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POVERTY AND WEATHER SHOCKS: A PANEL DATA ANALYSIS OF STRUCTURAL AND STOCHASTIC POVERTY IN ZAMBIA

By

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EXECUTIVE SUMMARY

While it is generally accepted that climate change will exacerbate poverty for small and medium sized farmers in Sub-Saharan Africa (SSA) over the coming years, at least due to rising variability and rainfall shocks (Mulenga, Wineman, and Sitko 2017; Hallegatte et al. 2016), a number of questions remain unanswered. Which types of the poor are more exposed to climate risk and how do the impacts of climate and weather shocks vary across stochastically and structurally poor households? Addressing these questions is crucial for improved targeting of interventions intended to build the resilience of smallholder farmers.

Smallholder farmers' reliance almost entirely on rain-fed agriculture and their limited capacity to cope with weather shocks exposes them to climate risks. Weather shocks negatively impact smallholders through their effects on agricultural productivity, which is the mainstay of rural smallholder households. If left unchecked, weather shocks can lead to increased poverty incidence and intensity.

In this paper, we utilize data from a nationally representative two-wave panel of recent agricultural household surveys to conduct a high resolution analysis of the spatial distribution of poverty, and how the different types of poverty are impacted by exposure to climate change variability. The data allows us to (a) control for observed and unobserved sources of household heterogeneity, and (b) distinguish between the structurally poor, i.e., those households that have very little assets or savings, and the stochastically poor, i.e., those households that have low savings but enough assets that they could liquidate if necessary to smooth consumption during a climate shock.

Out of the 14,508 rural households interviewed in Zambia in 2012 and 2015, about 51% were structurally poor (low income and assets) and 5% were stochastically poor (low income and high assets). About 23% of households that were structurally poor in 2012 remained structurally poor in 2015, hence, chronically poor. A third of the structurally not poor in 2012 fell into poverty in 2015, while about 19% of poor households in 2012 managed to escape poverty in 2015. Structurally poor households in Zambia are more exposed to drought risk. Lower than normal rainfall, as measured by a negative precipitation index, significantly increases the probability of being structurally poor by 2.3 percentage points.

Three implications follow from our findings. First, there is a need for well-structured and targeted social promotion programs to lift the viable but chronically and structurally poor and stochastically poor households from poverty. This can be achieved within the agricultural sector by using the electronic voucher delivery systems to better target large-scale, anti-poverty programs such as the farmer input support program. Along with improved targeting, the use of the electronic based voucher systems crowds-in private sector investments, which make available diverse inputs for farmers and also help develop the rural nonfarm sector where farmers can earn extra incomes. Smart-subsidies should be flanked by output market linkages and/or market development in order to enhance market participation and help improve incomes from agricultural production.

Second, for those not commercially viable, there is a need for a better targeted and sustained social welfare program specifically meant for this group. Thus there is need for sustained social protection (e.g., social cash transfers) in order to prevent the non-poor from falling into poverty. And lastly, the intricate linkages among climate variability, climate risk, and poverty call for more support to enable farmers not only adapt to, but also mitigate climate change and variability. Such support may be

directed towards climate-smart agriculture adoption, autonomous and planned adaptation, improved extension, and climate information services.

CONTENTS

LIST OF TABLES

TABLE **PAGE**

LIST OF FIGURES

TABLE **PAGE**

LIST OF ACRONYMS AND ABBREVIATIONS

CSO	Central Statistical Office
CRE	Correlated Random Effects
GRZ	Government of the Republic of Zambia
GDP	Gross Domestic Product
Ha	Hectare
IAPRI	Indaba Agricultural Policy Research Institute
km	kilometer
MAL	Ministry of Agriculture and Livestock
MoA	Ministry of Agriculture
PPP	Purchasing Power Parity
SPI	Standard Precipitation Index
RALS	Rural Agricultural Livelihood Survey
SSA	Sub-Saharan Africa
TAMSAT	Tropical Applications of Meteorology using Satellite Data and Ground-Based Observations

1. INTRODUCTION

Climate change and variability are projected to worsen poverty in Sub-Saharan Africa (SSA), partly because agriculture, which is the main source of livelihoods is mainly dependent on rainfall (Olsson et al. 2014; Hallegatte et al. 2016). Rainfed agriculture exposes rural households to climate shocks and limited capacities to mitigate shocks *ex-ante* or cope with shocks *ex-post* worsen vulnerability.

The reliance of rural households on rainfed agriculture makes clear the inextricable links between poverty and climate change. Agriculture is more effective at reducing poverty than nonfarm sectors—at least in early stages of development—because it is the main source of livelihood for a majority of rural households, however, its rainfed nature, which predisposes the sector to climate risks and climate change, emerges as a major obstacle in poverty alleviation (Hertel and Rosch 2010; Christiaensen, Demery, and Kuhl 2011; Thurlow, Zhu, and Diao 2012; Hallegatte et al. 2016). Hallegatte et al. (2016) estimate that climate change will cause 300 million people to fall into poverty by 2030 globally. In Zambia, where more than 90% of smallholder agriculture is rainfed, climate change was estimated to reduce growth in agricultural Gross Domestic Product (GDP) by 4% and push approximately 300,000 people into poverty between 2007 and 2016 (Thurlow, Zhu, and Diao 2012; Wineman and Crawford 2017). A recent study also demonstrates that weather shocks increase the proportion of poor households in Zambia and increases the poverty gap (Al Mamun et al. 2018). The impact of a 10% yield drop is higher for rural households at 1% compared to 0.1% among urban households (ibid). Besides the direct economic impacts of climate change on agriculture, Hamududu and Ngoma (2019) project rainfall to decrease by 3% and temperature to increase by 2^{o}C by 2050 in Zambia. Authors posit that these changes in rainfall and temperature are likely to reduce water availability by 13% by mid-century. Should these biophysical impacts of climate change occur, the impact on water availability will have far reaching implications on agricultural development and poverty alleviation efforts in Zambia.

While some work has been done on the impacts of climate change on poverty, economic growth, household incomes, farm revenue, productivity, and water resources availability in Zambia (e.g., Jain 2007; Thurlow, Zhu, and Diao 2012; Wineman and Crawford 2017; Alfani et al. 2019, Hamududu and Ngoma, 2019), the linkages among climate change, agriculture, and the different types of poverty remain poorly understood and quantified at household level. This paper aims to contribute towards filling this gap and asks: what types of the poor are more exposed to climate variability and what is the spatial distribution of the poor in Zambia; does climate variability worsen poverty among smallholder farmers in Zambia; and do these effects differ by poverty groups.

This paper complements and extends previous studies linking climate change, agriculture, and poverty in Zambia in the following three ways. First, unlike Thurlow, Zhu, and Diao (2012) who analyze the impacts of climate change on poverty at national level using a computable general equilibrium model, the current paper applies more recent, nationally representative, two-wave panel data that allows for an in-depth household level analysis of poverty dynamics, while controlling for unobserved heterogeneity. Second, we revisit and expand the analyses on the impacts of weather shocks on household welfare in Alfani et al. (2019) and Jain (2007) by incorporating unique exogenously defined drought and flood risks to measure exposure to climate risk, and the standard precipitation index (SPI) to measure rainfall variability. The standard precipitation index is computed as the difference between current season rainfall and the average for the last 16 years divided by the standard deviation of rainfall over the last 16 years. A positive (negative) SPI signals excess (deficient) rainfall. We defined exposure to climate risk depending on whether the household had an

SPI value less (more) than the enumeration area SPI mean minus (plus) two standard deviations of the enumeration area SPI. Lastly, we distinguish between the stochastically and structurally poor in order to better characterize poverty among smallholder farmers in Zambia.

Stochastic poverty—among farmers with an accumulation of assets that could be liquidated if necessary to smooth out consumption—may be caused by a shock to the household e.g., seasonal crop failure that is of a temporal nature and is likely to wane with the passage of time, while structural poverty—among farmers that do not have a high accumulation of assets nor income—can be deep-rooted chronic poverty that persists for a long time. Distinguishing categories among the poor is important because they are not a homogenous group and each category require a different set of policy options (Sen 1981; Jalan and Ravallion 2000; Hulme and Shepherd 2003). Unpacking the poverty groups matters for policy. It can help improve the targeting of antipoverty and resilience programs depending on poverty status and vulnerability or exposure to climate change.

Better targeting of anti-poverty programs requires a good understanding of *who* the poor are, *where* they are most concentrated, and the extent of *their* vulnerability and exposure to weather shocks. Such an understanding is particularly relevant for Zambia where there is strong political will to increase investments in social protection and social security, build resilience in smallholder agriculture, and to realign public spending in agricultural development to effectively fight poverty (GRZ 2017).

We briefly review the links between poverty and climate in Section 2 and present a conceptual framework on the impacts of climate change on poverty, through agriculture in Section 3. Section 4 presents data and methods and results in Section 5 are discussed in Section 6. We conclude the paper and offer some reflections in Section 7.

2. LINKAGES BETWEEN POVERTY AND CLIMATE CHANGE

The linkages between poverty and climate change are complex. Climate change directly affects poverty through reduced agricultural productivity and production, asset accumulation, and returns on assets. Indirectly, climate change affects output prices, labor productivity, and availability of off-farm employment opportunities. Like in other agrarian SSA countries, increased incidences of climate shocks such as droughts and floods have led to crop failure and increased outbreaks of pests and livestock diseases in Zambia, which in turn worsens poverty.

The add-on effects of climate change on poverty are more profound in Zambia where more than half (54.4%) of the population is poor and the incidence of poverty is highest among small scale (78.9%) and medium scale farmers (64.5%) (CSO 2015). In fact, the incidence of poverty is highest in some of the most agriculturally productive provinces such as Central (56.2%), Southern (57.6%), Eastern (70%) and Northern (79.7%). Except for Northern Province, the other three regions and Western Province are also prone to rainfall variability and they are located in low rainfall regions (Braimoh et al. 2018).

Climate shocks and variability are estimated to reduce agricultural GDP by 4%, gross GDP by 10%, cotton production by 68%, and 33% for each of maize and groundnuts in Zambia, (Thurlow, Zhu, and Diao 2012, Braimoh et al. 2018). In a cross-country study, Al Mamun et al. (2018) found that the El Niño weather phenomena worsens poverty in Eastern and Southern Africa. For Zambia, they found that while the increase in the poverty rate is lower, it is much higher for the poverty gap. Specifically, a 10% reduction in maize yields increases the poverty rate by 1 percentage point, and increases the poverty gap by 1.9 percentage points. As would be expected, the increase in the poverty rate and gap is respectively, about 16 and 10 times higher in rural than urban areas. Authors also found that a 10% drop in maize prices increases the poverty rate by 1.16 percentage points, and increases the poverty gap by 2.4 percentage points in the rural areas. Alfani et al. (2019) found that the 2015/2016 El Niño-induced shocks in Zambia were associated with about 20% and 37% reductions in maize yields and per capita incomes, respectively.

Zambia has continued to experience and is likely to continue experiencing increased incidences of weather shocks, with prolonged intra-season dry spells characterizing the 2017/2018 and 2018/2019 agricultural seasons. Future climate projections suggest that temperatures will increase and rainfall will reduce for most parts of Western, Southern, Eastern and Central Provinces by mid-century to end of the century in 2100 (Hamududu and Ngoma 2019). While it is generally believed that such weather shocks have the potential to worsen poverty, it remains unclear how such impacts vary across the poverty types and the extent to which, the different types of the poor are exposed to weather shocks in Zambia.

3. CONCEPTUAL FRAMEWORK

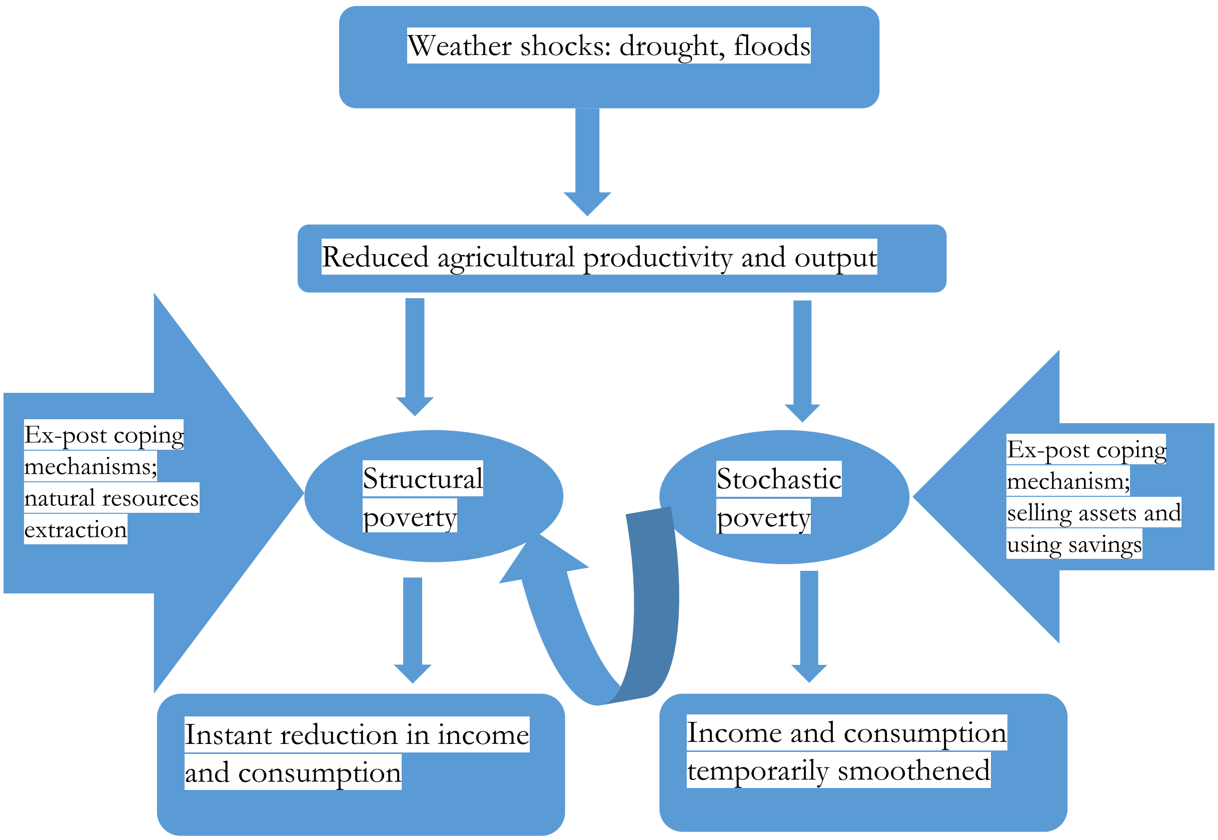
With over 90% of smallholder agriculture under rain-fed production system, climate and weather shocks—both floods and droughts—present a risk to rural livelihoods in Zambia. The impact of weather shocks on rural livelihoods is mainly transmitted through reduced agricultural productivity and output with subsequent reduction in incomes and consumption (Balisacan et al. 2011; Skoufias and Vinha 2012; Karfakis, Lipper, and Smulders 2012). Reduced agricultural productivity exerts negative shocks on rural livelihoods given the population's heavy reliance on agriculture.

However, it is important to recognize that climate shocks have varying effects on different sub-groups of smallholder farmers depending on their welfare status. Poor households with little or no assets or savings (structurally poor) are the most threatened by climate and weather shocks as they do not have assets to fall back on when agricultural output is reduced. Households with more assets than savings (stochastically poor) are equally threatened but to a lesser extent because in the event of shocks, they have an option to liquidate their assets and /or use their savings to bridge the food and income insecurity. Thus, the impacts of climate shocks on smallholder farmers are unlikely to be homogenous, but to vary depending on the poverty status of households. Thus, it is important to first identify the different household groups and their poverty status in order to get a more nuanced understanding of how climate shocks can impact poverty.

Figure 1 depicts the pathways through which climate and weather shocks could reinforce poverty and the different responses or coping mechanisms likely to be triggered based on a household's poverty status – whether structural or stochastic. This framework draws from Skoufias and Vinha (2012), where they show possible pathways of how changes in climate affect household income and consumption. Generally, large swings in weather tend to affect consumption and incomes of rural households. In the event of abrupt agricultural production decline, structurally poor households are more than likely to intensify extraction of natural resources (Mulenga et al. 2014; Angelsen and Dokken 2018), some of which cause environmental degradation (e.g., unsustainable charcoal production and logging).

Intensification of environmentally degrading livelihood activities further aggravate poverty for poor households whose livelihoods depend on natural resources to a sizeable extent. For the stochastically poor, selling of assets or using their savings or both could help smoothen income and consumption but only temporarily. If weather or climate shocks persist for a longer period, stochastically poor households may deplete all their assets and savings and could potentially fall into structural poverty and subsequently engage in environmentally degrading livelihood activities. Absent formal insurance or social protection, this creates a vicious cycle whereby poverty and environmental degradation are simultaneously reinforced by climate and weather shocks.

Figure 1. Effects of Weather Shocks on Rural Household Income and Consumption



Source: Adapted from Skoufias and Vinha (2012).

4. DATA AND METHODS

4.1 Data Sources

Data are drawn from the two-wave nationally representative Rural Agricultural Livelihoods Survey (RALS) conducted by the Indaba Agricultural Policy Research Institute (IAPRI) in collaboration with the Ministry of Agriculture and the Central Statistical Office in Zambia. These data are complemented by spatial long-term historical rainfall data collected by the Tropical Applications of Meteorology using Satellite Data and Ground-Based Observations (TAMSAT) (Maidment et al. 2014; Tarnavsky et al. 2014, Maidment et al. 2017). In particular, monthly data was used to calculate total growing season rainfall (both current season and prior 16-year average), the coefficient of variation over the prior 16 years. We used ArcGIS Model Builder to join the rainfall cell values of each indicator to each household GPS location. The spatial resolution is 0.0375^2 degrees, or about 16 square kilometers. In other words, the rainfall data can roughly be considered a measure at the village level.

The RALS data are large datasets collected from about 8,839 households in 2012 and 9,520 households 2015 (new households were added). Both RALS 2012 and 2015 are statistically representative at the provincial and national levels, and 7,254 panel households were successfully interviewed over the two-waves. This paper only uses data for the panel households. Sampling and survey details can be found here (CSO/MAL/IAPRI 2012; CSO/MAL/IAPRI 2015).

4.2 Variable Construction

4.2.1 Dependent Variables

We are interested in explaining structural and stochastic poverty, and transitions in and out of poverty in this paper. Structural poverty and stochastic poverty were computed using household income and the value of assets deflated to 2005 prices using consumer price indices for the survey years. The real per capita income and real asset value in 2005 prices from the first stage were then converted to international prices using the 2005 purchasing power parity (PPP) exchange rates. A household is poor if the per capita income in 2005 PPP is less than the standard poverty threshold of $1.25 per day.[1] We defined a relative asset poverty line as the median asset value in 2005 prices at the enumeration area level. A household is asset poor if their asset value is below the asset poverty line. Using these income and asset poverty metrics, we then defined structural poor households as those poor in both income and assets.. Households poor in income but non-poor in assets are stochastically poor. The stochastically not poor are non-poor in income but poor in assets and households non-poor in both income and assets are structurally non-poor. These definitions are summarized in Table 1. We focus on structural and stochastic poverty in our analysis.

[1] The World Bank raised the poverty line to USD 1.90 using 2011 PPP rates in October 2015, but to facilitate comparisons with 2012 RALS Survey, income poverty is provided using 2005 PPP rates.

Table 1. Definitions of Poverty Categories

		Value of assets in 2005 PPP	
		Poor (< median EA asset value)	Non-poor (> median EA asset value)
Household income in 2005 PPP	Poor (< \$1.25)	Structurally poor	Stochastically poor
	Non-poor (> \$1.25)	Stochastically not poor	Structurally not poor

Source of all tables: Authors.

We are also interested in understanding transitions in and out of poverty between 2012 and 2015. Using only structural poverty and the year 2015, a household is chronically poor if they were structurally poor both in 2012 and 2015. An escapee household is one that was poor in 2012 but not in 2015 and those that were not poor in 2012 but became poor in 2015 fell into poverty.

4.2.2 Independent Variables

In addition to the usual socioeconomic and demographic factors that may influence whether a household is structurally/chronically or stochastically poor, we computed variables to measure rainfall variability and exposure to climate chocks. We computed a standard precipitation index (SPI) that measures rainfall variability following Patel et al. (2007). Using the 16-year spatial rainfall data, the SPI was computed as: $SPI_{it} = (cag_{rainit} - \bar{cag}_{rain16}) / sdag_{rain16}$, where SPI_{it} is the standard precipitation index for household i in year t, cag_{rainit} is total rainfall for the agricultural season in year t, $\bar{cag}_{rain16}$ is the average seasonal rainfall over the last 16 years, and $sdag_{rain16}$ is the standard deviation for seasonal rainfall over the last 16 years.[2] Using the SPI, we defined a negative SPI $(SPI < 0)$ to measure deficient rainfall and a positive SPI $(SPI > 0)$ to measure excessive rainfall.

We computed drought risk to measure exposure to climate risk as an SPI less than the enumeration area mean SPI minus two standard deviations of the enumeration area SPI. Flood risk is defined as an SPI more than the enumeration area mean SPI plus two standard deviations of the enumeration area SPI. A priori, we expected a positive correlation between all rainfall variability and climate risk exposure measures and poverty. The rest of the variables are defined in Table 2.

[2] While we acknowledge that the 16-year span is limited, it is long enough to give a good picture of climate and weather shocks over the (nearly) two decades, within which the incidences of such shocks has increased in Zambia.

Table 2. Summary Statistics of Variables Used in the Regressions

	2012 *(n=7,254)*	2015 *(n=7,254)*	Pooled sample *(n=14,508)*		
	Mean	Mean	Mean	Min	Max
Dependent variables					
Structurally poor (yes =1)	0.51	0.53	0.51	0.00	1.00
Structurally not poor (yes =1)*	0.15	0.14	0.15	0.00	1.00
Stochastically poor (yes =1)	0.06	0.05	0.05	0.00	1.00
Stochastically not poor (yes =1)*	0.30	0.27	0.29	0.00	1.00
Chronic poor (poor in 2012 and 2015; yes = 1)		0.23			
Fell into poverty (not poor in 2012 but poor in 2015; yes = 1)		0.30			
Escaped poverty (poor in 2012 but not poor in 2015; yes = 1)		0.19			
Never poor (not poor in 2012 and 2015, yes =1)		0.28			
Key climate variables					
Negative standard precipitation index (yes = 1, SPI < 0)	0.67	0.27	0.45	0.00	1.00
Positive standard precipitation index (yes = 1, SPI > 0)	0.32	0.73	0.55	0.00	1.00
Flood risk (yes =1)	0.01	0.02	0.02	0.00	1.00
Drought risk (yes =1)	0.02	0.01	0.02	0.00	1.00
Current season rainfall (mm)/100	7.83	8.50	8.20	5.59	10.36
Other variables					
Share of off farm income to total income	0.30	0.37	0.34	0.00	1.00
Female head (yes =1)	0.23	0.26	0.24	0.00	1.00
Age, household held (years)	44.40	48.28	46.56	17.00	111.00
Education level, household head (years)	5.96	5.69	5.81	0.00	19.00
Dependence ratio	2.71	14.30	9.12	0.00	100.00
Land holding 0 – 2 ha (yes = 1)	0.43	0.48	0.46	0.00	1.00
Land holding 2 – 5 ha (yes = 1)	0.33	0.29	0.31	0.00	1.00
Land holding 5 – 20 ha (yes = 1)	0.20	0.19	0.20	0.00	1.00
Land holding > 20 ha (yes = 1)	0.01	0.02	0.02	0.00	1.00
Distance to market (km)/10	2.68	2.50	2.58	0.00	60.00
Distance to boma (km)/10	4.34	4.04	4.17	0.00	25.00

* added for completeness, not used in the models.

4.3 Empirical Strategy

The main aim of this paper is to characterize poverty into structural and stochastic poverty and to assess the role of climate or rainfall variables on the poverty status of a household. Since our outcome variables—the poverty measures—are dummy variables, this paper uses the random effects probit model. We can motivate the random effects probit from a latent variable framework:

$$\begin{aligned} y_{it}^{*} &= \boldsymbol{x}_{it}\boldsymbol{\beta} + c_i + \mu_{it} \\ y_{it} &= 1\left[y_{it}^{*} > 0 \right], \end{aligned} \tag{1}$$

where y_{it} is a binary outcome variable = *1* if household *i* is structurally or stochastically poor in year *t*. Note that y_{it} is only observed if the latent variable $y_{it}^{*} > 0$; $\boldsymbol{x}_{it}$ is a $k \times 1$ vector of explanatory variables, including an intercept; $\boldsymbol{\beta}$ is a $1 \times k$ vector of parameters to be estimated, c_i is time invariant unobserved individual heterogeneity and u_{it} is the zero-mean idiosyncratic error term.

The probability of a positive outcome in equation (1) is given by:

$$\Pr\left(y_{it} = 1 \mid \boldsymbol{x}_{it}, c_i \right) = \Phi\left(\boldsymbol{x}_{it}\boldsymbol{\beta} + c_i \right), \tag{2}$$

where Φ is the standard normal cumulative density function. The standard random effects probit in equation (2) assumes no correlation between c_i and x_{it}. This assumption is restrictive because time invariant unobserved individual characteristics (c_i), such as ability and business acumen might affect whether one is poor or not. Following Wooldridge (2010), we relaxed this restrictive assumption using the Mundlak and Chamberlain approach and explicitly modelled c_i as a function of the averages ($\overline{\boldsymbol{x}}_i$) of all time varying covariates in equations (1) and (2). Formally, we assumed $c_i = \psi + \overline{\boldsymbol{x}}_i\boldsymbol{\xi} + a_i$, where a_i is the error term with a constant variance and ψ is the intercept. We included ($\overline{\boldsymbol{x}}_i$) as additional regressors and modelled the probability of being poor using a correlated random effects probit model specified as:

$$\begin{aligned} \Pr\left(y_{it} = 1 \mid \boldsymbol{x}_{it}, c_i \right) &= \Pr\left(y_{it} = 1 \mid \boldsymbol{x}_{it}, \overline{\boldsymbol{x}}_i, a_i \right) \\ &= \Phi\left(\boldsymbol{x}_{it}\boldsymbol{\beta} + \psi + \overline{\boldsymbol{x}}_i\boldsymbol{\xi} + a_i \right) \end{aligned} \tag{3}$$

Adding ($\overline{\boldsymbol{x}}_i$) in equation (3) allows for correlation between c_i and x_{it}. Equation 3 was estimated separately for structural poverty and stochastic poverty. $\boldsymbol{x}_{it}$ includes all covariates defined in Table 2. We used a multinomial logit model to assess factors that explain transitions in and out of poverty between 2012 and 2015 using the 2012 covariates as baseline values.

5. RESULTS

5.1 Where Are the Poor Located and Do They Move in and out of Poverty in Zambia?

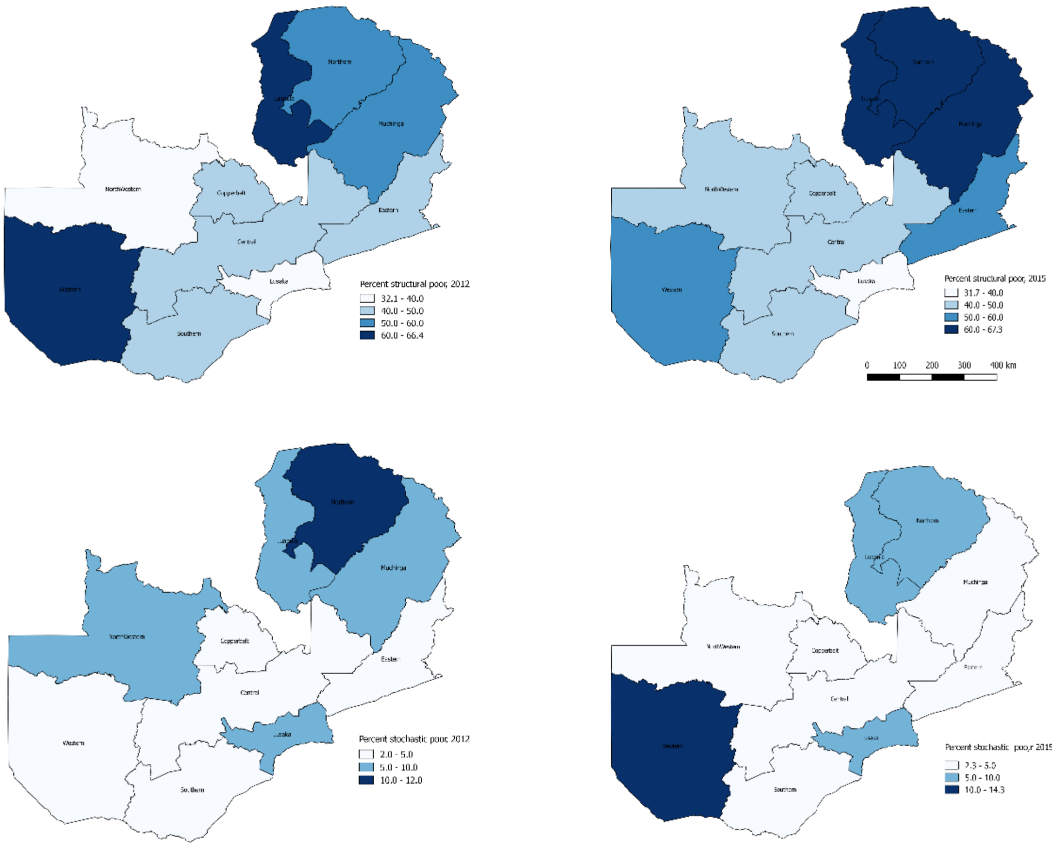
Out of the 14,508 rural households successfully surveyed in Zambia in 2012 and 2015, about 51% were structurally poor and 5% were stochastically poor (Table 3). Nearly a third (29%) were stochastically not poor and 15% were not structurally not poor. The loci of the structurally poor both in 2012 and 2015 appear to be concentrated in Northern, Muchinga, Luapula, Western and Eastern Provinces where at least more 50% of the smallholders were poor (Table 3 and Figure 2).

Table 3. Proportion of Structurally and Stochastically Poor Households by Province and Year

	2015		2012	
	Structurally poor	Stochastically poor	Structurally poor	Stochastically poor
Central	43.91	2.27	46.45	4.82
Copperbelt	40.81	4.40	48.15	2.73
Eastern	53.64	2.34	47.21	3.67
Luapula	60.43	5.71	63.24	9.39
Lusaka	31.67	7.39	32.08	8.49
Muchinga	62.13	3.68	58.49	6.94
Northern	67.27	6.88	59.92	12.00
Northwestern	47.97	4.55	33.58	5.90
Southern	44.54	3.20	41.08	2.05
Western	59.06	14.35	66.40	4.55
Total	53.12	5.09	51.08	5.81

Source: Authors.

Figure 2. Province Level Spatial Distribution of Structurally Poor (Top Panel) and Stochastically Poor (Bottom Panel) Rural Households in 2012 (Left Panel) and 2015 (Right Panel).



Source for all figures: Authors, unless otherwise stated.

There are various nuances regarding households' transitions in and out poverty. About 23% of households that were structurally poor in 2012 remained structurally poor in 2015, and were therefore deemed chronically poor. A third of the households that were structurally not poor in 2012 fell into poverty in 2015, while about 19% of poor households in 2012 managed to escape poverty in 2015. Twenty-three percent of the households were never poor structurally, both in 2012 and 2015.

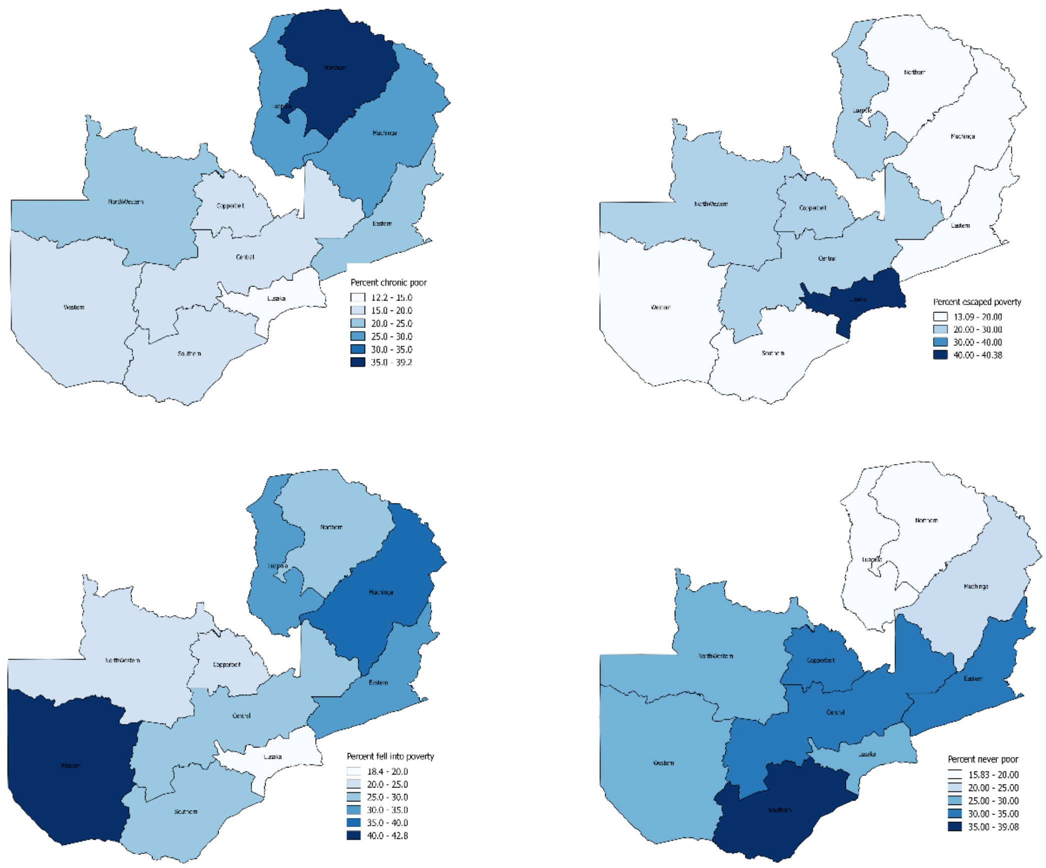
Although the incidence of chronic poverty was widespread, the locus was around parts of Northern, Luapula and Muchinga Provinces where the incidence of chronic poverty was more than 25% between 2012 and 2015 (Table 4 and Figure 3, top left panel). The incidence of people falling into poverty was more widespread across the country between 2012 and 2015, with Western, Muchinga, Luapula, and Eastern Provinces posting the largest margins at more than 30% (Table 4 and Figure 3, bottom left panel). Not many households who were poor in 2012 managed to escape poverty by 2015. The top right panel in Figure 3 shows that only Lusaka and Copperbelt Provinces had at least

25% of households escape poverty. In sum, within province poverty transitions suggest that Northern had more chronically poor households, Lusaka had the largest share of escapee households and a large share of households fell into poverty in each of Eastern, Luapula and Western. North Western, Southern, Copperbelt, and Central had more households that were never poor between 2012 and 2015.

Table 4. Transitions in and out of Structural Poverty by Province and Year

Province	Chronic poor	Fell into poverty	Escaped poverty	Never poor
Central	16.38	27.53	23.26	32.83
Copperbelt	18.2	22.60	27.34	31.85
Eastern	21.82	30.83	17.11	30.24
Luapula	25.60	34.83	21.79	17.78
Lusaka	12.25	18.43	40.38	28.94
Muchinga	26.17	35.88	16.22	21.73
Northern	39.24	28.03	16.90	15.83
North Western	24.60	23.37	22.52	29.51
Southern	17.30	27.24	16.39	39.08
Western	16.31	42.75	13.09	27.85
Total	22.66	30.31	19.25	27.78

Figure 3. Province Level Spatial Distribution of Households who Were Chronically Poor (Top Left), Escaped Poverty (Top Right), Fell into Poverty (Bottom Left), and Never Poor (Bottom Right) between 2012 and 2015



5.2 Are the Poor More Exposed and Vulnerable to Climate Variability in Zambia?

We used two approaches to answer this question. First, we used a means test reported in Table 5 to check for differences in key covariates by poverty status. Using this bivariate approach, a larger proportion of the structurally poor were more exposed to drought risk (1.8% vs 1.3%) and this result is statistically significant at the 5% level of significance (Table 5). The structurally poor households were mostly headed by younger, less educated females, had more economic dependents, and were farther away from main markets and district centers. Structurally poor households had a lower share of off-farm incomes to total income. In terms of landholding, the share of structural poverty was higher among households with farms 0 – 2 ha, but was lower among households with larger landholdings (5 – 20 ha and greater than 20 ha farms). We obtained qualitatively similar results by stochastic poverty, see columns 3 and 4 in Table 5. The main difference is that the stochastically poor households had larger shares of off-farm to total incomes and the incidence of stochastic poverty was, respectively, lower and higher among 0 – 2 ha and 5 – 20 ha farms.

The bivariate comparisons in Table 5 do not control for other confounding variables that could help explain structural and stochastic poverty. We extend this analysis using a multivariate correlated random effects probit and report the results in Table 6. Columns 1 and 2 present average partial effects for factors influencing structural poverty, while columns 3 and 4 present average partial effects for factors influencing stochastic poverty. We included the negative and positive SPIs in separate regression because the two variables are highly collinear. We will focus mainly on the results for structural poverty in columns 1 and 2.

After controlling for other potential confounders, lower than average rainfall as measured by the negative SPI is associated with a higher probability of being structurally poor. Households headed by females and that have higher dependence ratios are likely to be structurally poor. Human capital measured by education, a larger share of off-farm incomes to total incomes[3] and age of the household head are associated with reduced structural poverty among rural households in Zambia. Having smaller landholdings (0 – 5 ha) is associated with a higher probability of being structurally poor but larger landholdings (5 – 20 ha) reduce the chance of being structurally poor.

[3] A somewhat surprising result is that a higher proportion of off farm incomes is associated with an increased chance of being stochastically poor. This perhaps stems from the fact that off farm incomes are positively correlated with being asset non-poor.

Table 5. Mean Differences in Key Variables by Structural and Stochastic Poverty

	Structurally poor			Stochastically poor		
	(1) no	(2) yes	T-test (1)-(2)	(3) no	(4) yes	T-test (1)-(2)
	Mean/SE	Mean/SE	Difference	Mean/SE	Mean/SE	Difference
Negative standard precipitation index (yes =1)	0.449	0.446	0.004	0.449	0.425	0.024
	[0.008]	[0.008]		[0.006]	[0.022]	
Positive standard precipitation index (yes =1)	0.544	0.550	-0.006	0.546	0.570	-0.024
	[0.008]	[0.008]		[0.006]	[0.022]	
Flood risk (yes =1)	0.017	0.016	0.000	0.016	0.022	-0.006
	[0.002]	[0.002]		[0.002]	[0.007]	
Drought risk (yes =1)	0.013	0.018	-0.005**	0.015	0.021	-0.006
	[0.002]	[0.002]		[0.001]	[0.006]	
Share of off farm income to total income	0.391	0.285	0.106***	0.330	0.456	-0.126***
	[0.006]	[0.005]		[0.004]	[0.016]	
Current season rainfall	8.172	8.234	-0.062***	8.197	8.322	-0.125**
	[0.014]	[0.014]		[0.010]	[0.048]	
Female head (yes =1)	0.204	0.283	-0.078***	0.245	0.227	0.018
	[0.007]	[0.007]		[0.005]	[0.020]	
Age, household held	46.967	46.165	0.802**	46.629	45.297	1.332*
	[0.250]	[0.248]		[0.181]	[0.764]	
Education level, household head	6.613	5.039	1.574***	5.795	6.015	-0.220
	[0.060]	[0.052]		[0.042]	[0.158]	
Dependence ratio	8.248	9.941	-1.693***	9.222	7.328	1.894***
	[0.160]	[0.182]		[0.127]	[0.409]	
Land holding (0 – 2 ha) (yes =1)	0.403	0.508	-0.106***	0.459	0.419	0.039*
	[0.008]	[0.008]		[0.006]	[0.023]	
Land holding (2 – 5 ha) (yes =1)	0.319	0.298	0.021**	0.307	0.331	-0.024
	[0.007]	[0.007]		[0.005]	[0.022]	
Land holding (5 – 20 ha) (yes =1)	0.233	0.159	0.074***	0.194	0.215	-0.020
	[0.007]	[0.006]		[0.005]	[0.018]	

	Structurally poor			Stochastically poor		
	(1) no	(2) yes	T-test (1)-(2)	(3) no	(4) yes	T-test (1)-(2)
Land holding (> 20 ha) (yes =1)	0.024	0.015	0.009***	0.019	0.020	-0.001
	[0.002]	[0.002]		[0.001]	[0.007]	
Distance to market (km)	2.447	2.706	-0.259***	2.578	2.598	-0.019
	[0.050]	[0.049]		[0.036]	[0.128]	
Distance to boma (km)	3.950	4.381	-0.431***	4.172	4.142	0.030
	[0.052]	[0.052]		[0.038]	[0.142]	

The value displayed for t-tests are the differences in the means across the groups; ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

Table 6. Average Partial Effects of Factors Explaining Structural and Stochastic Poverty among Rural Households in Zambia

	Structurally poor (yes =1)		Stochastically poor (yes =1)	
	(1) Panel CRE Probit	(2) Panel CRE Probit	(3) Panel CRE Probit	(4) Panel CRE Probit
Negative standard precipitation index (yes =1)	0.023*		-0.000	
	(0.014)		(0.007)	
Drought risk (yes =1)	0.022		-0.004	
	(0.032)		(0.014)	
Positive standard precipitation index (yes =1)		-0.020		0.001
		(0.014)		(0.007)
Flood risk (yes =1)		-0.040		0.025
		(0.032)		(0.019)
Share of off farm income	-0.190***	-0.190***	0.058***	0.058***
	(0.018)	(0.018)	(0.009)	(0.009)
Current season rainfall	0.015	0.014	-0.008	-0.009
	(0.013)	(0.013)	(0.006)	(0.006)
Female head (yes =1)	0.067***	0.067***	0.005	0.005
	(0.010)	(0.010)	(0.005)	(0.005)
Age, household held	-0.004***		-0.000	
	(0.000)	(0.000)	(0.000)	(0.000)
Education level, household head	-0.030***	-0.030***	0.001	0.001
	(0.002)	(0.002)	(0.001)	(0.001)
Dependence ratio	0.001*	0.001*	-0.000	-0.000
	(0.001)	(0.001)	(0.000)	(0.000)
Land holding 0 – 2 ha (yes =1)	0.119***	0.119***	-0.012	-0.012
	(0.020)	(0.020)	(0.010)	(0.010)
Land holding 2 – 5 ha (yes =1)	0.046**	0.046**	0.004	0.004
	(0.020)	(0.020)	(0.010)	(0.010)
Land holding 5 – 20 ha (yes =1)	-0.035*			

	(0.021)	(0.021)	(0.011)	(0.011)
Distance to market (km)	0.002	0.002	0.000	0.000
	(0.002)	(0.002)	(0.001)	(0.001)
Distance to boma (km)	0.002	0.002	-0.000	-0.000
	(0.002)	(0.002)	(0.001)	(0.001)
Year fixed effects	yes	yes	yes	yes
District fixed effects	yes	yes	yes	yes
CRE variables included	yes	yes	yes	yes
Observations	14,058	14,058	13,991	13,991

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

5.3 Transitions in and out of Poverty among Rural Households in Zambia

This section attempts to explain why some households remained structurally poor, while others fell into or escaped poverty between 2012 and 2015, and assesses whether rainfall variability and exposure to climate shocks could explain the transitions. We estimated a multinomial logit regression model whose dependent variable has four categories: chronic poor, fell into poverty, escaped poverty, and never poor. The estimation was done using the 2012 covariates (as baseline covariates) with the poverty status realized in 2015 as the dependent variable. The estimation clustered standard errors at enumeration area level and as before, there are separate regressions for negative SPI and drought risk, and positive SPI and flood risk.

Results in Table 7 show average partial effects where our main interest is only to explain the direction of associations. High current growing season rainfall is associated with an increased likelihood of falling into poverty. Female headed households are more likely to be chronically poor, but are less likely to fall into poverty. When poor, female headed households are more likely to escape poverty. Households headed by older and more educated heads are less likely to be chronically poor, but are more likely to fall into poverty. And when, poor, such households are less likely to escape poverty.

On average, households with 2–5 ha farms are less likely to be chronically poor and if poor, these households are more likely to escape poverty. Households located farther away from district centers are more likely to be chronically poor, perhaps, due to limited access to markets.

Table 7. Average Partial Effects of Factors Associated with Transitions in and out of Poverty between 2012 and 2015 among Rural Households in Zambia

	(1) Chronic poor	(2) Fell into poverty	(3) Escaped poverty	(4) Chronic poor	(5) Fell into poverty	(6) Escaped poverty
Negative standard precipitation index (yes =1)	-0.031	0.012	-0.008			
	(0.024)	(0.021)	(0.024)			
Drought risk (yes =1)	0.055	-0.055	-0.029			
	(0.047)	(0.039)	(0.047)			
Positive standard precipitation index (yes =1)				0.039	-0.008	0.005
				(0.025)	(0.021)	(0.024)
Flood risk (yes =1)				0.004	0.028	0.060
				(0.049)	(0.057)	(0.063)
Share of off farm income to total income	-0.112***	0.079***	-0.068***	-0.112***	0.079***	-0.068***
	(0.021)	(0.020)	(0.024)	(0.021)	(0.020)	(0.024)
Current season rainfall	-0.021	0.038*	-0.012	-0.025	0.037*	-0.011
	(0.021)	(0.020)	(0.023)	(0.020)	(0.020)	(0.023)
Female head (yes =1)	0.040**	-0.044***	0.048***	0.041**	-0.045***	0.048***
	(0.016)	(0.015)	(0.017)	(0.016)	(0.015)	(0.017)
Age, household held	-0.002***	0.002***	-0.002***	-0.002***	0.002***	-0.002***
	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
Education level, household head	-0.013***	0.013***	-0.014***	-0.013***	0.013***	-0.014***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Dependence ratio	0.001	0.000	0.000	0.001	0.000	0.000
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
Land holding 0 – 2 ha (yes =1)	-0.046	-0.013	0.081**	-0.046	-0.012	0.082**
	(0.030)	(0.031)	(0.039)	(0.031)	(0.031)	(0.039)
Land holding 2 – 5 ha (yes =1)	-0.054*	-0.012	0.065*	-0.054*	-0.010	0.067*
	(0.030)	(0.030)	(0.039)	(0.030)	(0.030)	(0.039)
Land holding 5 – 20 ha (yes =1)	-0.046	-0.004	0.040	-0.046	-0.003	0.042
	(0.030)	(0.032)	(0.040)	(0.031)	(0.032)	(0.040)
Distance to market (km)	-0.000	-0.001	-0.001	-0.000	-0.001	-0.001

	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Distance to boma (km)	0.005**	-0.003	0.001	0.005**	-0.003	0.001
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
District fixed effects	yes	yes	yes	yes	yes	yes
Observations	7,048	7,048	7,048	7,048	7,048	7,048

Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

6. DISCUSSION

6.1 Characterizing Rural Poverty and Transitions in and out of Poverty in Zambia

Our results which distinguish between structural poverty (poor in both incomes and assets) and stochastic poverty (poor in income but not in assets) paint a different picture on the incidence of poverty in rural Zambia. We found that about 51% and 53% of rural households in Zambia were structurally poor in 2012 and 2015, respectively, while about 6% and 5% were stochastically poor between the two survey years. The rest of the households were not poor in a structural or stochastic sense.

Poverty estimates based on either income or expenditure are higher than those based on both income and assets as done in this paper. For example, income-based rural poverty was estimated at 76% and 78% in 2012 and 2015, respectively, while the official expenditure-based rural poverty estimates for the same period are 78% and 79%, respectively (CSO 2015; CSO/MAL/IAPRI 2015). And yet, our estimates suggest that about 51 – 55% of rural households were structurally poor, i.e., poor in both income and assets) between 2012 and 2015 in Zambia. Despite using different approaches to estimating poverty, our results are in line with the national estimates in suggesting that the loci for rural poverty in Zambia includes Western, Luapula, Northern, and Muchinga Provinces (CSO 2015; CSO/MAL/IAPRI 2015).

Findings on the incidence of poverty compliment the official national poverty estimates in at least three main ways. First, by distinguishing among the poor, our results show that just over half of the structurally poor rural folks might need more deep rooted assistance to lift them out poverty. A better targeted input subsidy programs (e.g., electronic voucher) flanked by output market linkages could help prop the structurally poor but viable farmers out of poverty, while a targeted social welfare program (e.g., conditional social cash transfer) can be deployed to assist the structurally poor and non-viable sub-group. Second, our results which show that 23% of households that were structurally poor in 2012 remained structurally poor in 2015, draws attention to this group of the poor which lacked the ability to move out of poverty over the three years. And, lastly, our results showing that a third of the households that were structurally not poor in 2012 fell into poverty in 2015 point to the need for sustained social protection in order to keep such households out of poverty.

6.2. Exposure to Climate Risk and Poverty in Zambia

Besides distinguishing among poverty typologies, we assessed the poor's exposure to climate shocks and how such shocks explain poverty. We found significant associations between climate risk and poverty incidence, and transitions in and out of poverty. A larger proportion of the structural poor household in Zambia were more exposed to drought risk compared to the non-structural poor for the study period. This result is in line with Angelsen and Dokken (2018) who found that poor households across 24 tropical countries were more exposed to climate variability and Azzarri and Signorelli (2020) who found that flood risk increases the probability of poverty in Sub-Saharan African countries. Our results suggesting that lower than normal (or the past 16-years average) rainfall as measured by a negative precipitation index significantly increases the probability of being structurally poor by 2.3% are in line with Alfani et al. (2019), who found that the El Niño weather phenomena was associated with reduced maize yields and per capita incomes in Zambia. This is reinforced by our finding suggesting that a high current growing season rainfall is associated with an increased chance of falling into poverty.

Although we did not directly examine the mechanisms through which climate risk might influence poverty outcomes, we can speculate that the primary impact channel will be through agriculture, which is the main source of livelihoods for the rural households in our sample. Earlier studies on the links between agricultural outcomes and poverty confirm this assertion. For example, Al Mamun et al. (2018) found that a 10% reduction in yield increases poverty rate by 1% in rural areas, while Alfani et al. (2019) found that the 2015/2016 El Niño shocks significantly reduced maize yields and per capita incomes by 20% and 37%, respectively in Zambia.

In sum, our findings lend support to widely held concerns that climate risks might worsen poverty for agrarian based economies (e.g., Thurlow, Zhu, and Diao 2012; Hallegatte et al. 2016; Angelsen and Dokken 2018; Azzarri and Signorelli 2020). We add to this literature by showing that climate shocks might actually worsen structural poverty too. Unlike stochastic poverty which might wane with the passage of time because it is temporal (to some extent), addressing structural poverty requires well-planned and long-term social promotion policies beyond the usual safety nets. Our findings showing that about 23% of the structurally poor households in 2012 remained structurally poor in 2015 and that 30% of the structurally not poor households in 2012 fell into poverty in 2015 buttress the need for more robust social promotion policies in Zambia.

7. CONCLUSION

This paper distinguished between structural and stochastic poverty and assessed the extent to which each type of the poor is exposed to climate variability and climate risks in Zambia. We honed in on transitions in and out of poverty and assessed the extent to which climate variability worsens poverty among smallholder farmers and whether these effects differ by poverty groups.

We used nationally representative two-wave panel household data and long-term spatial rainfall data to define unique measures of rainfall variability and climate risk. About half of all the smallholder farmers in Zambia were structurally poor in the sense that they had low income and assets relative to set thresholds. (This estimate is some order of magnitude lower than the official income or expenditure-based poverty estimates in Zambia). Of all structurally poor smallholder farmers in 2012, nearly one-fifth were chronically poor and about 19% escaped by 2015. A third of the households that were structurally not poor in 2012 fell into poverty in 2015. Our findings largely suggest that a larger proportion of the structural poor household in Zambia were more exposed to drought risk compared to the non-structural poor over the study period. We found some evidence suggesting that rainfall variability and climate risk are associated with an increased likelihood of being structurally poor.

We draw three main implications. First, since more than half of the smallholder farmers are structurally poor, well-structured and targeted social promotion programs are needed to pull these masses from poverty. Absent formal insurance options, this implies that large-scale antipoverty programs such as the farmer input support program should be better targeted, for example, through the electronic voucher delivery systems. Second, our results show that a larger proportion of smallholders fell into poverty, while one-fifth remained poor between 2012 and 2015, which points to the need for sustained social promotion and protection in order to help such households move out of or not fall into poverty. Whether the current social cash transfer schemes and the food security packs are effective is an empirical question. And lastly, our findings suggest that climate variability and risks worsen poverty and this calls for more support to enable farmers not only adapt, but also mitigate climate change and variability. Examples here include structured support towards climate-smart agriculture adoption, improved extension, and climate information services.

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