The age of the household food decision-maker had a significant and positive relationship with the negative effects of movement restrictions, institution closures, and social gathering bans (MnCnBn). This suggests that as household food decision-makers age, they are more likely to be negatively affected by COVID-19 measures. A possible explanation for this is that most older people were affected by the pandemic, so the COVID-19 measures did not benefit them but worsened the situation because they could not move around as freely as the younger generation as they were more susceptible to the virus. However, the age of the household food decision-maker had a significant and negative relationship with the negative effects of movement restrictions (MnCoBo). This is consistent with the findings of Shahbaz et al. (2022), who discovered that with government restrictions for older people in most countries, it was difficult for them to obtain food, negatively affecting their livelihoods [18]. Oyando et al. (2021) also found that older people were likely to be affected by disruptions following the pandemic measures.

The occupation of the household head was found to have a significant and negative association with the negative effects of movement restrictions and institution closures (MnCnBo) and movement restrictions (MnCoBo). The occupation of the household head was a significant determinant of how the COVID-19 measures would affect household food consumption patterns. Ideally, the closure of institutions such as schools and workplaces, combined with movement restrictions, had a negative effect on the majority of household heads, who were either laid off from work, went on half-pay, or missed work due to movement restriction, particularly within counties. It was worse for the self-employed who had to get products from different counties. As a result, the COVID-19 measures had a negative effect on such household food consumption patterns.

The study also found occupation was positively associated with the negative effects of institution closures and social gathering bans (MoCnBn). One plausible explanation for this is that, with the closure of eateries/restaurants, people were forced to shift from doing business physically to doing business online to retain their clientele and keep their jobs. While on the same, most residents in the study area are employed on a contract basis or are casual staff in schools, restaurants, or companies. Thus, COVID-19 measures caused stress in their occupations, negatively affecting their income. Despite their limited resources, they were able to do various activities/businesses to help support their families. The findings revealed a significant negative relationship between monthly household income and the negative effects of movement restrictions, institution closures, and social gathering bans (MnCnBn). Loss of jobs, half-pay, business failures that resulted in lower income, and income loss that forced households to bear the burden of the negative effects of the COVID-19 measures such as food insecurity, food price increases, and a lack of socializing amongst themselves. In contrast, monthly household income was found to have a positive relationship with the positive effects of movement restrictions, institution closures, and social gathering bans (MpCpBp). Many households in the study area were forced to consider alternative business ideas to generate income due to income reductions. This allowed businesses and individuals to reinvent themselves to reap the benefits of these positive effects. Mask production and sales, tailoring, and food deliveries at home and work were among these businesses considered at that time, resulting in an increase in their monthly income and demonstrating their entrepreneurial and innovative nature. Kansiime et al. (2021) observed that despite all possible entrepreneurial strategies, citizens in Kenya and Uganda experienced job losses and business closures/reductions, resulting in either a loss of income or a reduction or delay in payments. This contributed significantly to the measures' negative effects because households could not buy food on time, pay their debts and bills on time, and there were disruptions in income-earning activities (ILO, 2020.) because they lacked the necessary capital/resources [11].

The household's daily food consumption frequency was positively associated with the positive effects of COVID-19 measure combinations (MpCpBp). With most of the household members at home, most families experimented with new recipes, and the exchange of ideas on what to eat and the nutritional benefits of the foods was a primary concern. As a result, the beneficial effects of the COVID-19 measures were realized during the pandemic. These included deciding on what food to prepare, preparing food as a family, and spending family time together during meals, which was uncommon prior to the COVID-19 measures. Notably, households' daily food consumption frequency was found to be positive and significantly correlated with the positive effect of COVID-19 measures, according to Profeta et al. (2021).

A negative significant relationship was discovered between household money spending and the positive effects of COVID-19 measures (MpCpBp). An increase in spending would reduce the beneficial effects of COVID-19 measures. With COVID-19 presenting several challenges to households, they were now required to allocate funds equally among all household items, including food. Furthermore, consumers were sharply reducing their discretionary spending, preventing households from benefiting from the positive effects of COVID-19 measures. Being from a low-income household predisposes them to miss out on the benefits of COVID-19 measures. This is because, being from such low socioeconomic status, there is a good chance that they have little or no savings, and their informal employment limits their ability to spend money. As a result, their spending is limited, as documented by Oyando et al. (2021), who indicate that due to their low-income status, such households are more vulnerable to the negative effects of COVID-19 mitigation measures and hence disproportionately affected.

Contrary to expectations, the extent of advance meal planning had a negative significant association with the positive effects of movement restrictions, institution closures, and social gathering bans (MpCpBp). This meant that improving household meal planning would reduce the positive effects of COVID-19 measures. Following the COVID-19 pandemic, households had more time and were expected to be more efficient in food management. That is, planning for adequate and nutritious meals to strengthen their immunity against the COVID-19 virus. However, findings suggest that even with meal planning, households may not be able to reap the benefits of COVID-19 measures. Principato et al. (2022) established contradictory results, documenting that households were more cautious about what food they needed daily. So they planned adequately for their meals, allowing them to benefit from the positive effects of COVID-19 measures by ensuring available food stock last longer and avoiding food waste.

The frequency with which households tried out new recipes was negatively and significantly related to the positive effects of COVID-19 measures (MpCpBp). New recipes frequently have significant costs associated with them, such as research, recipe costs, and risks associated with them, especially during a pandemic. Instead of spending this money on developing new recipes, households would rather keep their old ones to reap the benefits such as immune system boosts and nutritional benefits. Nonetheless, trying out new recipes was the new norm in most parts of the world due to dietary changes and coping with food insecurity that the household experienced [20]. Contrary to the study's findings, trying out new recipes generally contributed to the positive well-being of households during the pandemic.

Meal frequency due to household behaviour change is key in determining whether households would reap the benefits of COVID-19 measures. From this study, this variable was found to be positively and significantly related to the negative effects of the movement restrictions and social gatherings (MnCoBn) and a combination of the three measures (MnCnBn). One plausible explanation is that every unit increase in household meal consumption increases the negative effects of COVID-19 measures. During the pandemic, most households arguably had to change their lifestyles, including their food and eating habits. This meant that whatever income they had, had to be distributed among various household items, or they would be unable to sustain the effects of the measures. Similarly, meal frequency was discovered to have a negative but significant association with the positive effects of the three COVID-19 measures (MpCpBp). With each unit increase in meal frequency, the positive effects of COVID-19 measures are reduced. As a result, any increase in meal frequency would require households to forego other necessities. This increased the adverse effects of the measures, such as being unable to pay rent, buy other household items, pay utilities, or obtain medical services due to the strain on their income also associated meal frequency with negative effects resulting from COVID-19 measures [21].

COVID-19 measures focused heavily on movement restrictions, with people being advised to stay indoors and exercise movement as little as possible. In this regard, the distance travelled to buy groceries from home was negatively and significantly associated with the negative effects of movement restrictions (MnCoBo) and ban on social gatherings (MnCoBn) at a 0.1 significance level. Needless to say, every kilometre a household member moved to buy food increased their chances of contracting the COVID-19 virus [22]. As a result, other household members would be at risk of contracting the virus. Furthermore, given the uncertainty of the pandemic, purchasing food away from home would require household members to buy food in bulk to cover the other days' meals, increasing food insecurity in stores for other households. As a result, every distance travelled to purchase food increased the negative effects of the COVID-19 measures, such as the risk of contracting the virus, food insecurity, and a rise in food prices [23-26].

Market visits became scarce as the country's public transportation cost increased. According to NBS-WB (2020), travelling far from the homestead only intensified the effects of mobility measures because public transportation costs had increased, causing households to spend more on travel [27]. Furthermore, due to the closure of open-air markets, the only available food stores were supermarkets, which benefited from monopoly benefits. They raised product prices, negatively affecting urban low-income households compared to rural households. Furthermore, the distance travelled to buy food was also discovered to have a positive and significant relationship with the positive effects of COVID-19 measures (MpCpBp). Essentially, this means that, due to the negative effects of travel, some households earned income through local door-to-door deliveries during the pandemic [28].

Income change due to COVID-19 was found to have a negative significant relationship with negative effects resulting from the closure of institutions (MoCnBo). Coming from a low-income family, even a small change in income means that the entire household budget must be affected. Because of the pandemic, most people lost their jobs or were forced to work on a rotating schedule with other colleagues, affecting their financial situation [29-31]. Additionally, those who relied on their businesses, such as grocery sales in open-air markets, were affected by the closure/shifting of such markets. Therefore, as much as households attempted to balance household budgets within a limited budget, they found it tough. To survive the pandemic's harsh economic times, a likely transition in their day-to-day life would be required, such as missing meals, food rationing, dietary changes, and increased short-term food availability [32]. These findings were supported by Shahzad et al. (2021), who found that after income changes, households were negatively affected by the negative effects of COVID-19 measures and that the government and charitable organizations had to step in to assist some families by providing financial assistance [33].

Farming by households before COVID-19 was positively and significantly related to the positive effects of COVID-19 measures (MpCpBp). Households that practised farming before the COVID-19 pandemic had a continuous supply of some food categories for their families and were able to sell farm products to get money to cater for other household items, thus greatly benefiting from the positive effects of COVID-19 measures [34]. In their study, Kansiime et al. (2021) found that most of those who practised farming reported losing business due to COVID-19 measures such as school lockdowns, which contradicted the study's findings. Some respondents stated that they used to sell their products in schools, but with restaurants and schools closed, they had no market for their produce, contributing to postharvest losses and thus could not benefit from the measures [35-39].

Table 4: Parameter estimates of alternative COVID-19 measures - using a multinomial logit selection model

Variables (Base category MoCoBo)	MnCoBn	MnCnBn	MnCnBo	MnCoBo	MpCpBp	MoCnBo	MoCnBn
	n=11	n=155	n=19	n=16	n=15	n=7	n=5
	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.
Household characteristics							
Gender of HFDM	0.3258	0.5885	-0.1142	0.7311	-0.5914	-0.0016	3.8391
HFDM level of education	-0.3598	0.2372	0.4067	0.2368	-0.9614	1.0756	-1.4076*
Age of HFDM	-0.646	0.2566	0.4428	-0.8746	0.2616	0.7189	-2.2129
Total household size	-0.0695	0.1094	0.1455	0.1117	0.1524	0.2175	0.3362

Occupation of HOH	-0.6356	0.061	-0.7477	-0.667	0.5806	0.2278	10.6685**
Household monthly income	-0.5429	-0.2852	-0.5033	0.2979	1.6274**	-0.2048	1.1778
Household Behavior Change							
Food eaten	-0.2701	0.1239	0.1481	0.1258	2.4224***	-0.5562	0.6199
Money spent on food	-0.0906	0.1079	0.1651	-0.0997	-1.7042**	0.1231	-1.4266
Extent of advance meal plans	-0.0254	0.1061	-0.1391	0.2167	-1.3914**	-0.1034	0.8262
New recipes often used	-0.4084	0.2571	0.5504	0.6126	-1.0585	-0.3355	-0.0854
Meals frequency	0.6928	-0.0618	-0.2854	-0.577	-2.5107***	0.6916	-4.4715*
Distance to buy food items	-0.8463*	-0.0872	-0.0872	-0.5814	1.1021**	-0.4365	-0.7519
Food thrown away	0.2055	-0.4305*	-0.4995	-0.5549	0.6602	0.0444	2.8357
Income change due to COVID-19	0.3723	1.1675*	1.7682*	0.64	-0.3351	-0.8847	-0.811
Changes in food prices	-0.6148	0.4356	0.7853	0.2481	4.0751	-0.1969	-0.1969
Farming before COVID-19	1.3784	0.1602	0.5651	-0.43	1.9233*	-1.5956	-1.2535
_cons	6.4064*	-0.9278	-2.2728	1.7828	-4.398	-4.0663	-22.7541

Note: *** 1% significance level; **5% significance level; *10% significance level.
Coef = Coefficient; n = Number of respondents

Table 5: Marginal effect, estimates from multinomial logit model (dy/dx)

Variables (Base category MoCoBo)	MnCoBn	MnCnBn	MnCnBo	MnCoBo	MpCpBp	MoCnBo	MoCnBn
	n=11	n=155	n=19	n=16	n=15	n=7	n=5
	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.
Household characteristics							
Gender of HFDM	0.0296	0.0307	-0.0327	0.0222	-0.0308	-0.01	0.0452
HFDM level of education	-0.0207	0.0358	0.0168	0.004	-0.0285	0.0221	-0.0185
Age of HFDM	-0.0293	0.0748*	0.0229	-0.0553*	0.0077	0.0156	-0.0299
Total household size	-0.0065	0.0031	0.0031	0.0006	0.0011	0.0028	0.0028
Occupation of household head	-0.0252	-0.007	-0.0535**	-0.0392**	-0.0009	-0.0006	0.1320**
Household monthly income	-0.0143	-0.0603*	-0.0235	0.0261	0.0473***	-0.0008	0.0143
Household Behaviour change							
Food eaten	-0.0157	-0.018	-0.0014	-0.0022	0.0614***	-0.016	0.0028
Money spent on food	-0.004	0.0553	0.0111	-0.0056	-0.0449**	0.0028	-0.0156
Extent of advance meal plans	-0.0023	0.0384	-0.0124	0.0107	-0.0404**	-0.0042	0.012
New recipes often used	-0.0229	0.0335	0.025	0.0236	-0.0343*	-0.0122	-0.0014
Meals frequency	0.0326*	0.0710*	-0.0079	-0.0215	-0.0572***	0.0211	-0.0509
Distance to buy foodstuff	-0.0278*	0.0185	0.0073	-0.0258*	0.0344***	-0.0066	-0.0097

Food thrown away	0.0191	-0.0762**	-0.0126	-0.0147	0.0217	0.0065	0.0378
Income change due to COVID-19	-0.0193	0.1303	0.058	-0.0159	-0.0324	-0.0411*	-0.019
Changes in food prices	-0.0393	0.0025	0.0228	-0.0112	0.1038	-0.0116	-0.0377
Farming before COVID-19	0.047	-0.0126	0.0257	-0.0355	0.0495**	-0.0409	-0.0196

Note: *** 1% significance level; **5% significance level; *10% significance level.

Coef = Coefficient; n = Number of respondents

Effects of COVID-19 Combinations on Household Food Consumption Patterns

The effects of COVID-19 measures combinations on household food consumption patterns are shown in Table 6. These effects were measured in three ways: positive, negative, and no effects. The MESRM model was used to calculate the estimated effects on household food consumption patterns from the COVID-19 measures for both the ATT and ATU effects. Thus, the results in Table 6 were interpreted in two ways: (1) household food consumption patterns were affected by a single COVID-19 measure (ban on social gatherings, closure of institutions, and movement restrictions), and (2) household food consumption patterns were affected by two or three COVID-19 measures [40-43].

The findings from the study indicate the ATE effect is positive for household food consumption patterns that were affected by a combination of MnCnBn at 1% and MnCnBo and MoCnBn at 5% significant levels [44]. The results revealed that negative effects from a combination of movement restrictions, the ban on social gatherings, and the closure of institutions (MnCnBn) would increase negative changes in household food consumption patterns by 0.28 units. Ideally, with COVID-19 measures in place, most households made bulk purchases of foodstuffs and stockpiles to protect themselves from periods of food scarcity. Fear of the unknown led to a desire to store food due to the ban on social gatherings and movement restrictions [45-48].

On the other hand, MnCnBo and MoCnBn combinations resulted in an increase in the negative changes in food consumption patterns by 0.11 and 0.16 units, respectively. The most likely explanation is that, due to the negative effects of movement restrictions such as border closures and curfews, as well as the closure of institutions (schools, open-air markets, and workplaces), most households had to readjust, necessitating negative effects on consumption patterns. The restrictions on movement restriction, combined with the closure of institutions, critically impacted urban low-income household's ability to reliably access and afford food [49].

In contrast, however, MnCoBn, MnCoBo, and MpCpBp had a significant but negative ATE value at a 1% significant level. The causal implication is that the effects of these combinations (MnCoBn, MnCoBo, and MpCpBp) are likely to reduce the negative changes in household food consumption by 0.21, 4.15 units, and reduce the positive effects on households by 0.38 units, respectively. This means households would be better off if neither of the measures combinations was present.

COVID-19 measures combinations of MnCnBn, MnCnBo, and MoCnBo had a significant ATE value at a 1% significance level, as indicated in Table 4.13 below. This shows that the effects of these combinations of COVID-19 measures were likely to increase the negative changes in household food consumption patterns by 1.95, 2.00, and 2.00, respectively [50].

Table 6: The average treatment effect of COVID-19 measures on household food consumption patterns: multinomial endogenous switching regression estimation

COVID-19 Measures Combinations (CMC)		Household food consumption patterns		
		Associated with CMC	Not associated with any CMC	Treatment effect: ATT/ATU
MnCoBn	Associated	1.73	1.65	0.08
	Not associated	1.64	1.85	-0.21***
	Heterogeneity effect	0.09	-0.2	0.29
MnCnBn	Associated	1.95	1.81	0.13***
	Not associated	1.95	1.67	0.28***
	Heterogeneity effect	0	0.14	-0.15
MnCnBo	Associated	2	1.91	0.93**
	Not associated	2	1.89	0.11***
	Heterogeneity effect	0	0.02	0.82
MnCoBo	Associated	0.76	1.85	-1.09
	Not associated	2.27	1.88	-4.15***
	Heterogeneity effect	-3.03	-0.03	-3.06
MpCpBp	Associated	2.06	2.09	-0.04
	Not associated	1.46	1.84	-0.38***

	Heterogeneity effect	0.6	0.25	0.34
MoCnBo	Associated	1.55	1.83	1.69
	Not associated	1.78	1.86	-0.08
	Heterogeneity effect	-0.23	-0.03	1.77
MoCnBn	Associated	2	1.67	0.33**
	Not associated	2	1.84	0.16***
	Heterogeneity effect	0	-0.17	0.17

Note: *** 1% significance level; **5% significance level; *10% significance level. M - movement restriction, C – closure of institutions, B – ban on social gathering; n – negative effect, p – positive effect, o – no effect

Conclusions and Recommendations

Households FCP were affected positively by the combination of the negative effects of alternative COVID-19 measures (MpCpBp, MnCnBo, and MoCnBn). On the other hand, the negative effects of movement restriction and the positive effects of alternative combinations of COVID-19 measures had a significant but negative ATU value at the 1% significance level. The causal effect is that the effects of these combinations reduced household food consumption. Finally, pandemic measures negatively affected 78% of urban low-income households [51]. Measures taken by the Kenyan Government resulted in significant changes and effects in the household FCP; it is essential that policymakers and the government effectively communicate these measures and their implications before and during implementation. This would help households adjust to new lifestyles without significant negative effects and enable entrepreneurs or businesses to produce locally the materials and tools necessary during a crisis. This spurs household incomes, subsequently minimizing any adverse effects from the policies by tapping any positive opportunity from such policies

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Data Availability

The data is available upon request to the corresponding author.

Conflict of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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