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Non-farm income and household welfare: Empirical evidence from a developing economy

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ABSTRACT

The drastic changes in the global economy such as population growth, and land degradation requires alternative income sources such as non-farm income to enhance household welfare. Prior attempts to enhance welfare have been directed to industrialized economies and have paid little attention on poverty status as a proxy of household welfare. The current study sought to establish how non-farm income enhances household welfare using nationally representative panel data. The study used secondary data from most recent Uganda National Panel Survey (UNPS) waves of 2013 /2014, 2015/2016, 2017/2018, and 2019/2020. Fixed effects, random effects, and probit models were used to estimate the instrumented variables. The results indicate that non-farm income significantly enhances household welfare proxied by poverty status and consumption expenditure. Education level of the household head, household size and living in urban rather than rural significantly influences household welfare. To the best of the researchers' knowledge, this is the first study to establish how non-farm income enhances household welfare using empirical evidence from Ugandan economy which is transforming from an agricultural economy to a service economy and more specifically using poverty status and consumption expenditure as proxies of welfare.

1. Introduction

The rapidly growing population, climate change and land degradation in Uganda's economy guarantees alternative means of generating income for welfare. Vickers (2017) argues that economies hit by such calamities like population growth ought to develop non farm income avenues to enhance the welafare of the citizens. However, because of its crucial role in maximizing overall economic growth, the welfare of households has drawn the attention of many experts (Kennedy, 2018; Nguyen and Nguyen, 2019). In a structural transition away from mostly agricultural activity, some developing nations have turned their focus to non-farm income sources. Such income sources produce amazing outcomes. Tsiboe et al. (2016) found that non-farm income influences significantly household welfare. Similar to how Peng et al. (2022) found that non-farm entrepreneurial activity increases welfare measured by income per-capita and food consumption expenditure.

In economic theory, welfare refers to the subjective quality of a person's life as perceived by that person (Glick, 2018). This study examines household consumption expenditure and poverty status as proxies to household welfare. The overall demand for all consumer products and services can be simply stated as consumption. Anyanwu (1995) defined consumption expenditure as the amount of money spent by households on products and services such as clothing, food, entertainment, health care and asset acquisition. Poverty status is another alternative measure of welfare because the household's poverty status strongly depicts the quality of living of the household (Nguyen and Tran, 2018). As noted by Ozughalu and Ogwumike (2019), a very important dimension of welfare that has emerged in recent times in literature is poverty status. This dimension of measuring household welfare has received relatively less attention to date (Sumner et al., 2020). Poverty status is the proportion of the population whose per capita income does not meet the poverty standard in the whole population (Xu et al., 2021). In respect to the works of Kristjanson et al. (2010), poverty status is a dynamic aspect as the group of poor people is itself constantly changing when individuals and households either escape from poverty or descend into it.

Whereas both consumption expenditure and household poverty status are welfare indicators that give insights into the household

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wellbeing, each of the indicators approach welfare from different perspectives. Consumption expenditure, the commonly used and often seen as the immediate welfare proxy measure, focuses on the resources households use on daily needs such as food, clothing, housing, health, education, among others. In this case high consumption expenditure reflects greater access to such resources and thus a higher happiness levels or welfare. While on the other hand poverty status of the household represents a broader indicator of household welfare categorizing individuals or households based on a composite poverty metrics. According to UBOS (2018), the poverty metrics in addition to the money metrics, more aspects were incorporated like the ownership of dwelling, the type of wall and floor for the dwelling, among others. The addition of indicators makes this measure of welfare a more comprehensive measure of welfare compared to other proxies.

Non-farm income are activities that fall in the category outside the agricultural sector irrespective of the location. In this study, non-farm income comprised of primary non-agricultural activities like mining and other extractive activities; Secondary activities like manufacturing and tertiary activities such as income from services like trading and transport in line with the categorization of non-farm income by prior scholars such as Reardon et al. (2007)

Uganda is predominantly an agrarian economy with over 70 % of the population embryoid in the agricultural sector (Ggoobi, 2017). The rest of the population engage in non-farm income activities. According to Mukoki et al. (2023), non-farm income activities provide economic stability and poverty reducing alternatives making them vital for both urban and rural dwellers in Uganda. Mukoki et al. (2023) have documented these activities to include trading, transport sub sector, agro-processing, wage employment, construction and mining among other activities. Households engage in non-farm income activities as a diversification strategy to shield against the associated farm sector risks. Most men are involved in physically intensive jobs such as civil and mechanical works, while on the other hand, women engage in the less physically intensive jobs such as trade and crafts. In addition, it is worth noting that pockets of cultural norms that discourage participation in non-farm income activities are prevalent in some parts of Uganda (Neglo et al., 2021; Mwesigye and Matsumoto, 2016). Nevertheless, in most of the semi-urban and urban areas, non-farm activities have gained enormous acceptance as a feasible way to economic stability.

The Ugandan economy has experienced a significant change. The economy's dependence on agriculture shrank from 56.6 % in 1986 to 24 % in 2016, reflecting fundamental changes in the country (UBOS, 2018). As a result, over time, the contributions of the industrial sector and the service sector to the Gross Domestic Product (GDP) increased, reaching 18.7 % and 50.2 %, respectively, in 2016 (UBOS, 2018). Although the GDP is tremendously growing with a reduction in the agricultural sector's contribution to GDP, Ugandans' earnings have not kept up with GDP growth. The per capita income growth rate in Uganda has been positive over the years (1990–2015), averaging 3.4 percent per year, although household income has been essentially at a standstill since the 1970s (World Bank, 2016). Over 70 % of Ugandans, according to Ggoobi (2017), are still employed in the agricultural sector, which has had a steadily declining GDP contribution. Additionally, the agricultural sectors' market share on the global market has remained negligibly low (0.3 percent) (World Bank, 2016). Moreso, Uganda's tax-to-GDP ratio (13 %) declined significantly in relation to the average for Sub-Saharan Africa (SSA), which is 27 %.

A plethora of literature has established the antecedent role of non-farm income in enhancing household welfare (Anang, 2017; Kowalski et al., 2016; Tsiboe et al., 2016; Peng et al., 2022). This study addresses the bi-causality of study components, a problem that has not yet been resolved in literature, as well as the endogeneity issue brought about by poorly measured household variables as a result of the self-reporting method of data collection. Furthermore, despite the fact that welfare dynamics vary among countries, the majority of studies (Al-Amin and Hossain, 2019; Neglo et al., 2021; Hwang and Lee, 2015; Tran, 2015) which have revealed the influence of non-farm income on household welfare have focused on industrialized countries. Uganda is an anomalous context in which to establish the impact of non-farm income on household welfare given strange structural economic path. Typically, economies move from agriculture to manufacturing before transitioning to a service-based economy, a progression seen in many developed and emerging economies. In Uganda, however, the economy has transited directly from agriculture to services, with limited development in manufacturing. Additionally, findings from earlier studies have been inconsistent. This study used a measure of household welfare that hasn't reaped as much attention as well as nationally representative panel data (Sumner et al., 2020).

Studying how non-farm income affects household welfare is important for forming and implementing national policy as well as for individual households. Additionally, it offers empirical data that may be helpful to economic policy makers in other nations that are undergoing similar structural transformations away from agriculture but still have a large rural population and an active agricultural economy. In addition, the study offers empirical data on the influence of non-farm income on welfare of households, while considering theory of welfare to empirical test using evidence from Ugandan context, which is a developing nation with distinct dynamics affecting welfare.

The remaining sections of the study are categorized into three sections. First, we give a summary of the pertinent literature with an emphasis on the influence of non-farm income on household welfare in various nations. The data and empirical techniques are then explained. The paper's conclusion is provided in the final part, along with a review of the most important findings and recommendations for future research and policy.

2. Literature review

The benefits a household receives through the consumption of goods and services that, on average, reflects the level of poverty in the household are referred to as household welfare (Anderson, 2020). There is no single indicator of household welfare. Due to the subjective nature of household welfare, literature has proposed a number of alternative measures. Some examples of these measures include consumption expenditure, asset value, poverty status, quantity and quality of commodities consumed, household surplus, household members' health, and education level. According to Anyanwu (1995), consumption refers to the money that households spend on services and goods such as food, health, clothing, education, asset acquisition and entertainment.

Household consumption expenditure closely relates to long-term average well-being, making it an excellent proxy for welfare (Balisacan et al., 2003). Another proxy measure of household welfare is the level of poverty since it provides a clear indication of the standard of life in the household (Nguyen and Tran, 2018). When a household is categorized as being in poverty, it means that its per capita income doesn't satisfy the poverty criterion (Xu et al., 2021). Non-farm income is income generated from non-farming sources, such as manufacturing, trading, capital gains, agro-processing, service industries and accumulated wealth (Rahman and Mishra, 2020). There is growing evidence that when non-farm income increases, it leads to an increase in household consumption and poverty decreases (Rahman and Mishra, 2020).

It is irrefutably true that non-farm income significantly affects how well a family is doing. Research on how non-farm income affects family well-being has produced mixed results, with some sources indicating a positive influence while others indicate a detrimental influence. For instance, Tsiboe et al. (2016) investigated the link between the availability of household food nutrients and non-farm work in northern Ghana and found that the availability of food nutrients for farming households that own non-farm enterprises achieve higher levels of nutrient levels and the degree of food security and as such non-farm work is positively influenced by farming. They also discovered that women working in non-farming occupations were responsible for the

largest rise in the availability of dietary nutrients for households. Additionally, according to Peng (2022), engaging in nonfarm entrepreneurial activities increased wellbeing in terms of per capita income and food expenditure, with empirical data demonstrating that the result of per capita expenditure on food was 2.6 %. Due to increased employment productivity, greater profits, more sustainability, and low exposure to natural disasters, and more organized nature of non-farm income activities, non-farm income does, in fact, have a significant impact on household welfare.

Anang (2017) conducted research on the elements that affect farmers' willingness to pursue non-farming careers as well as the relationship between this willingness and farmers' production. Their findings demonstrated a considerable boost in agricultural productivity due to employment outside agriculture. These non-farm economic activities comprise non-farm rentals, income from employment in the public sector, earnings from the transportation industry, retail and wholesale trade marketing, tourism services, self-employment activities, manufacturing, as well as construction and mining, from which households may benefit more significantly and for a longer period of time. The income generated by these non-farm activities tends to flow steadily to households, who can utilize it to fund investment opportunities, prepare for the future, and rely on it for planning purposes. In order to influence the welfare of households over the course of their lives, non-farm income becomes vital.

According to research, non-farm income is crucial in reducing income inequality in rural areas. The household receives the necessary resources from non-farm sources, which can then be invested in the farm to increase the household's revenue. Besides this, non-farm income enables a household to purchase household consumables, thus raising the members' standard of living and general satisfaction, which in turn enhances the household's welfare. A number of factors influence the involvement of a household in non-farm work, including bad harvests, household gender dynamics, insufficient food intake, household consumption expenditure, literacy levels, household size, general health of household members, presence or absence of domestic animals, availability of credit services, membership to cooperatives, overall number of employed household members and access to agricultural extension services (Neglo et al., 2021). Al-Amin and Hossain's research from 2019 revealed that non-farm income greatly raises a household's likelihood of having assets. The study indicated that poverty is reduced and the risk of getting into it is decreased when non-farm income is embraced.

Kowalski et al. (2016), however, found no indication suggesting households engaged by non-farm enterprises were better able to withstand the frequency or duration of food scarcity with in face of shocks, proving that non-farm firms do not shield spatially sensitive households from hazards. They also found no evidence that non-farm entities smoothed consumption or reduced risk. Non-farm income leads to potential income instability, overreliance on informal sectors, or increased disparities if only certain groups can access non-farm income opportunities.

Non-farm income positively affects consumption expenditure and household poverty thus enhancing household welfare. Households that engage in non-farm activities are able to earn extra income which acts as a buffer to agricultural shocks with the diversified income sources and thus providing additional resources for consumption expenditure (Neglo et al., 2021). Additionally, income earned from non-farm activities will in turn help the households to improve food security, access to social services such as health, education and leisure which in turn lead to higher welfare levels. Non-farm income also enables households to have increased disposable income leading to reduced poverty, increased assets accumulation (Watema et al., 2022; Alex, 2023a, 2023b). More specifically, non-farm income leads to increased consumption expenditure in the household, reduced poverty and overall financial pliability, thus contributing greatly to household welfare. In fact, this income pathway provides additional income resources which helps the household to diversify their income and in turn reduce over reliance of the household on the unpredictable farm income source especially in rural areas.

The diversified income sources enable the household to have better access to basic commodities such as health care, education, clothing and food for which higher consumption of these spur better standard of living. Additionally, non-farm income contributes greatly to reducing poverty levels in the household because it offers opportunities that generate higher returns than the traditional farm activities. As such, households are able to escape poverty through non-farm income activities especially the landless and those with limited farm resources. Through non-farm activities, skills development is harnessed leading to better integration into the broader economy.

The importance of nonfarm activities in providing income for the poor is shown by research on the impact of non-farm income in reducing poverty in a developing country. There is evidence that fewer households participate in low-return activities, hence a country specific study is required to establish the effect of these non-farm activities on household welfare whereas those who have higher resource endowments and increased income can take advantage of high-return non-farm opportunities. This study focuses on the household welfare across the entire Uganda. The purpose for the study was to investigate how structural shifts away from agriculture might enhance household welfare.

3. Methods

3.1. Data

The study used secondary data drawn from the most recent National Panel Survey (UNPS) waves collected between the years 2013 and 2020. The time frame entails the UNPS four waves, namely UNPS 2013/14, UNPS 2015/16, UNPS 2017/18 and UNPS 2019/20. Uganda Bureau of Statistics (UBOS) conducts the UNPS in each of the Uganda's regions with support from World Bank. UBOS samples a proportionate number of households from across all districts of Uganda with fair representation of regions, rural and urban households. The UNPS is a survey that examines the social, economic, and demographic characteristics of people, households, and communities in Uganda. Although there have been several annual time gaps since the first UNPS, which took place in 2009/2010, the data is supposed to be collected annually. Demographics, consumption expenditure, poverty, welfare correlate, and sources of income are all important household level information documented in the UNPS for this study.

The study employed a sample 3119 randomly selected households from across the nation as included in each UNPS. Although there are other data sources for studying household welfare, only the UNPS collects complete data on household characteristics on a nationally representative basis. The sources of income and expenditure are shown by UNPS. Consumption expenditure is broken down into a number of subcategories, such as clothing, education, energy, health, food, maintenance and buildings. Non-farm income, the variable of interest is one of the sources of income that supports all these household expenses. The data sets give a realistic picture of these costs. All income and other details are voluntarily reported by the households. The household income from non-farm sources, including non-farm business investments, public employment, stock gains, real estate, interest returns and all non-agricultural income, all delineates non-farm income and is expressed in US dollars.

Two proxies, consumption expenditure and poverty status were used to measure welfare. Consumption expenditure, expressed in US dollars, reflects the consumption expenditure for each household. The ability of a household to earn enough money to cover its basic needs is referred to as its poverty status. A household's consumption expenditure must be above the poverty line which was measured as a binary variable, with $POV = 1$ in that case and $POV = 0$ in all other cases. A household is considered poor, according to UBOS, if their consumption expenditure

for each adult equivalent is less than the absolute minimum needed to cover its basic necessities (food or non-foods) (UBOS, 2021). Uganda's updated benchmark for measuring poverty-stricken households is a daily consumption budget of USD 1.25.

In order to create the poverty index, UBOS added new welfare variables to complement expenditure each day per adult equivalent. These indicators include having a home or dwelling, having a wall made of mud, brick, or wattle, having a dirt or clean floor, having access to safe water, having a number of separate rooms, having a solid or non-solid roof, and having a certain form of housing.

3.2. Econometric models

To determine how non-farm income affects household welfare, the study used the conventional panel model (Newman et al., 2008). The methods used in this study to measure the proxy variables for household welfare had an impact on the empirical panel models' econometric forms. For instance, the estimation of household consumption expenditure as a continuous variable, two static panel models: Fixed Effects and Random Effects models, were defined for this welfare metric. The following empirical model fixed Effect (Model 1) was specified:

$$\begin{aligned}\text{Log(CONSEXP)}_{it} = {} & \beta_{oi} + \beta_1 \text{Log(NFINC)}_{it} + \beta_2 \text{hheducl}_{it} + \beta_3 \text{age}_{it} \\ & + \beta_4 \text{agesq}_{it} + \beta_5 \text{gender}_{it} + \beta_6 \text{marital}_{it} \\ & + \beta_7 \text{hhsize}_{it} + \beta_8 \text{residence}_{it} + \beta_9 \text{region}_{it} \\ & + \beta_{10} \text{Logtransfer}_{it} + \beta_{11} \text{employsec}_{it} + u_{it}\end{aligned} \tag{1}$$

The $\beta_{0i}'s$ denote the specific intercepts, that are fixed for a given household. Log(CONSEXP)_{it} denotes the logarithm of household level consumption expenditure at any time *t*, Log(NFINC)_{it} denotes logarithm of household level nonfarm income at any time *t*, hheducl_{it} denotes the highest level of education of the head of household *i* at any given period *t*, age_{it} denotes the household head's age (in years) at any time *t*, agesq_{it} denotes the square of the age variable, gender_{it} denotes at any time, household head's gender, marital_{it} denotes the *i*th household head's marital status at any given period, hhsize_{it} denotes the size of the household i at any time *t*, residence_{it} denotes where at any time, a household *i* resides, whether urban or rural, region_{it} denotes the region of the country where household *i* at any time *t* is found, Logtransfer_{it} denotes the logarithm of transfers of the *i*th household at any time and employsec_{it} denotes the sector of employment for household head *i* at any time *t*.

The household-specific unobserved variables in the FE model remain constant over time. According to Stock and Watson (2008) therefore, other variables rather than these constants must be responsible for changes in the dependent variable. The estimated results for the fixed-effects models are free from bias because all time-invariant variations between nations are accounted for by the model's controls. For such consistency in the FE model, the independent variable and error terms rather than the individual intercepts must be uncorrelated with the predictors.

Model 2, the Random Effects (RE) Empirical Panel Model is specified as follows:

$$\begin{aligned}\text{Log(CONSEXP)}_{it} = {} & \beta_o + \beta_1 \text{Log(NFINC)}_{it} + \beta_2 \text{hheducl}_{it} + \beta_3 \text{age}_{it} \\ & + \beta_4 \text{agesq}_{it} + \beta_5 \text{gender}_{it} + \beta_6 \text{marital}_{it} \\ & + \beta_7 \text{hhsize}_{it} + \beta_8 \text{residence}_{it} + \beta_9 \text{region}_{it} \\ & + \beta_{10} \text{Logtransfer}_{it} + \beta_{11} \text{employsec}_{it} + \alpha_i + u_{it}\end{aligned} \tag{2}$$

Such that β_o denotes an intercept which is random; $\alpha_i + u_{it}$ denotes the amalgamated error comprising of two parts: the individual household specific element which remains constant over the panel period denoted by α_i and the rest of the error that is not connected with the regressors is denoted by u_{it}. In the RE model, it is assumed that the two components of the compounded error are independent of one another. To be more specific, the within error is denoted by the u_{it} component and the between error by the α_i component. Whereas within relates to the variability within a single household during the panel survey periods, between assesses the variability between the different household.

The PROBIT panel model (Model 3), is specified as follows:

$$\begin{aligned}P_i = E(POV=1) = {} & \varphi(\beta_o + \beta_1 \text{Log(NFINC)}_{it} + \beta_2 \text{hheducl}_{it} + \beta_3 \text{age}_{it} \\ & + \beta_4 \text{agesq}_{it} + \beta_5 \text{gender}_{it} + \beta_6 \text{marital}_{it} + \beta_7 \text{hhsize}_{it} + \beta_8 \text{residence}_{it} \\ & + \beta_9 \text{region}_{it} + \beta_{10} \text{Logtransfer}_{it} + \beta_{11} \text{employsec}_{it} + u_{it})\end{aligned} \tag{3}$$

4. Findings

4.1. Descriptive statistics

Considering the descriptive analysis for annual consumption expenditure for households in Table 1, the estimated annual consumption across all households over the four waves was around $977 USD. The raw data analysis shows that the UNPS 2015/16 wave reported the least average annual household expenditure, which was slightly over $862 USD. This was the smallest average annual household expenditure among the surveyed households. An analysis of the raw data revealed that UNPS wave 2013/2014 had the highest average annual household consumption expenditure of about $1429 USD. This was the highest average annual expenditure among the surveyed households. Based on the statistical analysis in Table 1, the 2017/18 period had the greatest standard variation of average annual household consumption expenditure, with an average of about $2560 USD. Accordingly, the 2017–2018 UNPS wave showed the most differences in annual consumption expenditure between households compared to the other waves under study. Findings in Table 1 also reveal that the UNPS2015/16 wave had the fewest annual consumption expenditure discrepancies by many families, with a standard deviation of roughly $871 for the average household expenditure in the wave.

The majority of the households (82.9 %) were defined as non-poor in the four waves of the investigation, as demonstrated by the descriptive data for poverty status of households depicted in Table 2. While results in Table 2 conceals that 17.1 % of households under study were defined as poor. Table 2's descriptive statistics on household poverty status reveal that the UNPS wave 2019/20 had the highest percentage of non-poor families among the four waves. Whereas results from Table 2 demonstrate that majority of the impoverished households found throughout the waves under study were discovered in the UNPS wave 2013/14.

The average annual household non-farm income from the waves under study was slightly over eight hundred and sixty US dollars, as indicated by the findings in Table 3. The highest household annual mean non-farm income reported in 2017/2018 UNPS wave was around $921 USD but with the highest standard deviation over the period of study. The mean annual household non-farm income for the 2019/2020 wave

Table 1
Household consumption expenditure descriptive statistics (in US $).

Round	Mean	Minimum	Maximum	Standard deviation
2013/14	1429.88	105.51	24,481.14	1452.60
2015/16	862.10	7.45	5491.86	871.82
2017/18	1151.42	66.59	115,575.02	2560.68
2019/20	1418.15	117.37	15,737.88	1497.41
Overall	977.50	7.45	94,263.32	1752.55
Total number of observations	9834			

*Exchange rate: $1.000 USD = Ush3,660 UGX as of 2nd November 2024.
Source: Author's own computation.

Table 2
Household poverty status descriptive statistics (figures are counts, percentages in parentheses).

Wave	Non-poor	Poor
2013/14	1980	641
	(20.1 %)	(6.5 %)
2015/16	2217	516
	(22.5 %)	(5.2 %)
2017/18	1894	542
	(19.3 %)	(5.5 %)
2019/20	2218	341
	(22.5 %)	(3.5 %)
Overall	8150	1684
	(82.9 %)	(17.1 %)
Chi square = 146.082*** $p = 0.000$		
Total number of observations: 9834		

Source: Author's own computation.

Table 3
Nonfarm income descriptive statistics (in USD).

Wave 2013/14	Mean	Minimum	Maximum	Std. dev.
	877.65	3.09	6120.28	805.59
2015/16	681.91	2.65	7705.00	699.87
2017/18	921.48	6.19	6065.64	952.23
2019/20	579.70	1.34	1983.63	71.86
Overall	860.87	1.34	7705.00	863.43

*Exchange rate: $1.000 USD = Ush3,660 UGX as of 2nd November 2024.
Source: Author's own computation.

of the UNPS was the lowest at about $579 USD with the least standard deviation across the period under study.

4.2. Diagnostic tests

We conducted unit root testing using numerical measurements on the model variables. The Fisher-type panel test method was adopted since the empirical panel data used for this study set is suitable for both unbalanced panels and panel data points with spatial gaps. Given that all the four results reported by the panel unit root test procedure were significant statistically at the 5 % level, we rejected the null hypothesis that all panels in the empirical model's non-categorical variables contain unit roots. Categorical variables were stationary in levels, which is a priori known.

The Jarque–Bera normality test reveal a non-significant chi-square estimate with a *p*-value higher than 0.05. Thus, the diagnostic test findings support the hypothesis that the dependent variable (logarithm of consumption expenditure) is distributed normally. The dependent variable for models 1 and 2 is therefore assumed to have a normal distribution. The correlation findings in Table 4 demonstrates a substantial correlation between age squared and age variables which is far higher than the recommended threshold. When both control variables are incorporated simultaneously into the model, a correlation coefficient larger than 0.8 increases the likelihood that the model will exhibit severe multicollinearity. As a result, the study removed age squared and retrained age in the final model. Age squared was eliminated since it has a little stronger correlation with the outcome variable than age and the predictor variables.

4.3. Household welfare and non-farm income

4.3.1. Influence of non-farm income on household welfare

The study employed panel regression with two-stage least-squares to estimate the fixed-effects model as well as the random effect model with a quantitative dependent variable to address endogeneity issues with the independent variables brought on by measurement errors. For both models, instrumental variable (IV) estimation techniques were used. We estimate the models with robust standard errors to take into consideration for the individualistic error term, the within-panel causality and any heteroscedasticity. Table 5 displays the summary regression findings for models 1 and 2 for the logarithm of household consumption expenditure, which was used to measure household welfare.

The findings of the FE-RE test in Table 5 substantially supports the alternative hypothesis at 5 % significance level. The Hausman test findings demonstrate that a fixed-effects model properly represents the individual level impacts in this investigation. The estimates from the fixed effects model are therefore widely used in the analysis and discussion of the results.

The partial coefficient estimates for the logarithm of non-farm incomes estimated by models 1 and 2 are both significant and positive at the 5 % level of significance, as per Table 5's regression estimations. Estimates from the chosen fixed effect model show that household welfare increases by about 20.9 % for each 1 % increase in non-farm

Table 4
Model variables correlation matrix.

	logCONSEXP	Pov	logNFINC	Educ	Age	Agesq	Gender	Marital	HHsize	Reside	Logtrans	Emplysec
logCONSEXP	1.000											
Pov	−0.271	1.000										
	(0.000)											
LogNFINC	0.236	−0.304	1.000									
	(0.000)	(0.000)										
Educ	0.216	−0.213	0.109	1.000								
	(0.000)	(0.000)	(0.163)									
Age	0.158	0.065	0.167	0.244	1.000							
	(0.213)	(0.132)	(0.049)	(0.000)								
Agesq	0.129	0.143	−0.117	−0.214	0.998	1.000						
	(0.112)	(0.230)	(0.043)	(0.000)	(0.000)							
Gender	0.118	−0.103	0.076	0.023	−0.216	−0.213	1.000					
	(0.343)	(0.827)	(0.109)	(0.000)	(0.002)	(0.000)						
Marital	0.007	0.003	0.103	0.136	−0.201	−0.053	0.428	1.000				
	(0.101)	(0.438)	(0.230)	(0.158)	(0.003)	(0.000)	(0.000)					
HHsize	0.142	0.217	0.002	−0.001	0.276	0.231	−0.141	0.277	1.000			
	(0.000)	(0.000)	(0.265)	(0.647)	(0.000)	(0.000)	(0.404)	(0.000)				
Residence	0.232	−0.015	0.231	0.121	−0.009	−0.107	−0.111	−0.206	−0.157	1.000		
	(0.000)	(0.000)	(0.000)	(0.000)	(0.125)	(0.138)	(0.357)	(0.001)	(0.004)			
Logtransfer	0.009	−0.018	−0.144	−0.093	0.127	0.195	−0.256	−0.058	0.152	−0.109	1.000	
	(0.218)	(0.007)	(0.322)	(0.014)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.789)		
Employsec	0.102	−0.219	0.211	0.024	−0.118	−0.183	0.201	0.106	−0.005	0.263	0.157	1.000
	(0.349)	(0.000)	(0.000)	(0.112)	(0.128)	(0.011)	(0.000)	(0.569)	(0.031)	(0.000)	(0.361)	

Source: Author's own computation.

Table 5
Regression Estimates for Model 1 and model 2: Dependent Variable is **LOGCONSEXP**

Explanatory Variable	Model 1 2SLS FE – IV regression (Standard Errors in parentheses)	Model 2 2SLS RE – IV regression (Standard Errors in parentheses)
LOGNFINC	0.2092*** (0.0207)	0.2921*** (0.1272)
Control Variables		
LOGTRANSFERS	0.0141*** (0.0022)	0.0082 (0.0085)
HHH Education	0.0221*** (0.0154)	0.0241*** (0.0022)
HHH Age	0.0091*** (0.0007)	0.0082*** (0.0013)
HH Size	0.0753*** (0.0011)	0.0501 (0.0273)
HHH gender (Ref: female)	-0.1549*** (0.0045)	-0.1101*** (0.0465)
HH marital status (Ref: Monogamously married)		
Married polygamously	-0.0431*** (0.0083)	-0.0196 (0.0432)
Divorced/separated	-0.2839*** (0.0128)	-0.3040*** (0.0321)
Widow/Widower	-0.2814*** (0.0508)	-0.3498*** (0.0333)
Not married	-0.2704*** (0.0172)	-0.2883*** (0.0406)
HH area of residence (Ref: Rural)		
Urban	0.2375*** (0.0543)	0.3637*** (0.1265)
Region of the country (Ref: Central)		
East	-0.4587*** (0.0101)	-0.3777*** (0.0858)
North	-0.3156*** (0.0062)	-0.2823*** (0.0340)
West	-0.1233*** (0.0323)	-0.1665*** (0.0362)
HH sector of main employment (Ref: Agriculture)		
Industry	-0.1106*** (0.0066)	-0.1583*** (0.0593)
Services	0.1457*** (0.0156)	0.2868 (0.1742)
Other	-0.1757 (0.1677)	-2.1307*** (0.5862)
	Wald = 1299.66*** p – value = 0.000	Wald = 42.72*** p – value = 0.000
	Hausman chi-sq. = 965.83*** (p=0.000) Ho: RE is appropriate	

Source: Author's own computation, while *, **, *** is the significance level at 10%, 5% and 1% respectively.

income while holding other variables constant when consumption expenditure is considered as a household welfare proxy measure. As a result, household welfare can be significantly predicted by non-farm income.

Estimates from Table 5 show that household welfare is positively and significantly influenced by the control variables; household head education level, logarithm of transfers, size of household, household head age, main employment being services rather than agriculture and urban living rather than living in rural areas. While regression estimates in Table 5 indicate that the following control factors negatively influence welfare: male headed households versus female headed households; polygamous households versus monogamous households; divorced or separated households versus monogamous households; widowed households versus monogamous households; never married households versus monogamous households; and household's primary occupation being in industrial sector and region of residence.

4.3.2. *Impact of non-farm income on household welfare*

The results of the Wald test for exogeneity indicate that the chi-square estimate's p-value is less than 5 %, which is the level of significance. This indicates that the hypothesis of no endogeniety is not significant at the 5 % level and thus rejected. The IV-probit is thus appropriate for use, as shown by the Wald exogeneity test, proving that instruments were required for estimate.

Table 6 of the IV-probit model's summary estimates reveals that the impact of nonfarm income is statistically significant at 5 %. As a result,

Table 6
Estimates for model 3 with poverty status as the dependent variable.

Explanatory variables:	Model 3 IV-Probit regression: (Standard errors in parentheses)
LOGNFINC	−0.5951*** (0.2326)
Controls:	
LOGTRANSFER	−0.0677 (0.0326)
HH education	−0.0871*** (0.0023)
HH age (years)	−0.0059 (0.0065)
Size of household	0.2542*** (0.0136)
HH Gender (Ref=female)	
Male HHH	−0.0607 (0.1981)
HH Marital status (Ref=Married monogamously)	
Married polygamous	−0.3729 (0.2263)
Divorced/Separated	−0.1156 (0.2099)
Widow / Widower	0.2106 (0.3425)
Not married	0.3595 (0.2464)
HH are of Residence (Ref=Rural)	
Urban	0.4513** (0.0477)
Region of the country(Ref=Central)	
Eastern	0.2071*** (0.2866)
Northern	0.5320*** (0.1654)
Western	0.2518* (0.1488)
HH Sector of main employment (Ref=Agriculture)	
Industry	0.1455 (0.2546)
Services	−0.2300 (0.1984)
Other	−0.8233 * (0.3322)
Wald = 624.90*** *p*-value = 0.000 Wald test of no endogeneity: Ho: No endogeneity *p*-value = 0.000 Hausman exogeneity test Ho: Exogenous instrumented variables *p*-value = 0.001	

Source: Author's own computation, while *, **, *** is the significance level at 10 %, 5 % and 1 % respectively.

the data demonstrate that each 1 % increase in the non-farm income reduces the anticipated risk of a household becoming poor by roughly 59.5 %. This result suggests that non-farm income significantly affects households' ability to escape poverty and raise their level of living. The IV-probit findings demonstrate that households with greater non-farm incomes had higher welfare compared to households with lower non-farm incomes when using poverty as a substitute for gauging household welfare.

The IV-summary probit's results are displayed in Table 6 only show a significant and negative influence for the educational status of the household head at the 5 % level. This result shows that an extra year of schooling for the family head decreases the anticipated chance of the household head being poor by around 8 %, all other things being equal. According to the findings, having a family head who is more educated significantly improves a household's welfare.

Table 6's IV-probit estimates show that the following control variables significantly lower expected probability of poverty and, consequently, significantly lower welfare for households: household size,

urban rather than rural residence, Eastern rather than Central region residency, and Northern rather than Central region residency. The control variables, such as the current marital status, gender of the household head, industry of employment, and residence in the Western rather than the Central region, were all insignificant statistically at 5-percent and it was thought that they had no bearing on the possibility of household poverty, according to estimates summarized in Table 6.

5. Discussion

Just like any developing country, Uganda is struggling to enhance its household welfare. The current environment in the Uganda economy is characterized by land degradation, population growth and climate change which necessitates developing non-farm income as an alternative prerequisite to enhance household welfare. This study sought to determine how nonfarm income enhances poverty reduction and consumption expenditure as proxies of welfare using National survey data for 4 waves of 2013/2014, 2015/2016, 2017/2018, and 2019/2020. The study findings revealed that household welfare is significantly influenced by non-farm income. Non-farm income can increase household welfare, as shown by the findings from IV-fixed effects and IV-probit. The estimates met the a priori predictions, showing that they were statistically significant and theoretically tenable. The partial slope coefficient on the logarithm of non-farm income's statistical significance suggests that non-farm income is a significant determinant of household welfare. This suggests that raising the households' non-farm income can significantly improve household welfare. The fact that descriptive data also showed higher annual mean non-farm income supports the centrality of nonfarm income in terms of enhancing household wellbeing (mean annual non-farm income US $ 860.87). The main benefit of non-farm income for household welfare could be attributed to improved employment productivity, higher sustainability, higher returns, less vulnerability to natural vagaries, and are more formalized, which most non-farm income has, in addition to higher earnings.

In our study, non-farm income comprised of earnings from the transportation industry, wages from public service jobs, marketing, retail and wholesale trade, manufacturing, construction and mining, tourism services as well as self-employment activities. Households may depend on the income generated by these non-farm activities since it tends to be reliable and can be used to fund investments and establish long-term goals. As a result, non-farm income becomes important in impacting household welfare throughout the course of the household's lifetime.

According to Möllers and Buchenrieder (2011), non-farm income is a significant tool to help households escape poverty and thereby improve their welfare. According to research, non-farm income is crucial in reducing income inequality in rural areas. The household receives the necessary resources from non-farm sources, which can then be invested in the farm to increase the household's income. Despite this, non-farm income enables a household to purchase household consumables, so raising the members' standard of living and general contentment, which in turn enhances the household's welfare.

Our findings are consistent with that of Mat et al. (2012), who used survey data from rural Kedah to investigate the effects of nonfarm income on poverty and income disparity among Malaysian farmers. Their findings indicated how non-farm income households can either increase or decrease poverty levels. Our findings are comparable to those of Kazungu and Guuroh (2014), who looked at pertinent case studies, literature, and earlier research to come to the conclusion that non-farm rural jobs, like managing a small farm or shop, help farm families bridge income gaps and prevent rural-urban migration. The study findings further resonant with the findings by Tsiboe et al. (2016) and Peng et al. (2022) who established that non-farm income sources enhance household welfare. It should however be noted that the studies by Peng et al. (2022) and Tsiboe et al. (2016) used income percapita and food income expenditure to measure household welfare. Our study however used poverty status and consumption expenditure to measure household welfare. In line with the |arguments of Nguyen and Tran (2018) and Ozughalu and Ogwumike (2019) who argue that poverty status is an emerging dimension of welfare in literature that should be given scholarly attention (Sumner et al., 2020). Our study contributes to welfare theory by determining how non-farm income enhances poverty reduction as a proxy of household welfare.

Furthermore, our study findings are in consonance with the finding of Anang (2017); Kowalski et al. (2016); Tsiboe et al. (2016) and Peng et al. (2022) who established that household income increase household welfare. Prior studies however, fall short of addressing the endogeneity arising out of self-report data. Our study utilized instrumental variable analysis which estimates with robust standard error. More so, welfare is dynamic and varies among countries, yet prior studies have been directed to industrialized economies (Al-Amin and Hossain, 2019; Neglo et al., 2021; Hwang and Lee, 2015; Tran, 2015), hence a study in the Ugandan economy using nationally representative panel data (Sumner et al., 2020) is robust.

6. Conclusion

Utilizing panel data from UNPS's most recent four waves, the impact of nonfarm income on welfare in Ugandan households was investigated. Household welfare was measured using two proxies: consumption expenditure and poverty status. To estimate the parameters, models with fixed effects, random effects, and probit were utilized. The final model estimates were based on the IV-FE and IV-probit. The study finds that household welfare levels are positively and significantly influenced by non-farm income.

7. Implications

The current study provides important insights to theory and practice. The Ugandan economy is going through a drastic change where the dependence on agriculture shrunk from 56.6 % in 1986 to 24 % in 2016 (UBOS, 2018) giving room to the increasing contribution of non-farm sector to the economy's GDP reaching 18.7 % and 50.2 %, respectively, in 2016 (UBOS, 2018). Resultantly, in line with the recommendation by Vickers (2017) who argues that economies going through drastic changes ought to liverage non-farm income as a solution to enhance welfare, the findings of the current study are robust to provide important insights to Uganda's economy on how non-farm income enhances household welfare. The study findings further imply that the policy makers ought to implement economic policies and reforms that enhance the development of non-farm income activities so as to ultimately enhance household welfare. Studies such as Danso-Abbeam et al. (2020) postulate that an economy can enhance non-farm income activities by investing more economic resources in non-farm economic activities and providing subsdies to boosting trade and other non-farm activities. The study's findings indicate that households must engage in income-generating activities like self-employment, wage work, trade and commercial firms, domestic manufacturing, and rendering specialized services, among others, if they want to increase their level of welfare. The increased non-farm income that households get can therefore improve household welfare. Increased participation by households in non-farm income-generating activities may improve their welfare. A structural veer away from dominant economic activities such as subsistence farming toward the secondary economic activities such as services and manufacturing is required to promote household welfare.

8. Study limitations and future research suggestions

There are still gaps that could be filled by future studies, notwithstanding the contributions made by the current study. The study's focus on measuring the short-term welfare effect was constrained by the lack of time series data. Future research can concentrate on calculating the

dynamic welfare impacts using more sophisticated models such as GMM and ARDL.

Ethical statement

The study employed secondary data collected on household welfare collected from publicly available datasets (Uganda Bureau of statistics—UBOS and World Bank). The data sources used were anonymized and complied with ethical standards for data protection and privacy. No identifiable personal information was accessed or utilized in this research. The researchers adhered to all applicable laws and regulations governing the use of secondary data. Additionally, the study followed principles of research integrity, ensuring the accuracy, transparency, and reproducibility of the analysis. As the research was based solely on secondary data, no direct interaction with human participants occurred, and no further ethical approvals were required.

CRediT authorship contribution statement

Joash Robert Alex Watema: Conceptualization, Formal analysis, Methodology, Writing – original draft, Writing – review & editing. **Richard Kiplangat Siele:** Conceptualization, Writing – review & editing. **Edwin Kimitei:** Methodology.

Declaration of competing interest

The authors declare no conflict of interest.

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