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An Application of Random Effects Generalized Ordered Probit Model on The Drivers of Food Insecurity in Kenya

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ABSTRACT

Food insecurity is a leading health and nutrition issue for decades, especially in developing countries. Despite the good policies implemented by the national and county government to reduce food insecurity status among smallholder farming households, food insecurity is still a challenge in many parts of the country. Thus, the current paper sought to establish the drivers of food insecurity among households in Kenya. Using panel data from the Kenya Covid-19 Rapid Response Phone Survey, the Random effects Generalized ordered Probit model was employed to analyze the factors affecting food insecurity. The three variables revealed the unobserved heterogeneity in the dependent variable. A household being in the central region increased the probability of a household falling into the low dietary diversity (LDD) and medium dietary diversity (MDD) categories by 1.9% ($p<0.10$) and 2.9% ($p<0.01$) compared to households from other regions in Kenya. Also, a household living in the western region has a higher probability of being in the low dietary diversity (LDD) and medium dietary diversity (MDD) categories by 3.1% ($p<0.01$) and 2.1% ($p<0.01$). However, being a year older increases the probability of a household being in the high dietary diversity (HDD) level by 0.1 % ($p<0.01$). Summarily, internet access, mobile phone ownership, and gender had a significant effect across various levels of household dietary diversity. Thus, policy should be tailored to capture region-specific agroecological conditions while households should be encouraged to diversify differently in the crop and livestock production activities as a risk management strategy and as an adaptation strategy against climate change.

Keywords: Food Insecurity, Drivers, Random Effects Generalized Ordered Probit, Smallholder Households, Kenya

RÉSUMÉ

Depuis plusieurs décennies, l'insécurité alimentaire s'impose comme un problème majeur de santé et de nutrition, en particulier dans les pays en développement. Malgré les politiques pertinentes mises en place par les gouvernements nationaux et locaux pour atténuer l'insécurité alimentaire chez les petits exploitants agricoles, ce phénomène demeure un défi dans de nombreuses régions du pays. La présente étude vise ainsi à déterminer les principaux facteurs qui influencent l'insécurité alimentaire au sein des ménages au Kenya. Pour ce faire, nous avons exploité des données de panel issues de l'enquête téléphonique Kenya Covid-19 Rapid Response Phone Survey et recouru à un modèle Probit ordonné généralisé à effets aléatoires afin d'analyser les variables affectant l'insécurité alimentaire. Trois variables majeures ont fait ressortir une hétérogénéité non

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nobservée dans la variable dépendante. Le fait d'appartenir à la région centrale augmente la probabilité, pour un ménage, de se retrouver dans les catégories de faible diversité alimentaire (LDD) et de diversité alimentaire moyenne (MDD) de 1,9 % (p<0,10) et 2,9 % (p<0,01), respectivement, en comparaison avec les ménages d'autres régions. De même, le fait de résider dans la région occidentale accroît la probabilité d'être classé dans les catégories LDD et MDD de 3,1 % (p<0,01) et 2,1 % (p<0,01). En revanche, chaque année supplémentaire de l'âge du chef de ménage augmente de 0,1 % (p<0,01) la probabilité d'atteindre un niveau de haute diversité alimentaire (HDD). Dans l'ensemble, l'accès à Internet, la possession d'un téléphone portable et le genre produisent un effet significatif sur différents niveaux de diversité alimentaire des ménages. En conséquence, les politiques publiques devraient être adaptées aux spécificités agroécologiques de chaque région et encourager les ménages à diversifier leurs activités dans les secteurs de la production végétale et animale. Une telle diversification constitue à la fois une stratégie de gestion des risques et un mécanisme d'adaptation aux changements climatiques.

Mots-clés: Insécurité alimentaire, Facteurs déterminants, Modèle Probit ordonné généralisé à effets aléatoires, Ménages de petits exploitants, Kenya.

INTRODUCTION

Food insecurity is a social determinant of health and sustainable development (McIntyre, 2003), and it is a global concern, with approximately 10% of the world's population and 19% of Africans experiencing severe food insecurity (FAO *et al.*, 2020). That is, they have limited access to sufficient food as a result of inadequate financial capacity and other resources (Nord *et al.*, 2005; Nord *et al.*, 2008). Apart from that, with a Global Hunger Index (GHI) score of approximately 23, which indicates a serious level of hunger in Kenya (GHI, 2019), and the possibility of the COVID-19 pandemic increasing the aggregate number of malnourished people in the world between 83 and 132 million by 2020 (FAO *et al.*, 2020), hence, achieving food security for every Kenyan remains a difficult task. "Food security exists when all people, at all times, have physical and economic access to sufficient, safe, and nutritious food that fits their dietary needs and food preferences for an active and healthy life," according to the World Food Summit of 1996 (WFP, 2009).

A major problem in several Sub-Saharan African countries, including Kenya, is food insecurity, which has persisted since the 1990s (Mota *et al.*, 2019). According to FAO (2019), the number of undernourished persons in Sub-Saharan Africa remained high in 2018, at 239 million. Despite the fact that these Sub-Saharan African countries have made significant progress in terms of welfare and economic growth in recent decades, food security has not been entirely achieved in these countries (Mota *et al.*, 2019). Kenya, like the rest of Sub-Saharan Africa's developing countries, is no exception. The agricultural sector is the leading sector of the economy in most of the sub-Saharan countries and accounts for over half of the GDP and export earnings (IFAD, 2011). In Tanzania, over 80% of the poor live in rural areas and their livelihood depends on agriculture (IFAD, 2011). The main producer in the agriculture sector in sub-Saharan Africa is the smallholder farmer. In Ethiopia, Agricultural sector contributes about 43% of the Gross Domestic Product (GDP), 80% of employment, and also about 90% of export (Demese *et al.*, 2010). Smallholder farmers account for more than 85% of the rural population that relies on agricultural production in Ethiopia.

Nearly 16.4 million Kenyan households live in poverty, according to the Kenya National Bureau of Statistics (KNBS, 2018). According to FAO's most recent estimates, over 10 million Kenyans are food insecure, unable to meet their dietary energy requirements, with the majority relying on food aid (FAO, 2019). Food security, on the other hand, has long been a priority for Kenya's agricultural sector (GoK, 2018). Despite the fact that the agricultural sector is the backbone of Kenya's economy, accounting for 24 percent of GDP, 45 percent of government revenue, 50 percent of export earnings, 27 percent of GDP through linkages with manufacturing, distribution, and other service-related sectors, 75 percent of industrial raw materials, and 60 percent of total employment, the country's under-nutrition rate is 29.4 percent (FAO, 2017; KNBS, 2020). According to Food and Agriculture Organization (2017) report, food insecurity had decreased from 48.5 percent in 2003 to 26.7 percent in 2017. Over 80% of Kenya's population lives in rural areas, where they make their living mostly from agricultural pursuits (KNBS, 2019). More than 80% of these people are small-scale farmers with less than 5 acres of land. Smallholder households in Kenya are the most vulnerable to food insecurity because they lack access to land to deal with the unpredictability of their daily food supply (KNBS, 2019).

According to the Kenya Demographic and Health Survey (KDHS, 2014), 25% of children under the age of five are stunted in Kenya. Poverty, sickness, and household resource limits are among the contributing issues that many Kenyans experience. Acute malnutrition in childhood has irrevocable long-term consequences. A malnourished youngster is less able to resist sickness, cannot flourish, and often has poor cognitive and physical development. Due to poor attention, reasoning, learning, and memory, such youngsters are less likely to realize great academic achievement (KDHS, 2014). Individuals affected eventually become locked in a cycle of poverty and starvation that is difficult to break without outside assistance. As a result, accomplishing human development goals requires good nutrition balance through dietary diversification (Benin, 2016). According to Badiane and Collins (2016), it is critical to assure the availability of a broad, wholesome, and nutritious diet, not only for survival, but also for people to thrive and grow to their full potential in order to contribute meaningfully to the country's socioeconomic progress.

The Household Dietary Diversity Score (HDDS) is a qualitative technique that has been validated in a number of countries as a proxy indicator of food availability and accessibility (Hoddinatt and Yohannes, 2002; Ruel, 2003; WFP, 2009). The HDDS calculates the quantity of different food groups ingested in a household over a set time period, such as the previous 24 or 48 hours or the previous 7 or 14 days (FAO, 2008; WFP, 2012). As a result, a diversified diet is linked to a household's economic ability to obtain a variety of meals by obtaining a number of different food groups consumed throughout a set period of time (Cordero-Ahiman *et al.,* 2017; Koppmair *et al.*, 2017). In other words, a rise in dietary diversity is linked to stable socioeconomic position and increase in food security of households.

This study aimed to examine the determinants of food insecurity in Kenya and at the same time analyse the differences in household dietary diversity categories and a range of socio-economic, institutional, and regional factors influencing household dietary diversity to provide reliable information for policy suggestions to promote household dietary diversity and hence improved food security.

Food security is of programmatic importance to policy makers in low- and middle-income countries that are characterized by urban poverty and low rates of food production, high food prices and unemployment, yet there remains a paucity of information on the key drivers of food security especially among the poor households. The existing evidence on determinants of food security has several methodological limitations. First, most existing studies are cross sectional in nature and thus limited in the extent to which causal inferences can be made and fail to capture intra-household dynamics over time. Secondly, many studies categorize food security as a dichotomy and thus may fail to capture important nuances in household food security. Thirdly, most of the existing studies do not capture the heterogeneity in the categorized food security and determine which variables causes heterogeneity in the food security model.

Most papers use ordered probit or logit, assuming that the coefficients of independent variables do not vary between categories of the dependent variable. This assumption conceals possible heterogenous effects of some independent variables. To fill this gap, the current study used random effects generalized ordered probit model (Pfarr *et al.,* 2011) to identify the correlation with household dietary diversity and how the cut-points vary in assessing food security vary with its determinants. The current study addressed these limitations by using more than two categories of food security and used the random effects generalized ordered probit model which measures the heterogeneity effect in the model and identified the variables that drive heterogeneity in the model. Lastly, the current study used panel data to allow the causal inference over time and capture intra-household dynamics over time.

The second section contains a discussion on the methodology of the study; the third section provides a detailed discussion of the results while the fourth section contains the conclusions and recommendations of the study.

MATERIALS and METHODS

Data and Analytical Framework. This study relied heavily on the four-wave panel data from the household and individual survey questionnaire from the Kenya Covid-19 Rapid Response Phone Survey conducted by The World Bank in collaboration with the Kenya National Bureau of Statistics and Berkeley University.

The outcome variable is ordinal, which implies that there is a hierarchy of food security in terms of importance. The estimation of the determinants of household food security in this situation is best accomplished using an ordered probit model. When considering ordinal outcomes in an ordered probit model, it is assumed that there are cutoffs between them, but that the distance between them is not exact. Hence, following Pfarr *et al.,* (2010), the current study considered three observed categories of self-reported food security status with y^*as the underlying latent food security status. Thus, we let y be the ordered categorical outcome, a cross-section ordered probit model is written as:

$$\Pr[y \leq j|x] = F(k_j - x'\beta) \qquad j = 1, \dots, J \tag{1}$$

Where k_j and β are unknown threshold parameters and coefficients, respectively, and j is a vector of peculiar, ordered categories. The function F denotes a cumulative standard normal distribution. The discrete outcomes are explained by a vector of x covariates. Introducing the latent variable y* into Equation (1) gives:

$$y = j \quad \text{if and only if} \quad k_{j-1} \leq y^* = x'\beta + u < k_j \tag{2}$$

Where u is the unobserved disturbance term that, together with observable factors x influences the latent variable, y^*

The interpretation of the threshold is that it divides the linear slopes into j categories. The ordered model as specified in Equation (2) assumes a zero mean and a constant variance.

The probability that the respondent's self-reported household dietary diversity status would be one out of the possible three, which can be written in the form:

$$\Pr[y \leq j|x] = F(k_j - x'\beta) - F(k_{j-1} - x'\beta) \tag{3}$$

However, according to Pfarr *et al.* (2010), the standard ordered probit model (specified in Equations (1) through (3) is anchored on parallel-lines assumption. The assumption is that the parameter estimates are constant between the categories. This implies that the parallel-lines assumption ignores the possibility of heterogeneity of some of the independent variables. Generalized ordered probit is appropriate when the parallel-lines assumption is violated. According to Pfarr *et al.* (2010), the generalized ordered probit model assumes that the threshold parameters depend on covariates such that:

$$k_j = \overline{k_j} + x'\gamma_j \tag{4}$$

Where γ_j are the coefficients of threshold covariates. Introducing the threshold Equation (4) into (3) leads to a cumulative probability of generalized ordered probit model, hence:

$$\Pr[y \leq j|x] = F(\tilde{k}_j + x'\gamma - x'\beta) = F(\tilde{k}_{j-1} - x'\beta_j) \qquad j = 1, \dots, j \tag{5}$$

Equation (5) estimates $j-1$ binary probit models which allow further estimation of $x'\beta_j$ for each distinct category j. Thus, the generalized ordered probit model accounts for parameter heterogeneity (Pfarr *et al.*, 2010).

The true food security status, individual $i's$ status in time t, is an unobserved latent variable governed by the equation (6)

$$Y_{it}^* = \alpha_i + x'_{it}\beta + \varepsilon_{it}, \varepsilon_{it} \sim N(0,1) \quad (6)$$

Where; x'_{it} is the vector of independent variables which help to determine the true food security status. In the random effect panel data model, α_i represents an individual effect with zero mean and variance σ^2 so $\rho = \sigma^2/(1+\sigma^2)$ is the share of the total variability in Y_{it}^*, attributable to the individual effect. The vector β are parameters and ε_{it} is a random term independent of individual characteristics.

Considering Y_{it}^s, as the self-reported food security status indicator, which was later categorized into three ordinal points, the following underlying regression were assumed;

$$Y_{it}^s = 1 \leftrightarrow Y_{it}^* \leq \mu_{i1}$$

$$Y_{it}^s = 2 \leftrightarrow \mu_{i2} < Y_{it}^* \leq \mu_{i2} \quad (7)$$

$$Y_{it}^s = 3 \leftrightarrow Y_{it}^* > \mu_{i3}$$

$$\mu_{ij} = \mu_j + z_i'\gamma_j \quad (8)$$

Which is a form of censoring.

Where; $J = 1$ *is LDD* (Low Dietary Diversity), $J = 2$ *is MDD* (Medium Dietary Diversity) and $J = 3$ *is HDD* (High Dietary Diversity). These are the ordinal categories of food security status as utilized in the current study. The μ_{ij}'s are unknown individual specific parameters to be estimated with β.

With the three categories, two thresholds are established such that; $\mu_{i1} = 0, \mu_{i2} = \mu_2 + z_i'\gamma_2$. Where γ_2 is a parameter to be estimated and z_i is a subset of x_{it}. The model is equivalent to two binary probit regressions where categories of the dependent variables are combined. To find μ_{i1}, category $Y_{it}^s = 1$, is contrasted against categories $Y_{it}^s = 2,3$; to find μ_{i2}, categories $Y_{it}^s = 1,2$ are contrasted against category $Y_{it}^s = 3$ (William, 2006). If γ_2 is nonzero, the threshold is conditional on z_i, unlike the normal standard probit model where the thresholds are the same for all individuals since it assumes that the categories are "parallel" and differ only by the intercept. However, the generalized ordered probit does not impose this assumption, which is often violated in practice. Thus, the generalized ordered probit model accounts for individual heterogeneity through the thresholds. Therefore, imposing the functional forms for the thresholds, we have;

$$Y_{it}^s = 1 \; if \; Y_{it}^* \leq 0$$

$$Y_{it}^s = 2 \; if \; 0 \leq Y_{it}^* \leq \mu_2 + z_i'\gamma_2 \quad (9)$$

$$Y_{it}^s = 3 \; if \; Y_{it}^* \geq \mu_2 + z_i'\gamma_2$$

Considering the nature of the data used in this study as panel data, random effects (RE) generalized ordered probit model would be appropriate for fitting the household, farm, institutional and region characteristics affecting household food security. The probabilities of the RE generalized ordered probit model is given as;

$$\Pr(Y_{it}^s = 1|x_{it}, z_{it}) = [F(-x'_{it}\beta - \alpha_i)],$$

$$\Pr(Y_{it}^s = 2|x_{it}, z_{it}) = [F(\mu_2 + z_i'\gamma_2 - (x'_{it}\beta + \alpha_i)) - F(-x'_{it}\beta - \alpha_i)], \quad (10)$$

$$\Pr(Y_{it}^s = 3|x_{it}, z_{it}) = [1 - F(\mu_2 + z_i'\gamma_2 - (x'_{it}\beta + \alpha_i))]$$

Therfores, the MLE and corresponding log-likelihood function is estimated as shown in equation (11)

$$lnL = \sum_{Y_{it}^s=1} F(-x'_{it}\beta - \alpha_i) + \sum_{Y_{it}^s=2} [F(\mu_2 + z_i'\gamma_2 - (x'_{it}\beta + \alpha_i)) - F(-x'_{it}\beta - \alpha_i)] + \sum_{Y_{it}^s=3} [1 - F(\mu_2 + z_i'\gamma_2 - (x'_{it}\beta + \alpha_i))] \quad (11)$$

Given that the RE generalized ordered probit model is inherently nonlinear in its coefficients, its estimated parameters do not by themselves represent the marginal effects of the explanatory variables on the dependent variables. Instead, the marginal effects are functions of both parameters and the data. Thus, the category-specific marginal effects, can be computed as (Wooldridge, 2006; Greene, 2012):

$$\frac{\vartheta \Pr\left(Y_{it}^{s}=1 \middle| x_{it}, z_{it}\right)}{\vartheta x_{it}} = \left[-F(x'_{it}\beta - \alpha_i)\beta\right],$$

$$\frac{\vartheta \Pr\left(Y_{it}^{s}=2 \middle| x_{it}, z_{it}\right)}{\vartheta x_{it}} = \left[F(-x'_{it}\beta - \alpha_i)\beta - F\left(\mu_2 + z_i'\gamma_2 - (x'_{it}\beta + \alpha_i)\beta\right)\right], \quad (12)$$

$$\frac{\vartheta \Pr\left(Y_{it}^{s}=3 \middle| x_{it}, z_{it}\right)}{\vartheta x_{it}} = \left[F(\mu_2 + z_i'\gamma_2 - x'_{it}\beta - \alpha_i)\beta\right]$$

Where; F is the standard normal cumulative distribution function. The marginal effects of household, farm, institutional and region characteristics affecting food insecurity, shows the percentage points of reporting a given category of HDDS, since only one category can be reported at a time. Additionally, compared to the standard cross-section generalized ordered probit model, RE generalized ordered probit model "outcome probabilities are conditional on the individual effects (α_i)'' (Pfarr *et al.*, 2010). Furthermore, the model assumes a zero mean and a constant variance. The outcome variable in Equation (10) is self-reported household dietary diversity categories measuring household food security. The independent variables, denoted by x_{it}, include demographic, institutional, and regional variables. The data was analyzed using the REGOPROB2 command (Pfarr *et al.*, 2011)

ESTIMATION and DISCUSSION OF RESULTS Descriptive

Statistics: Table 1 shows the demographic characteristics of households by household dietary diversity category. The proportion of female headed household was slightly lower for MDD and HDD as compared to LDD by 1.3% and 1.2% respectively. This shows that more females are experiencing low dietary diversity. However, there was no significant relationship between gender and household dietary diversity. Summarily, the results indicate that females consisted of 34.07% on average across the dietary diversity categories as compared to males. This reveals that there is more male dominance on decision making about agricultural activities, in terms of resource use, production decision, leadership matters and use of income, making the voice of women unheard. Adubra *et al.* (2019) found that only 19% of the households were headed by the women and that most of the households were headed by men which further justifies the male dominance in decision making relating to all agricultural activities in the household.

The age of the respondent, on average, was 43.63 years with the lowest average age of 43.03 years falling in the HDD and highest average age of 44.35 years falling in the LDD while the average age of the respondents across the three categories of household dietary diversity was approximately 47 years. Most importantly, there was a very significant (p<0.01) relationship between age of the respondent and household dietary diversity. However, Hashmi *et al.* (2021) found that the average of the participants was 32.5 years in his study on 'Association between dietary diversity and food insecurity in urban households: a cross-sectional survey of various ethnic populations of Karachi, Pakistan'. This average age was lower than the average age of the participants for the current study. Also, Adubra *et al.* (2019) found that the average age of the women was 28.56 years with a standard age deviation of 0.13. Typically, most of the respondents were the elderly adults.

More than 50% of the households live in urban areas where on average, the proportion of households living in urban areas was approximately 55%. All the three categories of HDDS recorded more that 50% of the household lived in urban areas. However, there was no significant relationship between households living in urban areas and household dietary diversity. This can be due to the impact of devolution which has transitioned most of the small centres in the counties into towns, allowing for increase in economic activities hence creating better opportunities for the residents to improve their livelihoods. The average wealth index score was 3.290 units. While the lowest average wealth index score was about 3.263 in MDD category, HDD category recorded the highest average wealth index scores of 3.3306. Despite the low average wealth index scores reported across the three categories, there was a significant ($p<0.01$) relationship between wealth index and the household dietary diversity. On average, about 12.73% of the total sample size receive remittance, with HDD category recording the lowest proportion (11.56%) of receiving remittances while MDD category recorded the highest percentage (13.61%) of receiving remittances. However, the relationship between remittances and the household dietary diversity was insignificant. Remittances act as buffers to household food security. It enhances household's options of diverse diets by increasing their purchasing power.

Table 1. Descriptive Statistics

Variables	Measurement	HDDS Categories (Means/proportions)			
		LDD	*MDD*	*HDD*	*Overall*
Gender	1=Female, 0=Male	.3489	.3358	.3374	.3407
Age	Years	44.35	43.46	43.03	43.61***
Urban	1=Urban,0=Rural	.5363	.5502	.5311	.5392
Wealth index	Scores	3.303	3.263	3.306	3.290***
Remittances	1=Yes, 0=No	.1303	.1361	.1156	.1273
Credit access	1=Yes, 0=No	.1275	.1280	.1437	.1331
Internet access	1=Yes, 0=No	.0661	.0686	.0785	.0711**
School children	Numbers	1.387	1.369	1.431	1.396
Mobile phone	Numbers	2.206	2.190	2.192	2.196
Agricultural activity	1=Yes, 0=No	.5162	.4857	.4797	.4939**
Central	1=Yes, 0=Otherwise	.1905	.1973	.1695	.1858**
Western	1=Yes, 0=Otherwise	.5380	.5022	.5247	.5216***

NB: Chi-Square test was used to determine the relationship between the socioeconomic, institutional and region characteristics and the household dietary diversity.
****, **, * shows statistically significant relationship between independent variables and HDDS levels at 0.01, 0.05 and 0.1 levels respectively; LDD denotes low dietary diversity; MDD denotes medium dietary diversity; HDD denotes high dietary diversity*
Source: Author (2021)

Access to credit among households help to improve household food security. It enhances production of diverse food groups. In this study, the average proportion of households who accessed credit was 13.31%. The HDD Category revealed highest proportion (14.37%) of access to credit services compared to the LDD category that showed lowest proportion (12.75%) of households who reported to have access to credit services. The relationship between access to credit and household dietary diversity was insignificant. Access to credit services is very vital specially to farming households. Credit enhances their productivity by enabling them purchase farm inputs, expand their farm enterprises. A very small proportion (6.68% on average) of the households accessed the internet as shown in table 2. Access to the internet among households increased across the LDD to the HDD categories with LDD category recording 6.61%, MDD category recording about 6.86% while HDD category recording 7.85%. Thus, access to the internet among households increase their access to information on dieting, hence improving their dietary diversity. Though, the proportion of the households who accessed internet is small, there is a significant ($p<0.05$) relationship between access to the internet and household dietary diversity. Thus, internet access among households plays a key role in improving their diets and hence improved food security.

On average**,** every household had one school child. Also, across the three categories of HDDS, the average number of children per household was one child. However, the relationship between number of school children and household dietary diversity was insignificant. Having children in a household makes the households to plan well for their dietary diversity and thus the children nutrition enhanced. On the other hand, presence of school children can be seen as presence of dependants since they are depending on their parents for food, shelter, clothing, and education, though by rule of law, is their right for such basic necessities. The descriptive results in table 2 shows that on average, every household recorded to have at least two mobile phones across the three categories of HDDS. However, there was no significant relationship between the number of mobile phones owned by a household and the household dietary diversity. Having a mobile increases the rate of communication across the country. It also enhances financial access but also increases the cost of transactions especially in sending and receiving funds. Mobile phones enable households to receive remittances on time thus improving their dietary diversity. However, Butt (2015) cited that the possible reasons for owning and not using mobile phones are poor network coverage, weak electricity infrastructure, or insufficient mobile phone credit.

Households that participate in agricultural activities were about 50% on average with HDD category recording the lowest proportion (47.97%) of households participating in agricultural activities while LDD category recording the highest proportion (51.62%) of households participating in agricultural activities. Notably, there was significant ($p<0.05$) relationship between a household participating in agricultural activities and household dietary diversity. Engaging in agricultural activities promotes household dietary diversity and hence improving food security. There is a possibility that those who experience high dietary diversity could be relying on food purchases as compared to those who are experiencing low dietary diversity. On average, the total number of households from the Central region were about 18.58%. While those in MDD category recorded the highest proportion (19.73%) of households coming from Central region, the HDD category recorded the lowest proportion (16.95) of households coming from Central region. There was also as significant ($p<0.05$) relationship between households in central region and their dietary diversities. on the other hand, households from Western region were about 52.16% on average. Those in LDD category of the HDDS recorded the highest proportion of about 53.80% while those in MDD category recorded the lowest of proportion (50.22%) of households from Western region. The relationship between a household coming from western region and household dietary diversity was significant ($p<0.01$). This shows that regions play important role in household dietary diversity. Thus, different regions in Kenya have different climatic conditions. In addition, they have different agricultural ecological zones. These differences affect agricultural production and informs the households dietary diversity and hence household food security.

Empirical Results

The final model did not violate the parallel lines assumption as shown by the global Wald test of parallel lines assumption (chi2 (27) =32.19, Prob>chi2=0.2251) as suggested by Pfarr *et al* (2010). The random effects generalized ordered probit model was best fitting as shown by the Wald chi2(21) =90.93, significant at $p<0.01$. The autofit procedure was employed to trigger an iterative process that helped to identify the random effects generalized ordered probit model that best fits the data (Pfarr *et al.*, 2011). The first step in the estimation process was the model with full variation of all the twelve explanatory variables. After ten iterations, the null hypothesis of equal coefficients was rejected for the variables age, central and western. Hence the final model consisted of nine constrained and three varying variables. Thence, in contrast to the full varying model, the autofit specification was preferable as it reflected best the observable heterogeneity in the data. The influence of unobserved heterogeneity in the HDDS categories was measured by rho, which is the correlation of the error terms. Thus, the three variables, age, central and western drive the observed heterogeneity in the dependent variable household dietary diversity.

Table 2 shows the results for random effects ordered probit (REOPROB) model and the random effects generalized ordered probit

(REGOPROB) model. The random effects ordered probit model was used for robustness checks. Since the coefficients of the random effects ordered probit and the random effects generalized ordered probit model do not represent the magnitude of the effects of the explanatory variables, the marginal effects are discussed as shown in table 3. These marginal effects are interpreted based on the sign and the category. An estimated positive coefficient for a category indicates that an increase in that variable increases the probability of being in that category while a negative coefficient indicates a decrease in probability of being in that category. In addition, the marginal effects corresponding to the significant variables are also significant.

Gender was positively and significantly ($p<0.05$) related to LDD and MDD categories while it was negatively and significantly ($p<0.10$) related to HDD category. Thus, being a female headed household increase the probability of being in low dietary diversity and medium dietary diversity categories by 1.2% and 0.3% respectively compared to their male headed household counterparts. On the other hand, being a female headed household decreases the probability of being in high dietary diversity category by 0.02% compared to their male headed household counterparts. This explains the fact that female headed household roles in contributing towards food security are still undermined. They are not fully involved in production decisions, use of income for economic purposes and they also have limited access to financial resources compared to males who have full control over use of resources in the family (Alkire *et al.*, 2013). Men are the key decision makers in the household on utilization of productive resources, incomes and mainly hold several key roles in the society and even in farmer groups and cooperatives. Yet in real sense, women are the key players in household food production and consumption, they have better inputs in terms of dietary diversity and hence food security in the households. In tandem, gender of the household head has implications for the kinds of foods that the household purchases and ultimately consumes (Mofya-Mukuka and Kuhgatz, 2015).

The age of the household head is one of the variables that contributed to the observed heterogeneity in the dependent variable. Age of the household head had a positive marginal effect on HDD category. The relationship was significant at 1% level. Thus, increasing the age of the household head by one year increases the probability of being in high dietary diversity category by 0.1% respectively. Thus, with age increases the likelihood of experiencing high diversity in diets especially among the adults and the elderly. This implies that younger people can experience lower levels of dietary diversity since most of them either are in college or university or looking for jobs. The study findings do not agree with Merckel (2015) who found that children and youth were more likely to have a diet more diverse than their household average, while adults aged 36 to 55 were significantly more likely to have a diet less diverse than the household average. She also found that women are more likely to have a diet less than the household average especially those age 26 to 35 compared to their male counterparts. Moreover, the findings also resonate with the findings of Habtemariam *et al.*, (2021) who found that age had a negative but weak significant effect on food consumption of diverse diets among adolescents.

Being in an urban set up increases significantly ($p<0.05$) the probability of being in LDD category and MDD category by 1.3% and 0.3% respectively compared to rural households while at the same time decreases significantly ($p<0.10$) the probability of being in HDD category by 0.02% respectively compared to rural households. Thus, households in urban areas have limited options to enjoy highly diverse food because of several challenges such as limited farming space, high cost of living (Ren *et al.*, 2019), sometimes limited water for farming, legal barriers which negatively affects them from diversifying in food production for increased dietary diversity and hence improved food security (Sibhatu *et al.*, 2015). On the other hand, the rural households can enjoy diverse diets since they have relatively larger pieces of land for production and diversification, the cost of living is very low, they little income from farm can sustain their food security needs compared to those households in urban areas (Fischer and Qaim, 2012; Chiputwa and Qaim, 2016).

Access to the internet in a household has a negative and significant ($p<0.01$) effect on the probability of a household being in LDD category and MDD category 2.5%, and 0.7% respectively compared to those who have no access to the internet. On the other hand, access to the internet by a household significantly ($p<0.10$) increases the probability of a household falling in HDD category by 0.04% compared to the households who have no access to the internet. Overally, internet access had an increasing effect from LDD to HDD through MDD. These results are supported by the findings of Xue *et al.*, (2021) who found that internet access have a significant effect on nutritional intake among households. Internet access promotes various intake of diverse foods in both the urban and rural areas and, also increases their willingness to consume both food and other products through online shopping (Yuan *et al.*, 2019). The internet breaks the constraints of market access especially among the rural households (Hou, 2018). It also reduces the cost of transportation and save time for other economic and social productive activities (Ma *et al.*, 2020).

Mobile phones in household had a negative and significant ($p<0.05$) effect on the probability of a household falling in LDD and MDD categories by 0.5% and 0.1% respectively. On the other side, mobile phones had a positive and significant ($p<0.10$) effect of the probability of a household falling in HDD category by 0.01%. Generally, the marginal effect of mobile phones on the probability of a household to fall in any category of the HDDS is increasing from LDD to HDD through MDD. Mobile phones increase access to finances among the small holder farming households (Aker and Ksoll, 2016). They are also a promising tool to improve the livelihoods of smallholder farmers in developing countries (Aker and Mbiti, 2010; Nakasone *et al.,* 2014). In Africa, over the last few decades, research shows that mobile phones to promote several economic dimensions including agricultural productivity, market participation and nutrition and food security (Zanello, 2012; Lio and Liu, 2006; Butt, 2015). The study findings also agree with Beuermann, McKelvey and Vakis (2012) who found that mobile phones are associated with improved diets in coffee-producing farm households in Uganda using two rounds of a panel survey. Also, mobile phones adoption and use are positively and significantly associated with dietary diversity through better access to purchased food (Parlasca *et al*., 2020).

The variables central and western were used as regional dummy variables to control for regional variation. The two variables together with the age of the household contributed to the observed heterogeneity in the dependent variable. The variable central had a positive and significant relationship with LDD and MDD categories and a negative and significant relationship with HDD category. A household being in central region increased the probability of falling in lower dietary diversity and medium dietary diversity categories by 1.9% ($p<0.10$) and 2.9% ($p<0.01$) respectively while it reduced the probability of falling in high dietary diversity category by 1.8% ($p<0.05$) compared to households from other regions in Kenya. The regional variable western had significant and positive relationship on LDD and MDD category while it had a negative and significant effect on HDD category. Therefore, a household living in western region has a higher probability of being in low dietary diversity category and medium dietary diversity category by 3.1% ($p<0.01$) and 2.1% ($p<0.01$) respectively. On the other hand, a household being in western region decreases their probability of falling in high dietary diversity category by 3.1%. The two regions used in this study is to capture two different agricultural systems thus allowing to control for regional differences. Such differences in regional effects on the probability of a household falling in any category of the HDDS implies that probably household diversify differently in the crop and livestock production activities as a risk management strategy and as an adaptation strategy against climate change (Brüssow *et al.*, 2019). In addition, the regional variables can also represent the biophysical potential of the environment to produce food that, in turns, affects food availability and diets through direct consumption or as a source of income to purchased food. In tandem with this study, Habtemariam *et al.*, (2021) found that region as a control variable had a significant and positive relationship with food consumption of diverse diets.

Table 2. Random Effects Ordered Probit and Random Effects Generalized Ordered Probit

Variables	**REOPROBIT**	**REGOPROB**	
	HDDS	**MDD**	**HDD**
	Coef.	**Coef.**	**Coef.**
Gender	-0.039**	-0.040**	-0.040**
	(0.018)	(0.018)	(0.018)
Age	-0.001*	0.001	-0.002***
	(0.001)	(0.001)	(0.001)
Urban	-0.042**	-0.042**	-0.042**
	(0.017)	(0.017)	(0.017)
Wealth index	--0.006	-0.006	-0.006
	(0.005)	(0.005)	(0.005)
Remittances	-0.022	-0.022	-0.022
	(0.025)	(0.025)	(0.025)
Credit access	0.029	0.029	0.029
	(0.025)	(0.025)	(0.025)
Internet access	0.084***	0.082***	0.082***
	(0.032)	(0.032)	(0.032)
School children	0.004	0.004	0.004
	(0.006)	(0.006)	(0.006)
Mobile phone	0.016**	0.016**	0.016**
	(0.007)	(0.007)	(0.007)
Agricultural activity	-0.027	-0.027	-0.027
	(0.018)	(0.018)	(0.018)
Central	-0.035	0.026	-0.022*
	(0.025)	(0.030)	(0.030)
Western	-0.053***	-0.001	-0.055**
	(0.020)	(0.023)	(0.023)
_cons		0.799*** (0.048)	-0.115** 0.045)
_cut1 - cons	-0.834***		
	(0.042)		
_cut2 - cons	0.164***		
	(0.041)		
rho - cons	0.032***	0.032***	0.032***
	(0.008)	(0.008)	(0.008)
Log likelihood	-26146.006	-26120.133	-26120.133
LR chi2(12)	40.51		
Wald chi2(21)		90.93	90.93
Prob>chi2	0.0001	0.0000	0.0000
AIC	52326.01	52292.270	52292.270
BIC	52456.9	52492.450	52492.450

****, **, * shows coefficients are statistically significant at 0.01, 0.05 and 0.1 levels respectively. Standard errors are in brackets*

Source: Author (2021)

Robustness checks. The random effects ordered probit model was used to check the robustness of the results. The model was best fitting as shown by the log likelihood=-26146.006 where the Wald chi square likelihood ratio test=40.51 was significant at Prob> chi2=0.0001. being a female headed household and coming from an urban area in western region had a negative and significant influence on the household dietary diversity as compared to a male headed household who comes from a rural area in western region. The age of the household had a negative and significant effect on the household dietary diversity, thus the elderly had less diverse diets compared to the youth and young adults. The households who had access to internet and in possession of a mobile phone had positive and significant effect on the household dietary diversity in Kenya. However, the random effects ordered probit model has limitations since it cannot reveal the level of heterogeneity the household dietary diversity variable. Thus, the random effects generalized ordered probit model reveal the heterogeneity between the three outcomes of the dependent variable.

Table 3. Marginal effects of Random Effects Ordered Probit and Random Effects Generalized Ordered Probit

	Marginal Effects			
	REOPROBIT	**REGOPROB**		
	HDDS	**LDD**	**MDD**	**HDD**
	dy/dx	**dy/dx**	**dy/dx**	**dy/dx**
Gender	-0.039**	0.012**	0.003**	-0.0002*
	(0.018)	(0.005)	(0.001)	(0.0001)
Age	-0.001*	-0.00015	0.0003	0.001***
	(0.001)	(0.00024)	(0.002)	(0.0002)
Urban	-0.042**	0.013**	0.003**	-0.0002*
	(0.017)	(0.005)	(0.001)	(0.0001)
Wealth index	-0.006	0.002	0.0005	-0.00002
	(0.005)	(0.002)	(0.0004)	(0.00003)
Remittances	-0.022	0.007	0.002	-0.0001
	(0.025)	(0.007)	(0.002)	(0.0001)
Credit access	0.029	-0.009	-0.002	0.0001
	(0.025)	(0.007)	(0.025)	(0.0001)
Internet access	0.084***	-0.025***	-0.007***	0.0004*
	(0.032)	(0.010)	(0.003)	(0.0002)
School children	0.004	-0.001	-0.0003	0.00002 (0.00003)
	(0.006)	(0.002)	(0.0005)	
Mobile phone	0.016**	-0.005**	-0.001**	0.0001*
	(0.007)	(0.002)	(0.001)	(0.00004)
Agricultural activity	-0.027	0.008	0.002	-0.0001
	(0.018)	(0.006)	(0.001)	(0.0001)
Central	-0.035	0.019*	0.029***	-0.018**
	(0.025)	(0.010)	(0.009)	(0.009)
Western	-0.053***	0.031***	0.021***	-0.031***
	(0.020)	(0.008)	(0.007)	(0.007)

****, **, * shows coefficients are statistically significant at 0.01, 0.05 and 0.1 levels respectively. Standard errors are in brackets. dy/dx is for discrete change of dummy variable from 0 to 1*

Source; Author (2021)

CONCLUSIONS and RECOMMENDATIONS

The current study adds value to the body of knowledge by analysing the determinants of food insecurity in Kenya using random effects generalized ordered probit model that accounts the unobserved heterogeneity and time effects.

However, one key issue with generalized ordered probit models is that prior information or knowledge of the theories that underlie the violation of parallel line assumption may not be available in case of outcomes with more than two categories. Such that no one can tell in advance which variables violate or do not violate the assumption in an ordered outcome. However, this problem is overcome by using the autofit procedure as employed by Pfarr *et al.* (2011). The autofit procedure provides a robust analytical approach to identifying the variables that do not violate the parallel lines assumption by using sequential modelling and employing the Global Wald test. For this study, the age of the household and the two region dummy variables, central and western, did not violate the parallel line assumptions. They revealed the unobserved heterogeneity in the household dietary diversity variable.

Women experience high food insecurity as revealed by their low dietary diversity. This is associated with low access to financial resources, they are rarely involved in production decisions. The male dominance in household and farm related activities lowers their chances of utilizing the available opportunities to better their household diets. Age of the household positively influenced their dietary diversities while being in urban set up showed to lower the probability of being in a higher dietary diversity. Access to the internet was good determinant of influencing the probability of a household achieving a higher dietary diversity. Also, mobile phone affected the probability of a household falling in a higher HDD while it also reduced the probability of the household from falling in a lower dietary diversity.

Women should be empowered to positively contribute towards household dietary diversity. Households should be continually educated on good and better family diets, both the youth, adults, and the elderly. This will ensure increased high dietary diversity hence improved food security. Among households living in urban areas, kitchen gardening be encouraged to increase range of food items for the family which will lead to households shifting from LDD and MDD to HDD. Government can implement policies that reduces that cost of living in urban areas for households to afford variety of food items thus increasing their food security. Alternatively, the government can channel more resources to the rural areas for development and creation of employment opportunities. This will decongest the urban areas and lure the struggling households to migrate to the rural areas where cost of living is relatively low hence ultimately improving their food security**.**

Through public private partnerships, the government can help strengthen internet infrastructure, ensure stable electricity infrastructure, and reduce the cost of internet access for small holder households to afford and hence access information on improving their dietary diversity from LDD and MDD to HDD, hence leading to increased food security. Provision of farmer customised mobile phones coupled with reduced transactions cost can help improve their dietary diversity form LDD and MDD to HDD, thus improved food security for the households. The regional dummy variables represent different agroecological and agricultural systems. Thus, policies should be tailored specifically for different agroecological zones to encourage production of food items. This will support and improve households' dietary diversity. In addition, the current county government should encourage intercounty agri-trade by lowering the levies for farmers to get better market for their surplus and, also purchase food items and other goods that they could not produce on their farms.

For future research, the study recommends an examination on determinants of food security with focus on HFIAS as a measure of food security with specific application of REGOPROB2. There is need to include other determinants of food security not considered in this study.

CONFLICT OF INTEREST

The authors declare that they have no conflict of interest in this paper.

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