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Examining Poverty Dynamics in Ghana: Evidence from Longitudinal and Repeated Cross-Sectional Data

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Abstract

This article examines poverty dynamics in Ghana using the Ghana Socioeconomic Panel Surveys and a synthetic panel based on the Ghana Living Standards Surveys. It provides insight into the extent of poverty mobility and persistence in Ghana, and the factors that explain poverty transitions. The results show that upward mobility has been a key feature of Ghana's poverty transitions between 2006 and 2019. However, there are still high probabilities of poverty persistence and downward mobility among initially poor and non-poor households, respectively. Furthermore, notable heterogeneities exist in poverty transitions across socioeconomic groups. Poverty is more chronic in rural areas and the northern parts of Ghana compared with urban and southern regions, respectively, and among households headed by persons from opportunity-deprived backgrounds. Other characteristics such as the number of dependants, sex, occupation and level of education of the household head are important correlates of poverty persistence and downward mobility in Ghana. Hence, addressing chronic poverty requires targeted policies that foster more inclusive and sustainable growth in rural areas and northern parts of Ghana, and improved access to opportunities for people from disadvantaged backgrounds, the unemployed, and those in vulnerable employment.

Keywords: poverty dynamics, synthetic panel, Africa
JEL classification: D63, I32

1. Introduction

Ghana has witnessed high economic growth over the last three decades, with the country's per capita GDP[1] constantly being above the SSA median (World Bank, 2021). Between 1991/1992 and 2016/17, headcount poverty fell from 51.1% to 23.4%, a feat largely attributed to sustained economic growth. However, this average national progress on poverty reduction hides large differences across geographical locations and amongst socioeconomic groups (Teal, 2001; Coulombe and Wodon, 2007; Annim *et al.*, 2012). In many parts of the country, households are exposed to various shocks, particularly those deriving their income from traditional farming and low-productivity informal sectors. The

[1] GDP per capita (PPP constant 2011 international US$).

seasonality of agriculture, precipitation, and climate change shocks influence consumption, threatening the livelihoods of poor households as well as those near the poverty line (Senadza, 2012). The underdeveloped credit and insurance markets and existing market imperfections prevent consumption smoothing and limit human capital and productive investments for the most vulnerable, with adverse effects on future income growth. This situation is exacerbated by the COVID-19 pandemic with its negative effects on businesses, the labour market, and household income (World Bank, Ghana Statistical Service and UNDP, 2020). Many non-poor households have become vulnerable and more likely to fall into poverty, while poor households would likely witness poverty persistence. For policy-making, therefore, understanding welfare dynamics among households and across regions in Ghana as well as its underlying factors has become critical for future poverty reduction strategies.

Relevant in the Ghanaian context is the importance of providing equal access to development opportunities for all. As shown by Brunori *et al.* (2015), between 14% and 29% of existing inequalities in Ghana are explained by disparities in opportunities. When circumstances (e.g., social origin or sex) account for differences in outcomes between individuals, there is a position of unfairness where capabilities, access to productive resources and employment opportunities, and chances to escape poverty are unequal. Such a situation would likely lead to poverty traps and the persistence of inequality (World Bank, 2005; Marrero and Rodríguez, 2013). Hence, while analysing poverty dynamics is key, providing evidence on its correlates and the importance of disparities in opportunity for poverty persistence and transitions would give a better picture of the mechanisms through which long-term patterns of poverty and inequality are generated (Bourguignon *et al.*, 2007; Checchi and Peragine, 2010; Fleurbaey and Peragine, 2013).

This paper aims to first examine the dynamics of poverty in Ghana using actual and synthetic panel approaches. Second, the paper investigates the importance of household characteristics and opportunity deprivation in shaping households' transitions in and out of poverty. Until recently, analyses of poverty dynamics in Ghana and many other developing countries have been scant mainly due to the lack of longitudinal data and methodological limitations. Existing poverty studies about Ghana provided only snapshots of the state of poverty in a given year and used the available cross-sectional surveys to examine the country's progress on poverty and inequality (Cooke *et al.*, 2016; McKay *et al.*, 2016). The only exception is Dang and Dabalen (2019), which analysed poverty dynamics in Africa and reported Ghana's poverty transition estimates for the period 1998/99–2005/06 using the synthetic panel method. The present study contributes to the literature by providing a more recent, broader, and robust picture of poverty dynamics in Ghana. It employs three rounds of the GLSS data (2005/06, 2012/13 and 2016/2017) and three waves of the more recent Ghana Socioeconomic Panel Surveys (GSPS) (2009/2010, 2013/2014 and 2018/19). Using both data sets helps to confirm the robustness of the trends observed over time. Also, by linking opportunity deprivation with poverty transitions, this research adds to existing knowledge on the role of inequality of opportunity in explaining poverty traps. Following recent methodological advances in the poverty dynamics literature (see e.g. Dang and Lanjouw, 2013; Dang *et al.*, 2014; Dang *et al.*, 2021) we validate our results by comparing estimates based on the actual panel to its counterfactual (or synthetic panel), which ascertains the reliability of the latter in the absence of the former. The remainder of the paper is organised as follows. In Section 2 we present the literature on approaches to poverty dynamics, and in Section 3, we discuss the estimation strategy. Section 4 describes the data, while Section 5 presents and discusses the results. Section 6 concludes.

2. Measurement approaches to poverty dynamics

For many years, poverty dynamics studies solely depended on panel data (Calvo and Dercon, 2012; Clark *et al.*, 2016). However, such data are not always available in developing countries, and where they are, researchers often face issues such as small sample size, sample attrition, and measurement error (Perez, 2015; Moreno *et al.,* 2021). In the absence of longitudinal data, synthetic or pseudo-panels have been constructed to understand income mobility in developing countries (Deaton, 1985; Bourguignon *et al.,* 2004; Cuesta *et al.,* 2011; Salvucci and Tarp, 2021). Although pseudo-panel methods are known to yield precise estimates of poverty transitions (Cuesta *et al.,* 2011; Perez, 2015; Moreno *et al.,* 2021; Ribas, 2022), the use of synthetic panels constructed using data from repeated cross-sections to analyse poverty dynamics is rapidly growing (Herault and Jenkins, 2019; Dang *et al.,* 2021; Garcés-Urzainqui *et al.,* 2021; Mekasha and Tarp, 2021).

Novel approaches to estimating poverty transitions using synthetic panel data were introduced by Dang *et al.* (2014) and Dang and Lanjouw (2013). Unlike pseudo-panel approach, which employs cohort-level averages, the synthetic panel method uses time-invariant household or community-level characteristics observed in each round of the surveys to predict household welfare for the year where the actual observation is missing. The poverty dynamics estimates are then calculated using the national poverty line and the synthetic panel data obtained.

The bounds method of Dang *et al.* (2014) was refined by Dang and Lanjouw (2013) and Dang *et al.* (2021), which derived point estimates of poverty probabilities rather than bounds. In line with Dang and Lanjouw (2013)'s method, Bourguignon and Moreno (2020) proposed an alternative method for estimating the residuals' intertemporal correlation coefficient and relaxing the bivariate normality assumption used in estimating the point estimates. Relying on data from Mexico, the study argued that point estimates obtained are more precise than the outcomes of Dang and Lanjouw (2013) and are generally consistent with actual panel estimates. Assessing the Dang *et al.* (2014) bounds approach, Cruces *et al.* (2015) conducted a validation exercise by analysing intra-generational poverty mobility using cross-sectional data between two periods in Chile, Nicaragua, and Peru. The findings showed that the true estimates of poverty transitions lie within the lower-upper bound intervals obtained using the synthetic panel approach in all three-country contexts, particularly with rich model specifications. Working with the Chilean panel data, Fields and Viollaz (2013) argued that the bound estimates of the conditional probabilities based on Dang *et al.* (2014)'s approach are slightly less accurate with wider bounds compared to joint probability estimates.

Garcés-Urzainqui (2017) sought to validate Dang and Lanjouw (2013) and Bourguignon and Moreno (2020) approaches for estimating point estimates of poverty transitions based on a synthetic panel. Using data from Thailand, the study concluded that the general patterns of mobility described by synthetic panel estimates are consistent with the true dynamics when the autocorrelation parameter of the income residuals is well-estimated using the mean-based cohort approach. The author further shows that while Bourguignon and Moreno (2020) method is less sensitive to model specification, the approach of Dang and Lanjouw (2013) is simpler and performs well with an optimal income or expenditure model.

Using the Dang *et al.* (2014) bounds approach and the refinement proposed by Dang and Lanjouw (2013), Herault and Jenkins (2019) tested the accuracy of synthetic panel procedures relative to benchmarks based on estimates derived from actual panel data in the context of developed countries. Employing data from Australia and Britain, the authors examined the sensitivity of results to changes in the age group, survey periods, poverty line, and cohorts' definition for the estimation of the residuals' autocorrelation coefficient. The findings showed that Dang and Lanjouw (2013)'s point estimates approach performs poorly in the context of the two developed countries compared with earlier validation exercises in middle- and low-income countries. Salvucci and Tarp (2021) also provided a comparison between the synthetic panel estimates of poverty transitions with actual estimates using quarterly data from Mozambique. The authors demonstrated that the novel technique convincingly yields estimates of conditional and joint probabilities that are similar to the true estimates.

Other applications of the synthetic approach in the developing world include Bierbaum and Gassmann (2012) and Ferreira *et al.* (2021) in Kyrgyz Republic and Myanmar, respectively. For example, Ferreira *et al.* (2021) show that overall, there is a likelihood of poverty escape among the poor over the period, though the progress varies across regional boundaries and the probability of falling into the vulnerable group remains high, and that the state-level differences in poverty transitions are underpinned by household characteristics such as the education of the household head and area of residence.

In the context of Africa, Dang and Dabalen (2019) used synthetic panel data proposed by Dang *et al.* (2014) and Dang and Lanjouw (2013) to evaluate poverty transitions between two periods in 20 African countries. While the study revealed that most countries have experienced upward mobility, chronic poverty remained high, and a considerable proportion of the population remains vulnerable to poverty. In the case of Ghana, joint probabilities of chronic and downward mobility were estimated to be 20.4% and 5.7%, respectively, over the period 1998–2005. The findings further show that post-secondary education, female headship, and urban location are strongly associated with higher upward mobility and less with downward mobility.

Country-specific studies such as Mekasha and Tarp (2021) adopted a similar approach using Ethiopian cross-sectional data and an existing panel data set in a validation exercise. The findings showed that poverty was highly chronic in the country between 2011 and 2016, even though many households experienced upward mobility. By estimating poverty transitions across socioeconomic groups, the study revealed that the area of residence, the level of education and employment characteristics of the household head shape household consumption mobility in the country. Similar findings were obtained by Salvucci and Tarp (2021) for Mozambique using synthetic panels based on annual cross-sectional surveys as well as intra-year actual panel data.

The broader literature provides evidence of key factors explaining poverty dynamics. These include access to education and health (Schotte *et al.*, 2018), labour market outcomes such as employment opportunities (Bigsten and Shimeles, 2008), and labour market shocks including job losses and wage reductions (Bayudan-Dacuycuy and Lim, 2013). In Indonesia, Dartanto and Nurkholis (2013) showed that educational attainment, the number of household members, physical assets, employment status, health shocks, microcredit programme, access to electricity, and changes in the employment sector are the key determinants of poverty dynamics. Muyanga *et al.* (2013) used 1997–2007 panel data for Kenya and showed that fluctuation in household welfare is connected with various unforeseen shocks, such as the passing of a family member, persistent health issues, demographic factors, accessibility to infrastructure and the transfer of wealth between generations. In Malawi, based on nationally representative panel data for 1998 and 2002, Bokosi (2007) used the bivariate probit model to estimate poverty dynamics. The results indicate that household poverty in 2002 is considerably associated with the education level of the household head, the amount of land cultivated per person, and the changes in household size. These factors remain significant regardless of the household's poverty status in 1998. For households that were poor in 1998, the likelihood of being poor in 2002 was mainly affected by household size, the value of livestock owned, and the average time taken to access services. In contrast, residing in the Northern region was a crucial factor determining the likelihood of being poor in 2002 for households that were not poor in 1998.

Clearly, the empirical literature on poverty dynamics in developing countries is rapidly evolving with the use of new estimation techniques to address the paucity of panel data sets in low- and middle-income countries. Also, many studies highlighted the importance of household socioeconomic characteristics in influencing poverty mobility and immobility. Meanwhile, it is unclear how opportunity deprivation is shaping households' transitions in and out of poverty in developing countries. Amidst the dearth of poverty dynamics literature in Ghana, the current study analyses poverty dynamics over the period 2006–2019 and provides some evidence of the reliability of the synthetic panel approaches in examining poverty transitions. Additionally, we provide evidence of the importance of opportunity deprivation in poverty transitions.

3. Empirical strategy

3.1. Analysing poverty dynamics

To evaluate poverty dynamics using synthetic panel data, this study adopts two approaches. First, the upper and lower bound estimates of poverty dynamics, developed by Dang *et al.* (2014) are computed using the non-parametric approach. Second, the parametric approach is used to compute point estimates of measures of chronic and transient poverty following Dang and Lanjouw (2013, 2018) and Dang *et al.* (2021). The latter, unlike the former, assumes bivariate normality of the joint error distribution in the underlying models.

As a first step under the synthetic panel approach, a linear projection of aggregate welfare is done using time-invariant household or community-level characteristics (time-varying characteristics can also be used if the households observed in the two rounds can easily recall them). For example, based on Equation 1, linking the welfare outcomes to the time-invariant observed characteristics in time 1, the vector of coefficients, β_1', is estimated. The model is specified as:

$$C^1{}_{i1} = \beta_1' X^1{}_{i1} + \varepsilon^1{}_{i1} \tag{1}$$

Where: $C^1{}_{i1}$ and $X^1{}_{i1}$ represent the consumption expenditure of households and the time-invariant variables at time 1 for observations in the first round, respectively, $\varepsilon^1{}_{i1}$is the error terms. The estimated coefficients are then applied to impute the values of the welfare variable at time 1 for households in round 2, such that:

$$\hat{C}_{i1}^2 = \hat{\beta}_1' X^2{}_{i1} + \tilde{\varepsilon}_{i1}^2 \tag{2}$$

Where: $\hat{C}_{i1}^2$ denotes the retroactively predicted consumption expenditure of households at time 1 for households observed in the second round, and $\tilde{\varepsilon}_{i1}^2$ represents the error terms derived based on a set of assumptions discussed below. $X^2{}_{i1}$ denotes the set of covariates for households observed at time 2, and $\hat{\beta}_1$ are the parameters estimated using ordinary least squares (OLS).

The estimates of the degree of mobility in and out of poverty are then computed using the imputed values at time 1 and the observed welfare for households in round two. Estimates of poverty dynamics, mainly unconditional and conditional probabilities of poverty persistence, entry or exit are calculated. For example, the proportion of non-poor households at time 1 that are poor at time 2 (conditional probability of downward mobility) is given as:

$$\Pr\left(\hat{C}_{i1}^2 > Z \middle| C_{i2}^2 < Z\right) \tag{3}$$

While proportion of households that are non-poor at time 1 but are poor at time 2 (joint or unconditional probability) is given as:

$$\Pr\left(\hat{C}_{i1}^2 > Zand\ C_{i2}^2 < Z\right) \tag{4}$$

The computation of the non-parametric and parametric estimates relies on a set of assumptions. Mainly, the errors are assumed to be positively correlated. The bounds estimates proposed by Dang *et al.* (2014) use the extreme cases of no and perfect correlation between rounds for the upper bound and lower bound, respectively. The parametric point estimates assume a bivariate normal distribution of the error terms, with correlation coefficient, ρ, which could be estimated using the cohort-level correlation between the rounds or obtained from an auxiliary actual panel data set. The synthetic panel approach also relies on the assumption that the cross-sectional surveys used comprise samples that are drawn from the same populations. Thus, such analysis requires the comparability of the data across surveys and that the sample used in each survey is representative of the larger population.

To provide robust analysis of poverty dynamics in the Ghanaian context, in addition to the analysis of poverty dynamics based on the synthetic panel, the study estimates the measures of poverty mobility or immobility using actual panel data (the three waves of the GSPS). The use of household panel data helps provide a further detailed assessment of poverty dynamics and validate the findings from the synthetic panel analysis. Furthermore, although conditional probabilities tend to provide a better reflection of the extent of chronic poverty, upward mobility and downward mobility (Fields and Viollaz, 2013) by taking household's poverty status at time 1, both conditional and joint probabilities are reported to provide a full picture of poverty transition.

3.2. Poverty dynamic profile: Inequality of opportunity and other correlates of poverty dynamics

To provide insights on the importance of household 'opportunity deprivation' status as well as other socioeconomic characteristics in households' poverty dynamics, the study computes conditional transition probabilities across various household characteristics using the GSPS. The sub-groups that are considered include the sex of the household head, location (rural/urban) and the 'opportunity deprivation' status of the household head. The latter will provide important insights into the relationship between opportunity deprivation and poverty transition in Ghana. The 'opportunity deprivation' status of the household head is defined based on the household head's parental characteristics (education and occupation).

3.3. Identifying the opportunity-deprived group

To identify the 'opportunity-deprived' (OD) or the 'least advantaged group', Ferreira and Gignoux (2011) proposed the use of opportunity profiles. An opportunity profile is obtained by first partitioning the population into types—a type being a group of individuals with the same set of circumstances—and then ranking the type-mean (or other moments) of the distribution of outcome in ascending order. Given that the measure of inequality of opportunity is the between-type inequality, obtained after smoothing the distribution of outcome within groups by replacing the individuals' outcome with the type-mean, a ranking of these type-means provides valuable information on the groups that have relatively low or high chances of achieving an outcome. The types with the lowest rank in the opportunity profile can, therefore, be considered the least advantaged groups (since they have the lowest mean outcome).

3.4. Explaining poverty dynamics: Regression analysis

Furthermore, the study evaluates the correlates of poverty transitions using a multivariate regression approach developed by Cappellari and Jenkins (2004, 2008), following Schotte *et al.* (2018). The model explicitly allows for possible feedback effects from past poverty experiences and takes into account the potential endogeneity of initial conditions, unobserved heterogeneity, and non-random panel dropout, which may lead to biases in poverty risk estimates. Specifically, the multivariate probit model jointly estimates a system of three equations: (1) a first-order Markov process of poverty mobility between the two consecutive waves (to shed light on poverty persistence), (2) an equation for the household's initial poverty status (poverty status in the last period) that would help account for potential endogeneity of initial conditions and (3) a sample retention equation accounting for possible non-random attrition (e.g., households with more (less) favourable characteristics will be more likely to leave [remain in] the sample). Such modelling of poverty transition, which follows the standard Heckman (1976) approach, allows the covariates of the current poverty status to differ based on the initial poverty status of the household by accounting for state dependence. Past poverty experiences would likely increase the risks of future poverty due to factors such as risk aversion, behaviour and investment choices including in human capital, as well as observable characteristics which tend to reduce the chances of poverty escape (Bigsten and Shimeles, 2008; Schotte *et al.,* 2018). Additionally, sample iteration would likely be non-random as chronically poor households may tend to be more stable participants in each survey. A non-random panel retention (attrition)—households with certain favourable characteristics are more or less likely to remain (leave) in the sample—would lead to biases in the poverty risk estimates.

Cappellari and Jenkins (2004, 2008) proposed a trivariate probit model of poverty transition between years $t-1$and t with a system of three main equations. The first equation models the latent poverty propensity of individual i ($i = 1, 2, \ldots, n$) at $t-1$. It is given as:

$$p^*_{t-1} = \beta' Z_{it-1} + \pi_{it-1} \tag{5}$$

$$P_{t-1} = I\left(p^*_{t-1} > 0\right) \text{ with } P_{it-1} = 1 \text{ if poor at } t-1 \text{ and } 0 \text{ otherwise}$$

$$\pi_{it-1} = \sigma_i + \varphi_{it-1} \sim N(0,1)$$

In the second equation, $r^*$is latent propensity of retention between period $t-1$ and t, i.e., the chances that those households with consumption expenditure observed in period $t-1$ also have expenditure observed at period t.

$$r^*_{it} = \varphi' W_{it-1} + \vartheta_{it} \tag{6}$$

$$R_{it} = I\left(r^*_{it} > 0\right) \text{ with } \mathrm{R_{it}} = 1 \text{ if the expenditure is observed in period t and 0 otherwise}$$

$$\vartheta_{\mathrm{it}} = \tau_{\mathrm{i}} + \theta_{\mathrm{it}} \sim \mathrm{N}(0,1)$$

The equation for poverty transitions, with p^*_{it} being the latent propensity of poverty, can be specified as:

$$p^*_{it} = \left[\left(P_{it-1}\right)\delta'_1 + \left(1 - P_{it-1}\right)\delta'_2\right] * X_{it-1} + \mu_{it} \tag{7}$$

$$P_t = I\left(p^*_t > 0\right) \text{ with } P_{it} = 1 \text{ if poor at } t \text{ and } 0 \text{ otherwise}$$

$$\mu_{it} = \varepsilon_i + \varepsilon_{it} \sim N(0,1)$$

Where: $\pi_{it-1}, \vartheta_{it}$ and μ_{it} are the sum of individual-specific effects σ_i, τ_i and ε_i and idiosyncratic normal orthogonal errors $\varphi_{it-1}, \theta_{it}$ and ε_{it}, respectively. P_{it} and P_{it-1} are binary variables summarizing the individual's poverty status at time t and $t-1$, respectively. R_{it} represents a binary indicator of individual's expenditure retention. Where

$\delta_1, \delta_2, \varphi, \beta, Z_{it-1}, X_{it-1}$ and W_{it-1} are column vectors, ε_i is a normal individual-specific effect and μ_{it} normal orthogonal white noise error. Z_{it-1}, X_{it-1}, and W_{it-1} comprise variables selected based on existing literature and data availability. For exclusion restrictions, at least one variable must belong to W_{it-1} or Z_{it-1} and affect current poverty status only through initial poverty status or retention.

The joint distribution of the error terms $\pi_{it-1}, \vartheta_{it}$ and μ_{it} is assumed to be a trivariate standard normal and characterized by three correlation coefficients to be estimated. These are: (1) correlation between the error terms in Equation 5 and Equation 6, i.e., ρ_1, and a negative coefficient implying that individuals with a high tendency to be poor at $t-1$ are less likely to have observed consumption expenditure at t. The second correlation coefficient is between the error terms of the equations of poverty transition and initial poverty status—Equation 5 and Equation 7, i.e., ρ_2—testing the exogeneity of the poverty status at $t-1$. A positive coefficient suggests that individuals who were poor in the initial period have a high tendency to remain in poverty. Lastly, the correlation coefficient between the unobservables affecting retention and the conditional current poverty status, i.e., ρ_3. A negative sign indicates that individuals that are present in both periods are less likely to fall or remain into poverty at time t compared with those that have unobserved expenditure at t. Hence if $\rho_3 = 0 = \rho_1$, sample attrition is ignorable and a bivariate probit model with sample selection would provide unbiased estimates of the correlates of poverty transition. If $\rho_3 = \rho_2 = 0 = \rho_1$, then both state dependence and sample attrition are ignorable. In addition to the estimates of the trivariate model, results obtained from the bivariate probit model with endogenous sample selection were also reported.

4. Data

4.1. Data sources

The study employs the GLSS, which is a nationally representative household living standard survey, and the Ghana Socioeconomic Panel Survey data for the analysis. Seven (7) rounds of the GLSS data are available: Round 1 (GLSS 1), Round 2 (GLSS 2), Round 3 (GLSS 3), Round 4 (GLSS 4), Round 5 (GLSS 5), Round 6 (GLSS 6) and Round 7 (GLSS 7). The surveys were conducted in 1986/87, 1988/89, 1991/92, 1998/1999, 2004/05, 2012/13 and 2016/2017, respectively. However, due to important changes in the questionnaires between Rounds 2 and 3, it is difficult to compare the first three surveys and the four recent ones (Coulombe and Wodon, 2007). This analysis focuses on the three most recent rounds, namely the GLSS 5, 6 and 7 (Table A1 in the appendix). Similar to the GLSS, the GSPS—collected through the collaboration of University of Ghana, Yale University, and Northwestern University—are nationally and regionally representative and comprise data on household expenditure as well as other socioeconomic characteristics. So far, three waves of the survey are available from 2010 to 2019 (Table A2 in the appendix).

4.2. Descriptive statistics

We present descriptive statistics of poverty trends in Ghana based on the GLSS from 2006 to 2017 (Table 1) and the GSPS from 2010 to 2019 (Table 2). From Table 1, national headcount poverty fell from 31.9% in 2006 to 23.4% in 2017. Wide variations exist, however, in the incidence of poverty among the 10[2] administrative regions. Poverty in Ghana is largely a rural phenomenon. The incidence of poverty has consistently been lower among female-headed households than male-headed households. This finding is consistent with existing evidence on poverty in Ghana and is presumably attributable to the remittances received by female heads from a migrant spouse (Cooke *et al.,* 2016; Ghana Statistical Service (GSS), 2017). A north–south poverty divide is also noted, wherein

[2] Ghana had ten administrative regions at the time of the survey; however, there are currently 16 regions.

Table 1. Poverty Trends in Ghana Based on Cross-Sectional Data (GLSS) 2006–2017

	Headcount ratio (P_0) (%)			Poverty gap (P_1) (%)			Squared poverty gap (P_2)		
	2006	2013	2017	2006	2013	2017	2006	2013	2017
Ghana	31.9	24.2	23.4	11.0	7.8	8.4	5.4	3.6	4.3
Region									
Western	22.9	20.9	21.1	5.4	5.7	4.9	1.9	2.3	1.7
Central	23.4	18.8	13.8	5.6	5.6	3.6	1.8	2.5	1.3
Greater Accra	13.5	5.6	2.5	3.7	1.6	0.5	1.4	0.6	0.1
Eastern	17.8	21.7	12.6	4.2	5.8	3.1	1.6	2.4	1.2
Volta	37.3	33.8	37.3	9.2	9.8	13.0	3.2	4.0	6.4
Ashanti	24.0	14.7	11.6	6.4	3.5	2.7	2.4	1.3	1.0
Brong Ahafo	34.0	27.9	26.8	9.5	7.4	8.8	3.7	2.9	4.2
Northern	55.7	50.4	61.1	23.0	19.3	26.7	12.0	9.8	14.9
Upper East	72.9	44.4	54.8	35.3	17.2	23.8	20.4	9.0	13.2
Upper West	89.1	70.7	70.9	50.7	33.2	37.6	32.8	18.8	24.6
Location (Urban–Rural)									
Rural	43.7	37.9	39.5	15.4	13.1	15.1	7.6	6.3	8.0
Urban	12.4	10.6	7.8	3.7	2.5	1.8	1.6	0.9	0.7
Sex									
Male	34.9	25.9	25.8	12.4	8.4	9.6	6.2	3.9	5.0
Female	22.1	19.1	17.6	6.4	5.7	5.3	2.7	2.5	2.4
North–South									
Northern Ghana	65.6	52.4	61.1	30.7	21.2	27.8	17.6	11.2	16.1
Southern Ghana	23.3	18.5	15.7	6.0	5.0	4.4	2.2	2.0	1.9
Deprivation Status									
Head from a deprived background	43.6	36.6	38.6	15.8	12.6	14.8	7.8	6.0	7.9
Head from the least deprived background	10.6	6.6	5.9	2.2	1.7	1.5	0.8	0.7	0.6

Note: Sampling weights and clustering are considered. *Source:* Authors' computation using GLSS 5, 6 and 7 data sets.

northern Ghana, defined as the three northern-most regions (Northern, Upper East, and Upper West), seems to experience high poverty levels compared to the southern part of the country—the seven regions. Using the opportunity profile, the *least-advantaged* or *most deprived* group—the group with the relatively higher chance of achieving low consumption expenditure as a result of its socioeconomic background—is identified as comprising people whose parents have been employed in the agriculture sector most of their lives, and have at most primary education (Table A3 in the appendix). The least-deprived group comprises individuals who have at least one parent with secondary or tertiary education and at least one parent who has been in services, production, professional or administrative work most of his or her life. Poverty incidence is roughly seven times higher in the least-advantaged group compared with the least-deprived counterpart (Table 1). The statistics based on the GSPS data (Table 2) seem generally consistent with the trends observed in the GLSS data sets (Table 1).

5. Results and discussion

5.1. Poverty dynamics using cross-sectional data and the synthetic panel approach

Tables 3 and 4, respectively, report the joint and conditional estimates of the non-parametric bound and the parametric point estimates based on the synthetic panel approach. The

Table 2. Poverty Trends in Ghana Based on Panel Data (GSP) 2010–2019

	Headcount ratio (P_0) (%)			Poverty gap (P_1) (%)			Squared poverty gap (P_2)		
	2010	2014	2019	2010	2014	2019	2010	2014	2019
Ghana	30.5	20.6	20.5	9.0	5.8	6.5	3.7	2.3	3.0
Region									
Western	25.4	7.9	6.5	6.2	1.6	1.3	1.9	0.4	0.4
Central	17.8	35.9	9.9	3.5	11.1	1.7	1.0	4.6	0.5
Greater Accra	5.1	3.7	4.7	1.3	0.9	1.0	0.6	0.3	0.3
Eastern	31.8	19.1	9.5	11.6	3.9	2.3	5.6	1.2	0.9
Volta	43.1	10.3	23.9	13.7	2.7	7.8	5.9	1.0	3.6
Ashanti	27.7	17.9	11.0	6.9	4.3	2.2	2.5	1.5	0.7
Brong Ahafo	37.9	23.6	31.6	10.9	6.4	10.7	4.4	2.3	4.9
Northern	49.3	34.6	61.1	15.4	9.7	23.7	6.2	4.2	12.1
Upper East	61.6	46.5	43.5	19.8	18.0	14.2	8.2	9.3	6.2
Upper West	66.1	42.5	47.6	24.9	12.8	18.0	12.1	5.2	8.5
Location (Urban–Rural)									
Rural	47.5	29.3	30.9	14.9	8.2	10.4	6.2	3.3	4.8
Urban	13.7	11.8	9.6	3.2	3.2	2.5	1.2	1.2	1.1
Sex									
Male	34.0	21.7	22.6	10.3	6.2	7.8	4.2	2.6	3.7
Female	22.0	18.5	16.3	6.0	4.8	4.2	2.4	1.8	1.6
North–South									
Northern Ghana	55.0	38.7	54.5	18.0	12.2	20.4	7.6	5.6	10.0
Southern Ghana	25.4	16.2	12.8	7.1	4.2	3.4	2.9	1.5	1.4
Deprivation Status									
Head from a deprived background	41.4	26.9	27.5	12.7	7.4	8.9	5.3	3.0	4.0
Head from the least deprived background	6.3	0.5	0.4	1.6	0.7	1.9	0.6	0.2	1.1

Notes: Authors' computation using Waves 1, 2 and 3 of the Ghana Socioeconomic Panel Survey (GSPS). Sampling weights and clustering are considered.

correlation coefficient between the error terms (ρ) used in the computation of the parametric point estimates are obtained from the GSPS data. The coefficients of 0.27 for the period 2010–2014 and 0.34 for the period 2014–2019 are applied to the periods 2006–2013 and 2013–2017, respectively.

The bound estimates suggest that 4.7–11.3% of households remained in poverty in 2006–2013 compared to 4.6–9.4% in 2013–2017 (Table 3). However, 6.1–12.6% and 5.8–10.5% escaped poverty in 2006–2013 and 2013–2017, respectively. As shown in Table 4, nearly 32.3–83.7% of the poor in 2006 remained in poverty in 2013. These estimates are similar to those obtained for the period 2013–2017, where ~28.9–84.4% remained poor in 2017, having been poor in 2013. Moreover, the conditional probabilities of falling into poverty were 7.1–14.8% over the period 2006–2013 and 6.5–12.5% over the period 2013–2017. Overall, the bounds estimates appear quite wide, particularly the probability estimates of upward mobility and the estimated bounds of conditional probability of poverty persistence; and thus, do not provide clear evidence on the pattern of poverty transitions (Herault and Jenkins, 2019; Salvucci and Tarp, 2021).

The point estimates show that poverty has been transient rather than chronic in Ghana. Overall, the likelihood of poverty exit is greater than the chances of poverty persistence. Furthermore, there have been marginal changes in the probabilities of poverty mobility or immobility over time (Table 3). Upward mobility has also been a key feature of poverty transitions in Ghana between 2006 and 2017. At least 65% of the poor in 2006 and 2013

Table 3. Synthetic Panel Estimates of Poverty Dynamics from 2006 to 2017—Joint Probabilities (in %) Based on Cross-Sectional Data

Poverty status	2006–2013			2013–2017		
	Non-parametric bounds estimates		Parametric point estimates	Non-parametric bounds estimates		Parametric point estimates
	Lower bound	Upper bound		Lower bound	Upper bound	
Poor, poor	11.3	4.7	7.8	9.4	4.6	9.7
Poor, non-poor	6.1	12.6	17.3	5.8	10.5	16.1
Non-poor, poor	2.2	9.9	14.9	1.7	11.3	14.6
Non-poor, non-poor	80.4	72.7	60	83.1	73.5	59.6
Obs.	7389	7389	7389	6446	6446	6446

Notes: Authors' computation using household consumption expenditure per adult equivalent and the extreme poverty line of GHC 900 for 1999 and 2006, and GHC 1,314 and GHC 1,760.9 for 2013 and 2017, respectively. The estimates account for sampling weights and clustering. The values reported are the fraction of population aged 25–55 years in each of the four states. The descriptive statistics and the OLS regression estimates are reported in Tables A4 and A5 in the appendix.

Table 4. Synthetic Panel Estimates of Poverty Dynamics from 2006 to 2017 – Conditional Probabilities (in %) Based on Cross-Sectional Data (GLSS)

Poverty status	2006–2013			2013–2017		
	Non-parametric bounds estimates		Parametric point estimates	Non-parametric bounds estimates		Parametric point estimates
	Lower bound	Upper bound		Lower bound	Upper bound	
Poor, poor	83.7	32.3	34.4	84.4	28.9	40.0
Poor, non-poor	16.3	67.7	65.6	15.6	71.1	60.0
Non-poor, poor	7.1	14.8	22.4	6.5	12.5	21.3
Non-poor, non-poor	92.9	85.2	77.6	93.5	87.5	78.7
Obs.	7,389	7,389	7,389	6,446	6,446	6,446

Notes: Authors' computation using household consumption expenditure per adult equivalent and the extreme poverty line of GHC 900 for 1999 and 2006, and GHC 1,314 and GHC 1,760.9 for 2013 and 2017, respectively. The estimates account for sampling weights and clustering. The values reported are the probability of each of the four states (e.g., poor in time *t* given poverty status in *t-1*) for the population aged 25–55 years. The descriptive statistics and the OLS regression estimates are reported in Tables A4 and A5 in the appendix.

exited poverty by 2013 and 2017, respectively (Table 4). However, the chance of poverty entry for a non-poor individual remains high (22.4% between 2006 and 2017, and 21.3% over the period 2013–17). Furthermore, poverty has been more persistent among households between 2013 and 2017, compared to the period 2006–2013. Overall, these findings suggest that the slowdown in the progress on poverty reduction between 2013 and 2017 is attributable to higher poverty persistence and lower poverty exit across the population.

5.2. Poverty dynamics using actual panel data

The patterns of poverty dynamics based on the GSPS data are generally consistent with those observed in the GLSS data. Although joint probability estimates show a decline in the share of households that remain in poverty over the two periods, the estimates of conditional probabilities provide evidence of higher poverty persistence in 2014–2019 compared to 2010–2014 (Table 5). Moreover, ~32.5% of the poor in 2010 remained poor in 2014, and

Table 5. Poverty Dynamics Based on Actual Panel Data—Joint and Conditional Probabilities (in %)

Poverty status	Joint probabilities[a]		Conditional probabilities[b]	
	2010–2014	2014–2019	2010–2014	2014–2019
Poor, poor	10.5	8.3	32.5	38.6
	[8.8; 12.4]	[6.9; 10.0]	[28.4; 36.7]	[32.9; 44.2]
Poor, non-poor	21.8	13.2	67.5	61.4
	[19.5; 24.3]	[11.4; 15.3]	[63.3; 71.6]	[55.7; 67.0]
Non-poor, poor	11.0	13.0	16.3	16.6
	[9.5; 12.8]	[11.3; 14.9]	[13.9; 18.8]	[14.3; 18.9]
Non-poor, non-poor	56.6	65.4	83.7	83.4
	[54.8; 61.4]	[62.4; 68.3]	[81.2; 86.1]	[81.0; 85.7]
Obs.	3,407	3,407	3,407	3,407

Notes: Authors' computation using household consumption expenditure per adult equivalent and the extreme poverty line of GHC 1,314 for 2010 and 2014 and GHC 1,760.9 for 2019. The estimates are based on the entire sample and account for sampling weights and clustering. The lower and upper bounds for the 95% confidence intervals are reported in the brackets []. The descriptive statistics and the OLS regression estimates are reported in Tables A6 and A7 in the appendix. [a]The values reported are fractions of the population in each of the four states. [b]The values reported are the probability of each of the four states (e.g., poor in time *t* given poverty status in *t-1*) for the entire sample.

this likelihood of poverty persistence increased by roughly six percentage points between 2014 and 2019. Consistent with the results based on the GLSS data, a significant transition out of poverty is also noted with at least 60% of poor people moving to non-poor status across waves, although the likelihood of poverty exit decreased over the period 2014–2019, and ~16% of households plunging into poverty during both periods. Hence, while poverty has been a more transient phenomenon in the Ghanaian context, the likelihood of poverty escape has decreased over time while the likelihood of poverty persistence has increased.

5.3. Validation of the synthetic panel approach

To validate the findings of the synthetic panel approach, we present estimates of poverty transitions based on the GSPS data. The true estimates based on the actual panel are compared with those obtained using the synthetic panel, treating the waves as repeated cross-sections. The latter results are then compared with the former for the restricted sample considering the population aged 25 to 55 years (see the discussion in Section 3) to ascertain the accuracy of the bounds approach of Dang *et al.* (2014) and the point estimates of Dang and Lanjouw (2013) and Dang *et al.* (2021). Following existing literature, the correlation coefficient ρ is estimated using cohort-level correlation between periods. The cohort is defined using the age of the household head and his/her region of birth. The estimated coefficients of 0.25 and 0.41 fall within the expected range of (0.2, 0.8) considered as adequate in previous applications of the technique (Dang *et al.*, 2014; Salvucci and Tarp, 2021) and are close to the actual coefficients of 0.27 and 0.34 for 2010–2014 and 2014–2019, respectively. The time-invariant household characteristics are consistent with those utilized for the cross-sectional GLSS data.

Overall, the Dang and Lanjouw (2013) and Dang *et al.* (2014) methods perform well in estimating both the conditional and the joint probabilities of poverty transition (Table 6 and Table 7). Specifically, the true estimates of the conditional probability are within the interval defined by the lower and upper bounds of the synthetic panel. This finding also applies to the joint probability estimates, with the exception being the probabilities of remaining non-poor and experiencing upward mobility in 2010 and 2014. The estimated bounds are wide, however, particularly for the conditional probabilities, thus, providing unclear information on the pattern and trends in poverty dynamics over time consistent with the findings in the earlier estimates using the GLSS data. Similar to the Dang *et al.* (2014) approach,

Table 6. True versus Synthetic Panel Estimates of Poverty Dynamics from 2010 to 2019 – Joint Probabilities (in %) Based on Actual Panel Data (GSPS)

Poverty status	2000–2014				2014–2019			
	Non-parametric bounds estimates		Parametric point estimates	True estimates	Non-parametric bounds estimates		Parametric point estimates	True estimates
	Lower bound	Upper bound			Lower bound	Upper bound		
Poor, poor	16.1	6.8	8.7	9.0 [7.2; 11.0]	15.6	6.5	8.4	7.5 [6.1; 9.3]
Poor, non-poor	11.8	15.6	17.6	19.7 [17.3; 22.4]	6.9	11.2	14.0	11.8 [10.0; 13.9]
Non-poor, poor	4.3	13.5	14.6	10.4 [8.9; 12.3]	4.6	13.6	12.0	12.5 [10.6; 14.7]
Non-poor, non-poor	67.9	64.1	59.1	60.9 [57.2; 64.6]	72.9	68.7	65.6	68.1 [64.8; 71.3]
Obs.	2,134	2,134	2,134	2,338	2,072	2,072	2,072	2,338

Notes: Authors' computation using household consumption expenditure per adult equivalent and the extreme poverty line of GHC 1,314 for 2010 and 2014 and GHC 1,760.9 for 2019. The estimates account for sampling weights and clustering. The values reported for the non-parametric bounds and parametric point estimates are the fraction of the population aged 25–55 years in each of the four states. The true estimates are based on the entire sample excluding households that attributed between waves. The lower and upper bounds for the 95% confidence intervals are reported in the brackets []. The descriptive statistics and the OLS regression estimates are reported in Tables A6 and A7 in the appendix.

Table 7. True versus Synthetic Panel Estimates of Poverty Dynamics from 2010 to 2019—Conditional Probabilities (in %) Based on Actual Panel Data (GSPS)

Poverty status	2000–2014				2014–2019			
	Non-parametric bounds estimates		Parametric point estimates	True estimates	Non-parametric bounds estimates		Parametric point estimates	True estimates
	Lower bound	Upper bound			Lower bound	Upper bound		
Poor, poor	57.6	30.3	32.9	31.3 [26.7; 35.8]	69.2	36.7	37.6	38.9 [32.4; 45.5]
Poor, non-poor	42.4	69.7	67.1	68.7 [64.2; 73.3]	30.8	63.3	62.4	61.1 [54.5; 67.6]
Non-poor, poor	5.9	17.4	19.8	14.6 [12.1; 17.0]	5.9	16.6	15.4	15.5 [12.9; 18.1]
Non-poor, non-poor	94.1	82.6	80.2	85.4 [83.0; 87.8]	94.1	83.4	84.6	84.5 [81.9; 87.1]
Obs.	2,134	2,134	2,134	2,338	2,072	2,072	2,072	2,338

Notes: Authors' computation using household consumption expenditure per adult equivalent and the extreme poverty line of GHC 1,314 for 2010 and 2014 and GHC 1,760.9 for 2019.The estimates account for sampling weights and clustering. The values reported are the probability of each of the four states (e.g., poor in time *t* given poverty status in *t-1*) for the population aged 25–55 years for the synthetic panel estimates. The true estimates are also based on the restricted population aged 25–55 years and exclude households that attributed between waves. The lower and upper bounds for the 95% confidence intervals are reported in the brackets []. The descriptive statistics and the OLS regression estimates are reported in Tables A6 and A7 in the appendix.

the Dang and Lanjouw (2013) technique of generating point estimates of the poverty transitions yields estimates that are close to the true values; they fall within the 95% confidence interval of the true estimates. In several instances, the difference between the synthetic panel and the true estimates is around two points or less, apart from the joint and conditional probability of downward mobility over the period 2010–2014, and the conditional probabilities of staying non-poor. In this case, the synthetic panel approach overestimated the likelihood of falling into poverty such that the decline in downward mobility observed over time in the point estimates of conditional probabilities seems to contrast the marginal increase shown in true estimates. Nevertheless, the evidence provided shows that the Dang and Lanjouw (2013) techniques performed well in the Ghanaian context similar to previous applications in other low- and middle-income countries.

5.4. Estimates of poverty dynamics by sub-groups

To provide insights into the association between socioeconomic characteristics and poverty transition in Ghana, Table 8 reports the estimates of conditional probabilities across groups based on the sex of the household head, area and region of residence and deprivation status (the estimates of the joint probabilities are reported in Table A8 in the appendix). The estimates are based on the GSPS data. Poverty is more persistent in male-headed than female-headed households. Additionally, the probability of escaping poverty is greater for female-headed households. While this finding is consistent across periods, the overall increase in the likelihood of being chronically poor and the decline in upward mobility between 2014 and 2019 are associated with male headship but not female. The share of poor households in 2010 (2014) that remained poor in 2014 (2019) is higher for rural than urban, with lower probability of poverty escape and higher transition into poverty for the former than the latter. Similarly, people in the north of Ghana are more likely to remain chronically poor and also experience a downward mobility compared to those in the south. Compared to the less-deprived categories, households that belong to the most-deprived group have a lower chance of escaping poverty and higher incidence of chronic poverty over the periods 2010–2014 and 2014–2019. A north–south disaggregation of the most deprived group reveals that chronic poverty and downward mobility is much higher among the OD living in the northern part of the country. Specifically, ~66.4% of poor people in 2014 with a least-advantaged background remained in poverty in 2019, while over half of the non-poor in 2010–2014 fell into poverty in 2014–2019.

5.5. Explaining poverty transitions

Table 9 presents the correlates of poverty transitions in Ghana (the descriptive statistics of the variables used are reported in Table A9 in the appendix). In addition to the trivariate probit estimations (taking into account sample retention and state dependence), we report results of the bivariate probit with endogenous sample selection (in which sample attrition is ignored). The exogeneity of the initial conditions and sample retention are rejected at the 5% level. Specifically, individuals with expenditures observed in two successive periods were more likely to experience upward mobility compared to individuals who are likely to attrit. Also, those who were more likely to be initially poor are more likely to remain poor compared to the non-poor. Columns 1 and 3 show the average marginal effect of a change in the explanatory variables on the probability of poverty persistence, that is, the likelihood of a household being poor in both the previous and current survey periods. Columns 2 and 4 report the average marginal effects for poverty entry—the likelihood of a non-poor household in the previous survey period falling into poverty in the current survey period.[3]

[3] It is important to note that poverty persistence and poverty exit are mutually exclusive events. Thus, any variable that is estimated to increase (reduce) the likelihood of poverty persistence, will automatically reduce (increase) the chances of poverty exit to.

Table 8. Poverty Dynamics by Socioeconomic Groups from 2010 to 2019—Conditional Probabilities (in %) Based on Actual Panel (GSPS) Data

Poverty status	2010–2014	2014–2019	2010–2014	2014–2019
	Male		**Female**	
Poor, poor	34.0	44.5	28.9	26.4
Poor, non-poor	66.0	55.5	71.1	73.6
Non-poor, poor	16.8	18.1	16.6	13.6
Non-poor, non-poor	83.2	81.9	83.4	86.4
Obs.	2,113	2,071	970	1,118
	Urban		**Rural**	
Poor, poor	25.5	28.5	34.6	42.7
Poor, non-poor	89.3	71.5	65.4	57.3
Non-poor, poor	10.7	7.6	24.4	26.5
Non-poor, non-poor	74.5	92.4	75.6	73.5
Obs.	1,253	1,253	2,154	2,154
	South		**North**	
Poor, poor	25.5	25.3	46.3	62.3
Poor, non-poor	74.5	74.7	53.7	37.7
Non-poor, poor	14.3	10.5	29.3	49.2
Non-poor, non-poor	85.7	89.5	70.7	50.8
Obs.	2,612	2,612	795	795
	Most deprived		**Less deprived**	
Poor, poor	35.9	41.9	26.9	37.7
Poor, non-poor	64.1	58.1	73.1	62.5
Non-poor, poor	21.3	21.7	12.8	12.8
Non-poor, non-poor	78.7	78.3	87.2	87.2
Obs.	1,713	1,734	1,639	1,405
	Most deprived in Northern Ghana		**Most deprived in Southern Ghana**	
Poor, poor	44.8	66.4	31.1	28.8
Poor, non-poor	55.2	33.6	68.9	71.2
Non-poor, poor	31.1	53.4	19.8	14.2
Non-poor, non-poor	68.9	46.6	80.2	85.8
Obs.	443	473	1,270	1,261

Notes: Authors' computation using household consumption expenditure per adult equivalent and the extreme poverty line of GHC 1,314 for 2010 and 2014 and GHC 1,760.9 for 2019. The entire sample is considered for the estimations based on the GSPS data. The estimates account for sampling weights and clustering.

Our results indicate that households headed by persons with at least primary education are less likely to remain in or fall into poverty compared to those whose heads have no formal education. The effect is greater at higher levels of education. While the occupation of the household head seems to have no significant effect on the likelihood of poverty persistence, it is an important determinant of poverty entry among non-poor households. This suggests that having an employed household head, especially one not in vulnerable employment is a safeguard against poverty entry, as the household tends to be more resilient to income shocks. In addition, female-headed households are less likely to experience chronic poverty compared with their male-headed counterparts.

After controlling for the number of employed individuals in the household, the larger the number of dependents or working-age adults, the higher the risk of poverty persistence or entry. By contrast, ownership of assets plays a significant role in poverty exit or resilience, as households owning land or a house are less likely to remain in or fall into poverty. As

Table 9. Multivariate Probit Model Poverty Transition Estimates

Variables	Bivariate probit with endogenous selection (Conditional probabilities)				Trivariate probit with endogenous selection—accounting for sample retention (Conditional probabilities)			
	Poverty persistence		Poverty entry		Poverty persistence		Poverty entry	
	Avg. marginal effects	t-stats	Avg. marginal effects	t-stats	Avg. marginal effects	t-stats	Avg. marginal effects	t-stats
Characteristics of the household head								
Female	−0.042	−1.372	0.015	0.841	−0.088**	−2.291	−0.002	−0.178
Age	−0.000	−0.117	0.001	0.200	0.004	0.715	0.001	0.623
Age squared	0.000	0.477	0.000	0.608	−0.000	−0.315	0.000	0.227
Education level (base = No education)								
Primary education	−0.057**	−2.477	−0.041***	−2.694	−0.055*	−1.733	−0.047***	−3.969
Secondary education and more	−0.114***	−2.981	−0.087***	−3.907	−0.084	−1.427	−0.100***	−5.842
Occupation (base = No occupation)								
Paid employees	−0.035	−0.650	−0.112***	−4.086	−0.017	−0.244	−0.071***	−3.131
Self-employed (Non-farm)	0.050	1.075	−0.060**	−2.141	0.111*	1.680	−0.014	−0.626
Self-employed (Farm)	0.015	0.431	−0.064**	−2.362	0.008	0.168	−0.024	−1.259
Business or Farm contributor	0.017	0.480	−0.001	−0.027	0.007	0.126	0.011	0.619
Characteristics of the household								
No. of children (less than 18 years)	0.026***	3.895	0.013***	2.712	0.022**	2.382	0.014***	3.706
No. of adults (between 18 and 59 years)	0.034***	3.002	0.023**	2.328	−0.000	−0.019	0.021***	3.227
No. of elderly (more than 60 years)	0.004	0.164	0.020	0.974	−0.046	−1.526	0.002	0.151
No. of working household members	0.005	0.614	−0.002	−0.258	0.001	0.115	−0.003	−0.579
Household owns a land and/or a house	−0.017	−0.606	−0.046***	−2.866	−0.013	−0.321	−0.034***	−2.753

(Continued)

Table 9. Continued

Variables	Bivariate probit with endogenous selection (Conditional probabilities)				Trivariate probit with endogenous selection—accounting for sample retention (Conditional probabilities)			
	Poverty persistence		Poverty entry		Poverty persistence		Poverty entry	
	Avg. marginal effects	t-stats	Avg. marginal effects	t-stats	Avg. marginal effects	t-stats	Avg. marginal effects	t-stats
Household receipt of remittances (base = Regular)								
Not regular	0.008	0.180	−0.018	−0.787	−0.010	−0.165	−0.011	−0.598
Not at all	−0.041	−1.094	0.007	0.333	−0.067	−1.407	−0.012	−0.681
Resides in an urban area	−0.043	−1.542	−0.130***	−7.293	0.020	0.489	−0.096***	−6.369
Region of residence (base = Greater Accra)								
Western	−0.073	−1.067	0.012	0.300	−0.143	−1.374	−0.005	−0.140
Central	0.101*	1.699	0.184***	4.575	−0.010	−0.096	0.160***	4.934
Volta	0.040	0.704	0.089**	2.441	0.006	0.062	0.067**	2.084
Eastern	0.088	1.585	0.066*	1.711	0.019	0.204	0.070**	2.198
Ashanti	0.055	0.955	0.086***	2.634	−0.009	−0.101	0.079**	2.561
Brong Ahafo	0.136**	2.229	0.172***	5.179	0.072	0.703	0.157***	5.175
Northern	0.165***	2.906	0.237***	6.172	0.112	1.088	0.210***	6.424
Upper East	0.264***	4.282	0.175***	4.330	0.166*	1.688	0.197***	5.886
Upper West	0.222***	3.386	0.167***	4.077	0.107	0.988	0.187***	5.850
Time Effects	Yes		Yes		Yes		Yes	
Adjusted Wald test—Exogeneity of selection equations [df. 323] (Prob > F)								
Exogenous initial conditions (rho)	19.46	0.000						
Exogenous initial conditions (rho3 = rho2 = 0)					19.84	0.000		
Exogenous sample retention (rho1 = rho3 = 0)					19.88	0.000		
Joint exogeneity (rho3 = rho2 = rho1 = 0)					18.03	0.000		
Correlation coefficients between unobservables								
Poverty status at *t-1* & conditional poverty status at *t* (rho2)					0.446	0.037		
Sample retention and conditional poverty status at *t* (rho3)					−0.692	0.007		
Sample retention and poverty status at *t-1* (rho1)					−0.910	0.000		
Observations	6,918				8,139			

Notes: *** $P < 0.01$, ** $P < 0.05$, * $P < 0.1$. The estimates account for sampling weights and clustering.

expected, residing in an urban area lowers the likelihood of chronic poverty and the chances of poverty entry for initially non-poor households. Unsurprisingly, the likelihood of poverty persistence and descent is much higher for the three northern regions (Northern, Upper East and Upper West), which also happen to be the three poorest (the estimates of the correlates of initial poverty and the sample retention equation are reported in Table A10 in the appendix).

6. Conclusion

Despite sustained growth and various government interventions in Ghana, income disparities persist, indicating that certain groups have been unable to take advantage of whatever opportunities growth presents. This study on poverty dynamics in Ghana reveals significant insights into the country's socioeconomic landscape and challenges confronting poverty and inequality reduction efforts. The analysis, using both synthetic panel and actual panel data highlights the complexities of poverty mobility and immobility in Ghana, emphasising the role of household characteristics and opportunity deprivation in shaping poverty transitions.

The validation exercise using the GSPS data shows that the synthetic panel approaches proposed by Dang and Lanjouw (2013) and Dang *et al.* (2014) perform well in providing accurate information on poverty transition probabilities. These findings are consistent with similar studies in Mozambique by Salvucci and Tarp (2021). While the bounds estimates provide a general idea of poverty dynamics, the intervals are too wide to offer detailed insights. However, the point estimates are mostly within the 95% confidence interval of the true values, indicating that the synthetic panel techniques can be a reasonable substitute for actual panel data when the latter is unavailable or unreliable.

Our key findings suggest that between 2006 and 2017, upward mobility was prevalent, yet poverty persistence remained high among initially poor households, with non-poor households facing elevated risks of downward mobility. The slowdown in poverty reduction between 2013 and 2017 is largely attributable to increased poverty persistence and lower poverty exit levels. Poverty is more persistent among households headed by males compared to female-headed households. Moreover, female-headed households experienced a reduction in poverty immobility and a marginal improvement in upward mobility over time, possibly due to increased support and empowerment programmes for women over the years. As expected, most deprived households have a lower chance of escaping poverty and a higher likelihood of downward mobility. Additionally, poverty is endemic in rural areas and northern Ghana, compared to urban and southern Ghana.

The study underscores the importance of addressing chronic poverty in rural and northern Ghana, suggesting targeted policies to improve productivity in agriculture and informal sectors, bridging rural infrastructure gaps, and enhancing social programmes to build resilience to shocks among vulnerable households. Overall, the study suggests a more equitable access to opportunities, particularly for individuals from disadvantaged backgrounds to effectively reduce poverty and inequality in Ghana.

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Supplementary material

Supplementary material is available at *Journal of African Economies* online.

Data availability

The data underlying this article are available in its online supplementary material. The datasets were derived from sources in the public domain: Harvard Dataverse at https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi%3A10.7910/DVN/E5QP0F and the Ghana Statistical Service Central Data Catalog at https://www2.statsghana.gov.gh/nada/index.php/catalog.

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