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Household Consumption Volatility and Poverty Risk: Case Studies from South Africa and Tanzania

by Matthieu Bellon, Carlo Pizzinelli, and Roberto Perrelli

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Household Consumption Volatility and Poverty Risk: Case Studies from South Africa and Tanzania

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Abstract

Economic volatility remains a fact of life in Sub Saharan Africa (SSA). Household-level shocks create large consumption fluctuations, raising the incidence of poverty. Drawing on micro-level data from South Africa and Tanzania, we examine the vulnerability to shocks across household types (e.g. by education, ethnic group, and economic activity) and we quantify the impact that reducing consumption volatility would have on aggregate poverty. We then discuss coverage of consumption insurance mechanisms, including financial access and transfers. Country characteristics crucially determine which household-level shocks are most prevalent and which consumption-smoothing mechanisms are available. In Tanzania, agricultural shocks are an important source of consumption risk as two thirds of households are involved in some level of agricultural production. For South Africa, we focus on labor market risk proxied by transitions from formal employment to informal work or unemployment. We find that access to credit, when available, and government transfers can effectively mitigate labor market shocks.

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I. INTRODUCTION

Large consumption fluctuations can make households fall into poverty, highlighting the need for consumption smoothing mechanisms. In the context of a region with vast development challenges, it is then crucial to understand the extent of household consumption volatility, quantify its impact on poverty, and identify risk-sharing gaps and policy solutions.

In this paper we study SSA households' ability to maintain stable levels of consumption when facing adverse economic conditions based on two case studies. We focus on South Africa and Tanzania, two countries that illustrate the diverse challenges of the region. Using micro-level longitudinal data, we examine consumption and poverty dynamics in these countries through a common framework. For South Africa we employ the National Income Dynamics Study (NIDS), while for Tanzania we use the Living Standards Measurement Survey (LSMS). We propose a simple metric to measure the potential benefits in terms of poverty reduction from mitigating household-level consumption volatility. We study salient dimensions of household heterogeneity, the key sources of risks faced by households, and the presence of mechanisms for reducing consumption volatility.

Our research is framed into two parts. First, we analyze how consumption fluctuates across households, connecting volatility to country-specific consumption-based poverty measures. More specifically, we compute the fall in the headline poverty rate that would result from a counterfactual drop in household consumption volatility of a given proportion. This approach provides a useful method for quantifying the impact of resilience-enhancing policies. In Tanzania, we find that policies that would achieve a 50-percent decline in the standard deviation of consumption would lower the baseline poverty rate by approximately one fifth. In South Africa the same reduction would lower the poverty rate by one eighth. This difference suggests that the link between consumption volatility and poverty is stronger in Tanzania than in South Africa, likely due to weaker coping mechanisms in the former.

The second part of our research is guided by key characteristics of each country's economic structures. We zoom into household-level shocks and study their relation to consumption fluctuations. Our analysis proceeds as follows.

- For Tanzania, given households' reliance on agricultural production for subsistence, we proxy agricultural shocks as a large fall in either the reported price or quantity produced of each household's primary crop (i.e. the crop comprising the largest share of income). We find that agricultural shocks are frequent for both agriculture-intensive and other types of households, being on average associated with moderate falls in consumption. The magnitude of the fall in consumption is significantly larger (approximately 10 percent) for agriculture-intensive households. However, agricultural shocks predict a fall in food consumption and higher risk of poverty for all households regardless of their primary source of income.

- Given South Africa's large urban population and high incidence of urban poverty, we focus on labor market uncertainty. We proxy income shocks through transitions from formal to informal work or unemployment, controlling for several dimensions of heterogeneity (e.g. education, ethnicity, etc.).[2] We find that, on average, employment loss reduces pre-transfer income by about 60 percent. We also observe that government transfers halve the impact of the shock on total income while access to credit is associated with a reduction of two thirds in the negative impact of employment loss on consumption. Importantly, this result holds across different demographic groups.

The remainder of this paper is structured as follows. Section II presents a brief review of the literature while Section III describes the micro-level data. Section IV examines consumption smoothing and poverty dynamics in the two case studies, providing a metric for linking the two and analyzing heterogeneity in consumption composition. Section V discusses the availability of financial services and government transfers as coping mechanisms. Section VI summarizes country-specific analysis of idiosyncratic shock mitigation. Section VII concludes. Further details on the longitudinal micro-data and econometric results are provided in the Appendix.

II. A Brief Review of the Literature

The literature on household consumption in Tanzania and South Africa is somewhat extensive but lacks econometric applications linking it to volatility and to fiscal policies that enhance coping mechanisms.

In the case of Tanzania, Mkenda et al. (2010) provide a detailed account of poverty between 2000 and 2007, investigating demographic characteristics that are associated with low levels of consumption. They highlight the importance of understanding the agricultural context for designing poverty-reducing policies. Atkinson and Lugo (2010) study poverty and inequality in Tanzania using micro-data but not through a longitudinal perspective. Some works focus on specific components of consumption, like energy or food (Hosier and Kipondya, 1993; Weinberger and Sai, 2003; Abdulai and Auber, 2004, Mason et al., 2015, Kaminski et al., 2016). Few studies examine the nexus between agricultural volatility and consumption. Sarris and Karfakis (2006) study the impact of idiosyncratic and aggregate agricultural shocks on household consumption focusing on two heavily crop producing regions of Tanzania. Through the Living Standards Measurement Survey (LSMS) data, our analysis can cover all regions of the country and different types of consumption although with a simpler definition of shocks. With regards to fiscal policy, Younger et al. (2016) find that Tanzania's taxation system and expenditure programs are highly redistributive but have limited impact on poverty reduction compared to other economies in the region.

[2] The main ethnic groups in the NIDS are White, Black Africans, Coloured and Asian/Indian.

There is a relatively larger literature on household income and consumption volatility in South Africa. The recent work of Schotte et al. (2017), based on the NIDS, seeks to classify and study households based on their likelihood of transitioning into or out of poverty. Flato et al. (2017) examine the impact of abnormal variations in rainfall across households, while Anand et al. (2016) analyze the determinants of flows in and out of unemployment and its consequence on inequality. Redistribution through fiscal policy and especially the system of social grants has been long recognized as an effective mechanism to reduce poverty (Finn and Leibbrandt, 2017). Recent papers (Tondini, 2017; Tondini et al., 2017) have found mixed evidence on employment showing (i) that government transfers can reduce incentives for the unemployed to transition to informal employment, but (ii) that transfers can also facilitate transitions from informal to formal jobs.

III. MICRO-LEVEL DATA

This section presents an overview of the micro-level panel data for South Africa and Tanzania used in our research. As the data sources for each country are different, we homogenize our analysis to the extent possible but also follow country-specific methodologies when needed.[3] Our main interests lie in comparing household-level poverty dynamics over time using poverty measures that are appropriate for each individual country.

A. South Africa

Our analysis is based on the National Income Dynamics Study (NIDS) dataset, which uses a combination of household- and individual-level questionnaires, with unique individual identifiers allowing for individuals tracking over time. The data provides information on consumption, income, financial access, and standard household characteristics (e.g., composition, education, location). It covers all resident members of a sample of 7,305 households, who were interviewed bi-annually in five waves: in 2008, over 2010/11, in 2012, over 2014/15 and in 2017. Because individuals leave households and form new ones, households are defined anew every wave.

We construct a household identifier consistent across waves based on household heads. New household identifiers are created when a household is formed with members that did not head a household previously. Households that change heads keep the same identifier if the former head remains in the household. We keep the 5,400 households that responded in at least two consecutive waves.

[3] For instance, the consumption-based poverty line that we apply in each country are defined with different criteria. For South Africa we use the national food poverty line, an amount that corresponds roughly to the World Bank USD 1.9 per day threshold. Meanwhile, for Tanzania we use the consumption-based definition of poverty proposed by the World Bank for the study of living standards in the LSMS (see Appendix B for details). Hence, the measures of poverty are not directly comparable across the two countries.

Throughout the analysis, we compare households along different dimensions that do not perfectly overlap, namely ethnicity (Black African, Colored and White), education (up to 9th grade, secondary education above 9th grade, tertiary education) and living areas (urban, rural and traditional).[4] When comparisons across time are warranted, nominal values in South African Rand (R.) are reported in December 2016 prices. Summary statistics are presented in Appendix A.

B. Tanzania

We use the Living Standards Measurement Survey (LSMS) conducted by the World Bank bi-annually in collaboration with Tanzania's National Bureau of Statistics (NBS). We employ all four waves, collected in 2008/2009, 2010/2011, 2012/2013, and 2014/2015. Since Wave 4 involves a fully new sample, only the first three waves can be used for longitudinal analysis. For Waves 1-3 we only keep the sample of households that are present in all waves, for a total of 3,088 household-level observations. For Wave 4 we use all 3,352 observations. Nominal values in Tanzanian Shillings (Tsh.) are reported in 2009 prices. Summary statistics on basic household demographic characteristics by wave, consumption, and income are presented in Appendix B.

The key dimension of heterogeneity on which we focus is the household's primary source of income. We group households into "agricultural" (approximately 40 percent of the sample) and "non-agricultural" based on the main source of their income. Sample weights provided by the survey are applied throughout the analysis. Further details on the data and the construction of the agricultural categorization are also provided in Appendix B.

IV. Poverty Dynamics and Consumption Smoothing at the Household Level

A. Transition Probabilities of Poverty

We start off examining the main features of the aggregate poverty rate for each country across waves of the surveys. Since the poverty definitions are country-specific, our main interest is in within-country changes in the rate.

Using the definition of the national food poverty line proposed by its national statistical institute, in South Africa we observe levels of poverty in the NIDS sample of around 20 percent, consistent with those observed in the general population (STATSSA, 2018).[5] Despite a short-lived increase in

[4] We dropped Asians and Indians from the analysis because of a limited number of observations in our sample (less than 1%)..

[5] We chose to focus the most extreme measure of poverty as the national statistical institute reports on two additional levels of poverty, the lower- and upper-bound poverty lines (see Appendix A for more details).

the poverty rate in the middle of the sample, there is no clear upward trend from 2008 to 2017 (Table C.1 in Appendix).

In Tanzania, based on the LSMS definition, poverty increased from 12 percent to 18 percent between 2008/9 and 2012/3 and then fell moderately in the last wave to 15 percent.[6]

A closer look at the disaggregate country-level reveals that, in South Africa, poverty is more prevalent in households with less education, those living in rural or traditional areas, and among Black Africans (Table A.3). In Tanzania, poverty is higher among agriculture-based households, who also account for the main portion of the increase over time (Table B.3).

Next, we report the conditional transition probabilities in and out of poverty from one wave of the survey to the other (Table 1).[7] This analysis reveals that a sizeable share of the population crosses the poverty line both from below and from above. In other words, there is a substantial fraction of the population that is at risk of poverty at any point in time. For South Africa, more than 13 percent of the non-poor population falls below the poverty line between two survey waves, even among educated and urban households (Table A.4 in the appendix). There are also many transitions out of poverty (47 percent of poor households), indicating that many households drop into poverty, at times for short durations. In Tanzania, non-poor households face a 13-percent chance of falling into poverty within the two-year period between the two surveys. Once poor, a household has about 57 percent of chances of exiting poverty within the same time horizon. A breakdown of the transition probabilities across groups of each country's population is provided in the Appendix.

This exercise highlights that poverty embeds a dynamic component. Even a constant aggregate poverty rate at the national level can mask large flows of households into and out of poverty. Thus, when considering poverty reduction strategies, establishing safety nets to prevent entrance into poverty may be as important as programs aiming to lift people out of it. Evidence based on micro-data can help target these measures to the more vulnerable demographic groups, i.e. where such transitions appear to be more frequent. In the next sub-section, we propose a simple

[6] Note that the values reported in the table do not coincide with those reported the Wave 3 Final Report of Tanzania's National Bureau of Statistics (NBS, 2013). They are about 2 p.p. lower in each wave. However, the increasing trend is comparable to that of the World Bank's report. The difference is due to the slightly different sample selection we carry out in order to obtain a balanced panel structure. Further details on the construction of this poverty measure are provided in Appendix B.

[7] These probabilities are derived by computing the fraction of households that in wave t are (poor) not-poor but are poor (not-poor) in wave t+1. For conciseness, we report the average probability across all waves of each dataset. A rise in poverty from one wave to another can be due to a rise in the probability of entering poverty, a fall in the probability of exiting poverty, or a combination of the two. Hence, wave-by-wave analysis can also be informative. For Tanzania, the analysis only uses Waves 1-3 because Wave 4 is collected with a different sample.

metric to help appraise the strength of the link between consumption volatility and poverty, which may be useful to assess quantitatively the benefits of volatility-reducing policies.

Table 1. Transition Probabilities into and out of Poverty in South Africa and Tanzania

South Africa				Tanzania			
		Wave t				Wave t	
		Not Poor	Poor			Not Poor	Poor
Wave t-1	Not poor	87%	13%	Wave t-1	Not poor	87%	13%
	Poor	47%	53%		Poor	58%	42%

Source: LSMS, NIDS, and authors' calculations.

Note: For a given t-1 state (i.e. not poor or poor), each column shows the fraction of workers who were in each state in period t. These fractions are hence interpreted as transition probabilities. Time periods correspond to waves of the survey.

B. Increasing Resilience via Consumption Smoothing: A Counterfactual Analysis

The previous subsection showed that in both South Africa and Tanzania there are high transition rates into poverty. We now establish a quantitative link between the aggregate poverty rate (a measure central to policy design) and consumption volatility (the subject of extensive theoretical work). To this end, we present a simple metric to quantify the contribution of consumption volatility to a country's aggregate poverty rate. To our knowledge, this is a novel metric that can serve as a proxy for the potential gains in poverty reduction from policies designed to mitigate transitory shocks.

A vast theoretical literature has focused on measuring the cost of household consumption volatility, starting from seminal works like Deaton and Muellbauer (1980) and Lucas and Stokey (1987). Large consumption fluctuations suggest a household's inability to insure against income risk and contradict optimal intertemporal decisions (Carroll, 1997). It indicates households' inability to contract some form of insurance, lack of accesso to social assistance, and their inability to spend in bad times using savings from good times. Even a temporary rise in consumption could reflect a lack of insurance mechanisms, suggesting a hand-to-mouth behavior and some inability to save for rainy days. While the literature tried to quantify the welfare consequences of consumption volatility, we focus on its implications for poverty rates, a concept that is easier for policy-makers to communicate and monitor.

We first investigate the poverty-mitigating impact of policies that would improve household's ability to save for rainy days by considering a counterfactual consumption allocation where both upside and downside volatility are reduced. We then study the case of insurance and assistance policies that only reduce downside volatility. To draw a connection between consumption volatility and poverty (defined through consumption measures) we present a simple metric that can be computed using household-level panel data.

For a household *i* observed in repeated waves *t=1,…,T*, let logarithm of real consumption per adult-equivalent (c_{it}) be expressed in terms of its household-specific mean (c_i) plus a deviation term: $c_{it} = c_i + (c_{it} - c_i)$. The household is considered poor if $c_{it} < c^{poor}$, where c^{poor} is the (inflation-adjusted) log of the poverty line. Define $c^{\alpha}_{it} = c_i + \alpha^*(c_{it} - c_i)$, for $0 \leq \alpha \leq 1$. We interpret c^{α}_{it} as a counterfactual value of c_{it} where consumption deviations from the household-specific mean are shrunk by a factor α. For households where $c_i < c^{poor}$, any $\alpha<1$ increases the likelihood that $\hat{c}^{\alpha}_{it} < c^{poor}$, while for $c_i > c^{poor}$ the chance of poverty in any given period falls. For the extreme case of zero volatility (i.e., $\alpha=0$), only households with $c_i < c^{poor}$ are poor in each period.[8] For each value of α, a counterfactual poverty rate can thus be calculated as the percent of households for which $c^{\alpha}_{it} < c^{poor}$.

The blue dots of Figure 1 report the average counterfactual poverty rate across the waves of the survey obtained by decreasing α from 1 to 0, or equivalently, by reducing inter-temporal consumption volatility from 100 to 0 percent. In the case of Tanzania, the effect of reducing volatility by half lowers the poverty rate by 25 percent: from just above 15 percent to just above 11 percent.[9] In South Africa, the same reduction in volatility would lead to a lower reduction in the poverty rate. The difference stems from the fact that poverty is more persistent in South Africa than in Tanzania, as reflected in the poverty transition matrices (Table 1).

How can a reduction in volatility that reduces both positive and negative shocks lead to a reduction in poverty? In both countries, the share of the population that is above the poverty line on average is greater than the share of households that is below it. Temporary negative shocks to households that are non-poor push many of them below the poverty line. By comparison, transitory positive shocks push fewer households above the poverty line because there are fewer poor households. Thus, a symmetric reduction in volatility implies that there are more households that avoid becoming temporarily poor compared with the number of poor households that are prevented from becoming temporarily non-poor.

To clearly show this point, the blue dots in Figure 1 report the counterfactual poverty level where both upward and downward volatility is muted while the grey diamonds repeat the exercise when exclusively mitigating downward volatility. When mitigating only downside risk (grey diamonds), chances to temporarily exit poverty are not reduced.[10] As a result, the reduction in the aggregate poverty rate is steeper as volatility falls.

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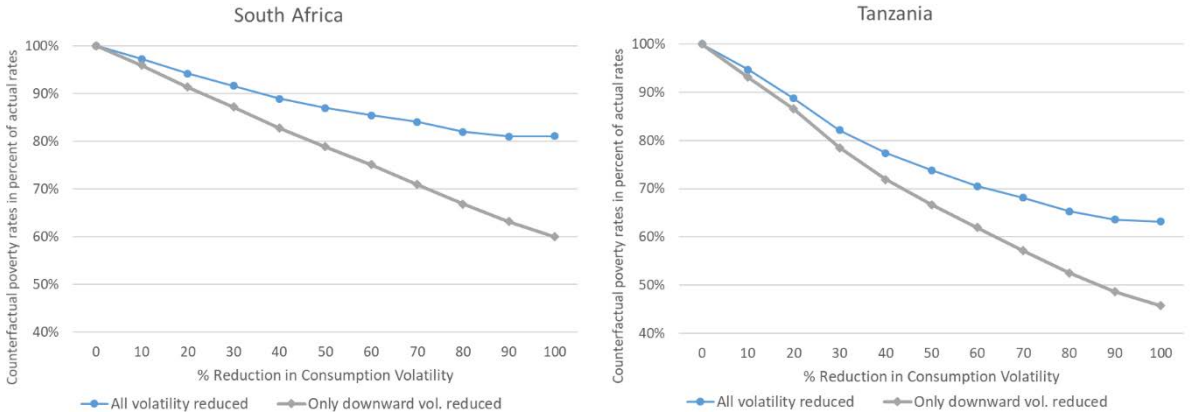
[8] Carrying out this exercise using logarithms can be interpreted as looking at approximate percent deviations in consumption levels. However, it also provides a conservative estimate of the effects of reducing volatility since, through the concavity of the logarithmic function, the mean log consumption is lower than the log of the mean consumption. Hence more households will qualify as poor at their mean log consumption.

[9] For Tanzania this analysis is carried out not using the raw consumption value but with the "real" consumption measure created by the LSMS developers that adjusts for regional price differences through a Fisher Index.

[10] This exercise captures the effect of eliminating downward risk only, which can be more informative to think about the impact of certain safety net programs like unemployment insurance. However, the baseline analysis of

As shown in the figure, entirely eliminating volatility does not yield a full reduction in poverty. The blue dots of Figure 1 corresponding to a full reduction in volatility represent the fraction of households whose average consumption is below the poverty line. A general implication of this exercise is that different policy tools are needed for poverty reduction. While income-enhancing measure are can eradicate the portion of poverty caused by permanently low income, resilience-enhancing measures, such as temporary safety nets, can reduce poverty by abating volatility.

Figure 1. The Impact of Reducing Consumption Volatility on Poverty



Source: LSMS, NIDS, and authors' calculations.
Note: The poverty rate empirically observed in the surveys is normalized to 100 percent for comparative purposes. Each line shows the country-specific counterfactual poverty rate after reducing the consumption volatility.

V. Coping Mechanisms for Consumption Smoothing in Sub-Saharan Africa

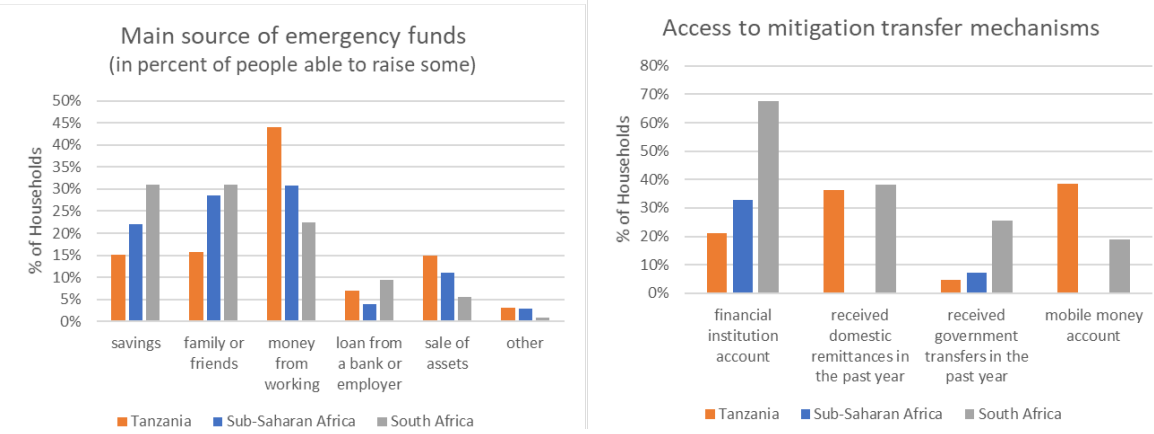
When households are faced by adverse economic shocks, standard economic theory predicts that they will smooth their consumption according to their inter-temporal and risk preferences and depending on the constraints they face (Carroll, 1997; Schulhofer-Wohl, 2008). We focus on idiosyncratic household shocks that have greater potential to be smoothed using domestic resources. We abstract from economy-wide shocks that are expected to have greater impact on consumption in the presence of financing constraints (Jack and Suri, 2014). Moreover, idiosyncratic shocks are large even in the absence of aggregate shocks. Even though both South Africa and Tanzania have stable GDP growth rates over the period of study, idiosyncratic shocks are substantial in both countries, as illustrated by the large shares of households crossing the poverty line.[11]

symmetric volatility remains more applicable to the study of self-financed smoothing mechanisms where households reduce consumption in "good times" to save for the "rainy days".

[11] The annualized real GDP wave-on-wave growth rate has fluctuated between 0.9 and 2.2 percent for South Africa and between 5.6 and 7.0 percent in Tanzania over our sample period.

In general, households smooth consumption by borrowing, by reducing their savings and assets, by benefiting from transfers, and/or by adjusting their labor supply. In Sub-Saharan Africa, labor supply adjustment and private transfers from family and friends are the most commonly reported source of emergency funds, with important differences across countries. For instance, Tanzanian households are more likely to adjust their labor supply and less likely to draw from their own or their relatives' savings, while the opposite is true for South Africa (Figure 2, left panel).

Figure 2. Incidence of Mechanisms for Consumption Insurance in South Africa and Tanzania from the Global Findex Database 2017



Source: Global Findex Database 2017

Differences in average responses across countries can be related to differences in access to coping mechanisms for consumption smoothing. For example, in South Africa 30 percent of households receive private transfers from residents, thereby indicating that personal networks may play an important role in risk mitigation. The corresponding figure for Tanzania is only 15 percent. Moreover, South African households are almost three times more likely to have an account at a financial institution than Tanzanians, which may explain why they are more often able to rely on savings when coping with shocks. Additionally, labor market rigidities and availability of government transfers may also explain why South Africans are less likely to respond to shocks by working more compared to Tanzanians. Finally, while lacking traditional financial depth, Tanzania stands out by the large coverage of mobile money (Figure 2, right panel).

Population averages can mask substantial heterogeneity in the access to each type of coping mechanism within each country. For instance, the use of formal banking services differs substantially across ethnic and education groups in South Africa. Urban residents, the highly educated, and ethnically white households are more likely to own a bank account and to have borrowed in the past year (Table 2). In Tanzania, only 20 percent of households have a bank account and less than 10 percent borrowed money in the previous year, often through informal channels and Savings and Credit Cooperatives (SACCOs).

Evidence of borrowing and bank account ownership are very correlated with household income, implying that access to financial services may be hindered by cost. In both countries, the percent of households using financial services is higher for the upper-income percentiles. In the case of South Africa, account ownership is high because social grants are distributed via bank accounts, but account usage is relatively low as illustrated by the fact that only 22 percent of the population saves at a financial institution (Global Findex Database 2017). The data also shows that bank account ownership is substantially lower for the least educated, implying that financial literacy may also be a relevant barrier for some households. In Tanzania, this positive relationship between income and financial use holds for both agricultural and non-agricultural households, being more pronounced for agricultural households (Figure 3).

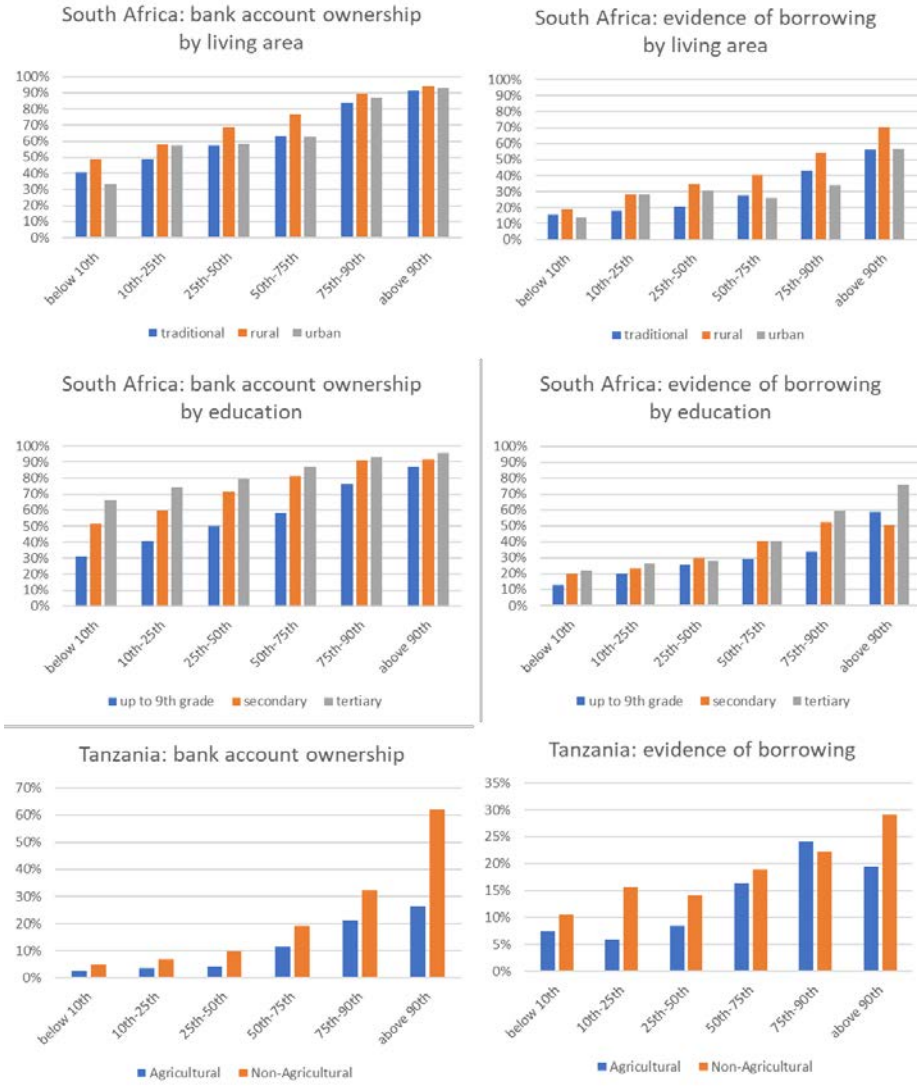
Table 2. Use of Financial Services Across Groups

	Have bank account	Evidence of borrowing	Source of borrowing			
			Formal secto	Informal	Microcredit	SACCO
TANZANIA						
Total	21%	13%	14%	51%	13%	30%
By main income source						
Agricultural	7%	9%	5%	65%	9%	26%
Non-Agricultura	24%	18%	17%	47%	14%	31%
SOUTH AFRICA						
Total	65%	33%	23%	9%	2%	
By education group						
up to 9th grade	46%	23%	12%	10%	1%	
secondary	71%	33%	21%	10%	2%	
tertiary	88%	53%	46%	6%	2%	
By population group						
Black African	63%	31%	20%	9%	1%	
Coloured	69%	40%	31%	6%	3%	
Whites	93%	58%	55%	3%	1%	
By living area						
traditional	54%	22%	12%	9%	1%	
rural	62%	28%	19%	8%	1%	
urban	75%	44%	33%	9%	2%	

Source: LSMS and authors' calculations.
Note: Average across waves. Entries only include those who report borrowing in the last 12 months. Sources of borrowing can add up to more than 100 percent because a single household can borrow from multiple sources.

Beyond traditional banking services, two country-specific coping mechanisms warrant further examination: mobile money in Tanzania and government transfers in South Africa. We discuss them next.

Figure 3. Use of Traditional Financial Services by Income and Population Group



Source: LSMS, NIDS, and authors' calculations.

Note: Percentiles are computed separately for each survey wave. Averages are then taken across waves.

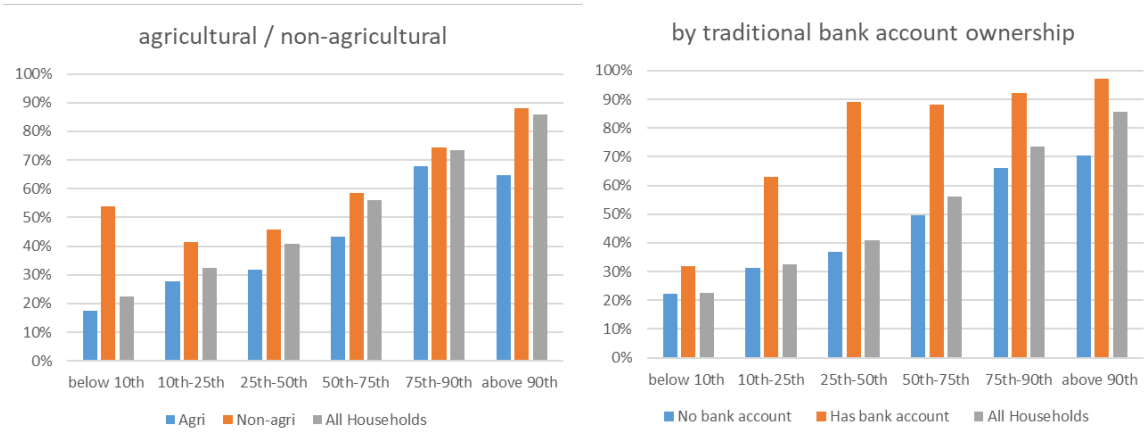
A. Mobile Money in Tanzania

Over the past decade mobile money has become increasingly common in many countries in Sub-Saharan Africa. In a detailed survey of the literature, Aron (2017) highlights the potential of this technology to overcome key challenges of traditional banking, including the scarcity of formal banks in rural areas and high transaction costs. IMF (2016) reports that, by 2015, mobile money transactions already amounted to 52 percent of GDP, compared with less than 1 percent in 2010. While mobile money may not offer all the functionalities of traditional banking, it provides a first "foot in" for those with no access to mainstream finance, allowing them to receive transfers from informal networks, and hence constituting a critical mechanism of consumption smoothing. Riley (2018) shows that Tanzanian households with a mobile money account are more likely to receive

remittances during years of particularly high or low rainfall in their village, which in turn allows them to buffer their consumption compared to other households in the village.

For Tanzania, Wave 4 of the LSMS contains a question on households' use of mobile money. The survey data reveal that, while the use of mobile money is positively correlated with household income, the average level of access to this service is higher than for formal banking, especially for low-income groups. For instance, while only 5 percent of households in the lowest income percentile group have a bank account, 20 percent use mobile money services. Moreover, mobile money is less unequally spread between agricultural and non-agricultural households (conditional on a given income level), suggesting that it can reach those who may not have access to traditional financial instruments, perhaps because they live in rural regions (Figure 4, left panel). The service also reaches the "unbanked", especially at higher income levels. For instance, in the 75th-90th percentile income interval, between 20 and 30 percent of households have a bank account (Figure 3) but 70 percent use mobile money (Figure 4, right panel).

Figure 4. Tanzania: Use of Mobile Money Versus Traditional Banking



Source: LSMS and authors' calculations.
Note: The data used only comprises Wave 4 of the survey.

B. Transfers in South Africa

The NIDS micro-data allows us to study how public and private transfers are distributed within South Africa. Public transfers are markedly directed to the bottom two-thirds of the income distribution as most conditionalities (e.g. having a disability, income below a certain threshold, children of school age, and elderly people) attempt to target vulnerable groups (Figure 5, left panel). The fraction of households receiving private transfers is much lower than the fraction of public transfer beneficiaries. However, private transfers are somewhat more evenly distributed than public transfers across the income distribution (Figure 5, right panels). For every income category, urban and educated households tend to benefit slightly less from public transfers, possibly reflecting that these households less often meet non-income conditions such as disability or having children. For both public and private transfers, Table A.5 in the appendix

confirms that the amount transferred follows the same pattern by group: the share of transfers in total income is lower for the most privileged groups while the share of private transfers are more evenly distributed.

Figure 5. South Africa: Public and Private Transfer Beneficiaries by Income and Group

Source: NIDS and authors' calculations.

Note: Percentiles are computed separately for each survey wave. Averages are then taken across waves.

VI. Country-Specific Analysis of Idiosyncratic Shock Mitigation

In this section we depart from the comparative approach we have followed so far to delve into topics that provide a deeper understanding of the impact of coping mechanisms to smooth consumption volatility from idiosyncratic shocks in Tanzania and South Africa.

A. Tanzania: Coping with Agricultural Shocks

The Tanzanian economy is heavily centered around agriculture, which comprised 32 percent of GDP in 2017 (NBS, 2018). Almost three quarters of households in each LSMS wave report some level of personal agricultural production, with 40 percent of households relying on agriculture as their primary source of food and income. Fluctuations in the quantity harvested of each crop and the potential selling price constitute a source of risk for a large fraction of the population.[13]

In this section we zoom-in on shocks to agricultural income using the panel dimension of Waves 1-3 in the LSMS. To this end, we create two variables representing price and quantity shocks to agricultural production. For each household that reports some agricultural production (for personal use or for sale), we identify the crop constituting the main source of agricultural income (i.e. the primary crop). We then construct a "price shock" variable as a proxy for large falls in the reported price of that crop—that is, when the wave-to-wave log change in price is within the bottom quartile of the raw distribution for all crops (pooling across the two waves). We define a "quantity shock" in a similar way using the distribution of the wave-to-wave change in logarithm of the quantity for all primary crops or a full discontinuation in the production of the crop (i.e. the reported quantity is 0 in the latter wave). We also construct a combined agricultural shock that is a dummy variable for either a price or a quantity fall.[14] Overall, shocks are frequent: about 50 percent of agricultural households in a given period face large drops in either the price or the quantity of the main produce they grow (Table 3). Clearly, the agricultural shocks are less common for non-agricultural households, as some of them do not have any income from agriculture at all. Also, the shocks were more common in Wave 2 than in Wave 3.

To examine the impact of agricultural shocks on household consumption, we estimate a fixed-effects panel data regression for household i in time (wave) t:

$$Log\,(Consumption_{it}) = \beta_0 + \beta_1\,\mathbb{I}(Shock_{it}) + \gamma' X_{it} + \delta_t + \eta_i + \epsilon_{it}, \qquad (1)$$

where X_{it} is a vector of household-level control variables, δ_t and η_i are wave- and household-level fixed effects, and $\mathbb{I}(Shock_{it})$ equals one when a household experiences a shock between time *t-1* and *t*, and zero otherwise. We estimate a series of specifications where $\mathbb{I}(Shock_{it})$ is either the combined shock or is separated into price and quantity shocks. We also include specifications where the shocks are interacted with a binary variable ($\mathbb{I}(Agricultural_i)$) equal to one for agricultural households. This interaction term captures the differential effect of the shock on agricultural households relative to non-agricultural ones. The controls include the number of household members, the number of working-age members, the logarithm of non-agricultural

[13] For instance, Hill and Mejía-Mantilla (2014) show how in the case of Uganda exogenous rises in crop prices contributed to poverty reduction.

[14] Appendix B contains the details of the construction of these two variables, as well as an analysis of volatility in agricultural value at the household level.

income, and the age and education of the household head. For the dependent variable, we use total consumption, food consumption, and non-food consumption.

Table 3. Tanzania: Incidence of Agricultural Shocks Among Households

	Wave	% price shock	% quantity shock	% combined
All HH's	2	22%	30%	47%
	3	10%	31%	39%
non-Agri HH's	2	17%	26%	39%
	3	7%	28%	34%
Agri HH's	2	29%	36%	59%
	3	14%	35%	46%

Source: LSMS and authors' calculations.

Note: The table reports the fraction of households who experience either type of shock across two waves of the survey (e.g., Wave 2 refers to shocks occurring between Waves 1 and 2). See Appendix B for details on the definition of the shocks.

The regression estimates (Table 4) suggest that an agricultural shock is associated on average with a fall of 4½ percent in total consumption (Column 1).[15] However, the impact of the shock is almost three times larger for agricultural households, whereas it is non-existent for the others (Column 2). Interestingly, price shocks hurt mainly agricultural households while quantity shocks are statistically insignificant (Column 4). For food consumption, the combined shock matters for both groups (Columns 5-6), with price shocks only relevant for agricultural households and quantity shocks bring relevant for both groups (Columns 7-8). A candidate explanation for the latter result is that, since non-agricultural households mostly produce crops for their own consumption, they are affected by a drop in the total quantity produced but not by the potential selling price of the crop. Meanwhile, agricultural households' purchasing power is affected by a fall in the price of the crop due to their trade activities. Finally, we find that non-food consumption is only associated with the agricultural shock for agricultural households (Columns 9-10), with the relationship being mostly driven by quantity shocks (Columns 11-12).

Next, we examine the link between volatility and poverty through a similar regression specification in which the dependent variable $Poor_{it}$ is equal to one if household i's consumption in period t is below the poverty line:

$$Poor_{it} = \beta_0 + \beta_1 \mathbb{I}(Shock_{it}) + \beta_2 \mathbb{I}(Agricultural_i) + \gamma' X_{it} + \delta_t + \epsilon_{it}, \quad (2)$$

[15] The baseline estimation sample includes only households with positive non-agricultural income. Results are robust to including all households by adding 1 Tsh. to non-agricultural income before taking the log.

In this exercise we once again run an alternative version of (2) in which the shock variable is interacted with $\mathbb{I}(Agricultural_i)$ to measure the differential impact of the shock across household types. Note also that while we do not include household fixed effects in (2), we consider an alternative specification where add the lag of the dependent variable in X_{it} to capture persistence in poverty.[16]

Table 5 presents the results of estimating (2) both through a linear probability model (OLS) and a logistic regression. The OLS results have an intuitive interpretation. The estimated coefficient for $\mathbb{I}(Shock_{it})$ implies that, all things equal, the incidence of poverty is 4 to 5 percentage points higher among households affected by a large fall in price or quantity of their primary crop. Interestingly, the shock does not have a differential impact for agricultural and non-agricultural households, as the interaction coefficients is negative but not statistically significant (particularly when accounting for poverty persistence in Column 4). This result is important because while Table 4 indicates that shocks seem to have a larger effect on agricultural households in terms of consumption changes, Table 5 suggests that the impact of the shock on the likelihood of crossing the poverty line is similar across groups. This implies that while on average non-agricultural households are less exposed to agricultural shocks, there must be a fraction of them for which volatility in crop prices and quantities has important welfare implications. The results from the Logit regression (Columns 5-8) corroborate these findings.

Overall, our econometric analysis identifies two key relationships. First, agricultural volatility is very important at the individual household level in Tanzania as the country has a large rural population. Second, agricultural shocks seem to be more relevant for food consumption since a large share of agricultural production is intended for personal subsistence. Hence, the economic relevance of the shock for total consumption is determined by (i) the total share of agriculture in household income, (ii) the total share of food in the consumption basket. Not only are agricultural households more exposed to agricultural shocks, but their lower income also makes them more vulnerable as food constitutes a larger fraction of their total consumption. Additional analysis in Appendix B shows that turnover of crops accounts for a large fraction of total income volatility.

[16] Household fixed effects would make the interpretation of β_1 conditional on a household's average poverty rate over time.

Table 4. Tanzania: Estimated Coefficients of Consumption Regression

	Log (Consumption)				Log (Food Consumption)				Log (Non-Food Consumption)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Agricultural shock	-0.0449*	-0.0247			-0.0934***	-0.0818***			-0.0262	0.0107		
	(0.0248)	(0.0279)			(0.0280)	(0.0301)			(0.0443)	(0.0502)		
Agricultural shock*Agricultural Household		-0.116**				-0.0641				-0.212**		
		(0.0585)				(0.0784)				(0.100)		
Quantity shock			-0.0579**	-0.0461			-0.0950***	-0.0983***			-0.0624	-0.0316
			(0.0267)	(0.0295)			(0.0309)	(0.0328)			(0.0457)	(0.0512)
Quantity shock*Agricultural Household				-0.0642				0.0322				-0.187*
				(0.0669)				(0.0903)				(0.108)
Price shock			0.0262	0.0640*			-0.0199	0.0258			0.0743	0.108
			(0.0318)	(0.0356)			(0.0360)	(0.0395)			(0.0599)	(0.0714)
Price shock*Agricultural Household				-0.164**				-0.195**				-0.146
				(0.0706)				(0.0849)				(0.117)
Log non-agricultural income	0.0634***	0.0630***	0.0639***	0.0633***	0.0276*	0.0274*	0.0277*	0.0273*	0.105***	0.105***	0.107***	0.105***
	(0.0120)	(0.0120)	(0.0120)	(0.0120)	(0.0142)	(0.0143)	(0.0143)	(0.0142)	(0.0208)	(0.0208)	(0.0207)	(0.0207)
R-squared	0.250	0.249	0.246	0.243	0.146	0.144	0.1446	0.141	0.227	0.228	0.222	0.221
Number of households	2,626	2,626	2,626	2,626	2,605	2,605	2,605	2,605	2,626	2,626	2,626	2,626

Source: LSMS and authors' calculations.

Note: Heteroskedasticity-robust standard errors in parentheses. Other controls include: education and age of head, household size, number of workers, wave fixed effects, constant term. *** p<0.01, ** p<0.05, * p<0.1

Table 5. Tanzania: Estimated Coefficients of Poverty Regression

	OLS				Logit			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Agricultural Household	-0.0180	-0.00103	-0.0172	-0.0136	-0.207	0.0655	-0.188	-0.0286
	(0.0185)	(0.0250)	(0.0183)	(0.0247)	(0.140)	(0.199)	(0.143)	(0.208)
Agricultural shock	0.0479***	0.0558***	0.0486***	0.0503***	0.464***	0.606***	0.499***	0.582***
	(0.0139)	(0.0155)	(0.0136)	(0.0151)	(0.117)	(0.136)	(0.119)	(0.139)
Agricultural shock*Agricultural Household		-0.0321		-0.00686		-0.472*		-0.279
		(0.0341)		(0.0336)		(0.254)		(0.264)
Log non-agricultural income	-0.0518***	-0.0515***	-0.0435***	-0.0434***	-0.504***	-0.503***	-0.462***	-0.463***
	(0.00589)	(0.00590)	(0.00580)	(0.00581)	(0.0529)	(0.0530)	(0.0546)	(0.0547)
Poor in t-1			0.227***	0.227***			1.304***	1.290***
			(0.0264)	(0.0264)			(0.135)	(0.135)
Number of household-wave observations	4,469	4,469	4,469	4,469	4,469	4,469	4,469	4,469
R-squared	0.100	0.100	0.144	0.144				
Pseudo R-squared					0.138	0.139	0.176	0.177

Source: LSMS and authors' calculations.

Note: Heteroskedasticity-robust standard errors in parentheses. Other controls include: education and age of head, household size, number of workers, wave fixed effects, constant term. *** p<0.01, ** p<0.05, * p<0.1

B. South Africa: Coping with Labor Shocks

Unlike many other sub-Saharan African countries, labor income is the main source of pre-transfer earnings in South Africa (less than 10 percent of income comes from agriculture). This holds true even in rural areas, where most agricultural production is conducted by firms relying on salaried work.[17] Therefore, our analysis focuses on employment shocks. The micro-data allows us to identify three employment statuses: formal employment, informal employment (including self-employment), and unemployment. We define an employment shock as the transition out of formal employment or from informal employment to unemployment for the household member with the highest labor income.[18] These events correspond to a substantial reduction in household income per capita. We find that low-educated, non-Whites, and people living in traditional and rural areas are more likely to lose (less likely to gain) a formal job (Table 6).

To assess how coping mechanisms can mitigate the effect of employment losses on household consumption and income in South Africa, we estimate the following panel data regression:

$$\Delta y_{ijt} = \alpha + \beta \cdot Shock_{ijt} + \gamma \cdot (Shock \cdot X)_{ijt} + \eta \cdot X_{ijt} + \xi \cdot Z_{ijt} + \theta_{jt} + \epsilon_{ijt} \qquad (3)$$

where individuals are indexed by *i*, regions are indexed by *j*, and waves are indexed by *t*. The dependent variable Δy is the wave-on-wave difference of the logarithm of household income and the logarithm of household consumption, depending on the model.[19] *Shock* is a dummy variable indicating whether a household suffered from some employment shock. The set of variables *X* includes household composition variables (the number of females, children, adults of working-age, and the total number of adults), group dummies (education dummies, ethnic group dummies, and living area dummies) and a financial access indicator.[20] The additional set of controls *Z* includes the lag number of workers, the average age and years of education of working-age adults and a second-order polynomial in the change in household composition variables. All specifications include region-time fixed effects and standard errors are clustered at the region and household level.

[17] The NIDS reports wages on formal and informal jobs.

[18] Estimation results in appendix table A.6 shows that changes in real income is very tightly associated with employment transitions.

[19] By focusing on wave-on-wave differences, we control for all households fixed characteristics. All numerical income and consumption variables are deflated using the average CPI over the survey period (the CPI index is normalized to equal one in December 2016) and are normalized to a value per adult equivalent

[20] Following Carlson et al. (2015), we focus on a variable indicating whether households had an outstanding loan from a formal institution in the previous period (loans from a bank, student loans, credit card ownership, home bond, hire purchase agreement, vehicle finance and micro-loans are included). The variable definition is based on the previous period to avoid endogeneity in the form of reverse causality.

Table 6. South Africa: Transitions Across Employment Statuses by Group

Household main earner status (**population shares** / transition probabilities)	**Education group**			**Population group**			**Geographic group**		
	<9th grade	secondary	tertiary	African	Coloured	White	Traditional	Rural	Urban
formal employment	**46%**	**53%**	**72%**	**53%**	**61%**	**56%**	**37%**	**72%**	**64%**
to formal employment	74%	78%	86%	79%	71%	77%	72%	84%	82%
to self or informal employment	14%	13%	10%	12%	11%	19%	15%	11%	12%
to no employment	11%	9%	4%	9%	8%	3%	13%	6%	6%
self or informal employment	**21%**	**22%**	**16%**	**19%**	**18%**	**33%**	**21%**	**16%**	**19%**
to formal worker	41%	44%	52%	41%	50%	42%	36%	54%	49%
to self or informal employment	37%	36%	37%	37%	24%	54%	38%	34%	36%
to no employment	22%	20%	10%	22%	15%	4%	26%	12%	15%
no employment	**34%**	**25%**	**12%**	**28%**	**21%**	**12%**	**42%**	**11%**	**17%**
to formal worker	26%	36%	43%	31%	20%	32%	28%	35%	38%
to self or informal employment	26%	24%	18%	24%	12%	30%	25%	20%	23%
to no employment	49%	40%	39%	44%	57%	38%	47%	45%	39%
Number of observations	3,489	4,229	2,533	8,411	1,494	342	3,817	955	5,590

Source: NIDS and authors' calculations. Note: Bold numbers represent the percentage of households where the member with the highest income is either formally employed, informally and self-employed, or without employment. Thus, the sum of bold numbers is equal to one in every column. For each employment status, the numbers not in bold represent the percentage of households that transition to the same or another employment status. For each employment status block, the sum of the percentages in a column is equal to one.

Table 7 presents estimates from Equation (3). For each specification, we can infer the average percent gain or loss resulting from the employment shock for the entire population or for specific groups (while averaging or otherwise integrating over the remaining covariates).[21] The first column shows that employment losses are associated with a 60 percent drop in income before transfers are accounted for. Columns (2) and (3) show that both private and public transfers increase by about 60 percent when households are hit by the shock. Thus, after-transfer income does not fall as much as pre-transfer income: the drop is estimated in Column (4) to be 33 percent on average. The substantial response of government transfers may be puzzling given the very small size of unemployment insurance in South Africa. However, the magnitude of the response of public transfers can be explained by their design. The bulk of these transfers are the "Old-Age pension" and the "Child Support grant", which are both means-tested programs. When a shock hits, some households that were previously too rich to qualify suddenly become eligible. Consequently, these transfers act as mitigating mechanisms and provide some insurance against employment loss even though they were not explicitly designed to achieve that objective.

Turning our attention to consumption, we find in Column (5) that employment losses are associated with a 17-percent consumption drop. This decrease in consumption differs starkly for households that demonstrated access to borrowing services and those that did not. We find that consumption losses are on average only 7 percent for the former group compared with 21 percent for the latter. We relate consumption losses to changes in the incidence of poverty by considering a linear probabilistic model. We find that the probability of being poor following an

[21] These average effects are calculated based on the coefficient estimates reported in the appendix.

employment shock increases by 9 percentage points without credit access whereas it only increases by 4 percentage point with credit access. The results hold even as we control for the fact that the response of consumption varies with household characteristics.

Table 7. South Africa: Baseline Difference-in-Difference Estimation

Dependent variable:	(1) Pre-transfer income	(2) Government transfers	(3) Private transfers	(4) Total income	(5) Total consumption	(6) Poverty indicator
Average effects of an employment loss:						
average % gain or loss from employment shock	-0.602***	0.577***	0.570***	-0.332***	-0.172***	0.074***
average % change without credit access				-0.336***	-0.206***	0.091**
average % change with credit access				-0.320***	-0.074***	0.041**
difference between changes w./w.o credit access				0.016	0.132***	0.050**
Specification:						
interaction term between shock and controls	yes	yes	yes	yes	yes	yes
uninteracted controls	yes	yes	yes	yes	yes	yes
region-time fixed effects	yes	yes	yes	yes	yes	yes
Observations	12,066	12,314	12,314	12,314	12,314	12,314
R-square	0.321	0.073	0.062	0.214	0.180	0.344

Source: NIDS and authors' calculation.
Note: Credit access is a variable indicating if a household had an outstanding loan at a financial institution in the last period. Coefficient estimates and standard errors are presented in detail in appendix Table A.7. *** p<0.01, ** p<0.05, * p<0.1

We perform several robustness checks. We find that non-food consumption drops more (24 percent) than total consumption (17 percent), which is consistent with households being willing to minimize cuts to more essential spending items. We also consider whether access to informal borrowing (from friends, family or others) or to formal means of saving (bank account, stocks, private pension scheme) make a difference. We find that informal borrowing matters, but formal savings do not seem to make a significant difference for the results.

Finally, we use the following triple differences-in-differences specification to investigate whether the shock-mitigating effect of financial access varies across demographic groups (indexed by *g*):

$$\Delta y_{igjt} = \sum_g \alpha_g + \beta_g \cdot Shock_{igt} + \gamma_g \cdot (Shock \cdot X)_{igt} + \eta \cdot X_{igjt} + \xi \cdot Z_{igjt} + \theta_{jt} + \epsilon_{igjt} \qquad (4)$$

After estimating (4), we test whether the coefficients γ_g differ by group. More specifically, we separately consider education groups, population groups, and living area groups. In the odd-numbered columns of Table 8, we first consider whether losses in non-food consumption for households with access to finance differ by group. A standard Wald test fails to reject the null hypothesis that the difference in consumption drop between households with and without access to finance is the same across group. Similarly, the even-numbered columns of Table 7 suggest the changes in government transfers in periods of employment losses are not significantly different across groups. These results suggest that access to coping mechanisms, either financial services or government transfer, is what matters the most because these mechanisms are estimated to have the same quantitative effect for all groups.

Table 8. Difference in the Magnitude of Mitigation across Groups: Triple Difference-in-Difference Estimation Results

	(1)		(2)	(3)		(4)	(5)		(6)
	Education groups			**Population groups**			**Geographic groups**		
DEPENDENT VARIABLE:	Non-food consumption		Public transfers	Non-food consumption		Public transfers	Non-food consumption		Public transfers
Access to finance:	no	yes	any	no	yes	any	no	yes	any
Average percentage net gains after an employment loss by group:									
- up to 9th grade	**-0.256*** **	**-0.106**	**0.705*** **						
difference within the above group	0.150*								
- secondary	**-0.290*** **	**-0.0599**	**0.541*** **						
difference within the above group	0.230*								
- tertiary	**-0.307*** **	**-0.138**	**0.501** **						
difference within the above group	0.169**								
Are differences the same across group?	yes (p-val = 0.193)		yes (p-val = 0.796)						
- White				**0.323**	**-0.271***	**0.142**			
difference within the above group				-0.594					
- Black African				**-0.286*** **	**-0.113**	**0.628*** **			
difference within the above group				0.173					
- Coloured				**-0.307*** **	**-0.0913**	**0.407** **			
difference within the above group				0.216***					
Are differences the same across group?				yes (p-val = 0.113)		yes (p-val = 0.476)			
- traditional areas							**-0.257*** **	**-0.0796**	**0.585*** **
difference within the above group							0.177		
- rural areas							**-0.187**	**0.0843**	**0.0161**
difference within the above group							0.271***		
- urban areas							**-0.311*** **	**-0.511*** **	**0.682*** **
difference within the above group							0.200		
Are differences the same across group?							no (p-val = 0.000)		yes (p-val = 0.134)
Specification:									
interaction term between shock and controls	yes		yes	yes		yes	yes		yes
uninteracted controls	yes		yes	yes		yes	yes		yes
region-time fixed effects	yes		yes	yes		yes	yes		yes
Observations	12,314		12,314	12,314		12,314	12,321		12,321
R-square	0.123		0.073	0.123		0.073	0.124		0.073

Source: NIDS and authors' calculation. Note: All specifications include region-time fixed effects and the standard errors in parentheses are clustered at the region and household level. Financial access is a variable indicating if a household had an outstanding loan at a financial institution in the last period. Coefficient estimates and standard errors are presented in detail in appendix Table A.8. *** p<0.01, ** p<0.05, * p<0.1

VII. CONCLUSIONS

In this paper, we used longitudinal micro-data to study consumption volatility at the household level in South Africa and Tanzania, two Sub-Saharan African countries with very different economic features. Using consumption-based definitions of poverty, we showed that there exists an important link between volatility and poverty. In both countries, non-poor households face on average a 13 percent probability of entering poverty across two periods of the survey due to a fall in consumption. Meanwhile, about half of poor households exit poverty in each period as their consumption levels rise. These results highlight the inherently dynamic nature of poverty. A key implication is that, while some fiscal policies aimed at reducing poverty should target those households whose consumption level is persistently below the poverty line, other policies should focus on helping households just above the poverty line cope with adverse shocks.

To inform policies, the nexus between poverty and volatility should be appropriately quantified. To this end, we propose a simple metric to measure the potential benefits in terms of poverty reduction from mitigating household-level consumption volatility. As period-to-period fluctuations in consumption are muted, fewer households experience the temporary negative shocks that lead to poverty. We show that, in relative terms, this channel is quantitatively more important for Tanzania than South Africa.

We zoom into household-level shocks and study their relation to consumption fluctuations. Given South Africa's large urban population and high incidence of urban poverty, we focus on labor market uncertainty. We find that, on average, employment loss reduces pre-transfer income by about 60 percent. We also observe that government transfers contribute to halve the impact of the shock on total income while access to credit is associated with a reduction of two thirds in the negative impact of employment loss on consumption. For Tanzania, given households' reliance on agricultural production for subsistence, we find that agricultural shocks are frequent for both agriculture-intensive and other types of households, but the magnitude of the fall in consumption is significantly larger (approximately 10 percent) for agriculture-intensive households.

Access to coping mechanisms to smooth consumption remains incomplete and unequally distributed. In both countries, the use of banking services is highly correlated with income. In Tanzania unequal access is partially offset by the recent spread of mobile money services, which are common among those without a traditional bank account. In South Africa, the combination of government transfers and a relatively large financial coverage are quite effective risk mitigators for those who have access to them.

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Appendix

A. South Africa: Data Details, Descriptive Statistics, Further Analysis

Table A.1. South Africa: Households Demographic Summary Statistics by Wave

	Wave 1	Wave 2	Wave 3	Wave 4	Wave 5
	2008	2010/11	2012	2014/2015	2017
Mean no. of household members	4.02	4.35	4.34	4.20	4.15
Mean no. of working age adults	1.56	1.64	1.56	1.68	1.70
Mean no. of children	1.44	1.50	1.47	1.45	1.42
Mean age of adults in households					
15-29	29%	28%	29%	29%	26%
30-39	41%	44%	44%	43%	45%
40-64	30%	28%	27%	29%	29%
Education of head					
Up to grade 9	46%	43%	37%	30%	26%
Secondary	35%	37%	41%	43%	44%
Tertiary	19%	19%	22%	27%	30%
Population group					
Majority Black African	82%	81%	82%	83%	83%
Majority Coloured	13%	13%	13%	13%	14%
Majority Asian/Indian	1%	1%	1%	1%	1%
Majority White	4%	4%	4%	3%	3%
Area type					
Traditional	39%	47%	45%	52%	51%
Urban	21%	15%	19%	17%	17%
Rural	39%	39%	36%	32%	33%

Source: NIDS and authors' calculations.

Table A.2. South Africa: Household Summary Statistics on Annual Consumption and Income

	25th percentile	50th percentile	75th percentile	Mean	percent of HHs with > 0
Consumption					
Total	20,615	33,185	62,479	64,838	100%
Food	8,139	12,144	18,578	15,672	100%
Health & Education	2,650	5,911	16,243	16,160	32%
Other non-food	4,782	10,510	25,901	30,246	100%
Income					
Total	27,963	49,824	96,849	92,665	100%
Wages	20,643	45,541	100,058	87,919	65%
Government Grants	8,744	17,878	27,292	20,684	68%
Remittances	6,072	11,045	18,766	16,935	17%
Other	3,401	6,227	13,733	20,923	90%

Source: NIDS and authors' calculations. Note: All waves are pooled, and values are deflated to 2010 prices using the national CPI. The rows relating to sub-component of consumption and income only include households for which that sub-component is positive. The last column reports the fraction of households with a positive value for a given sub-component, averaged across waves.

Poverty Line Definition

The national poverty lines are provided by STATSSA, the national statistics institute, and were constructed using the cost-of-basic-needs approach which links welfare to the consumption of goods and services. There was not methodological break over the sample period, but STATSSA adjusts poverty lines every year to account for inflation. STATSSA defines three poverty lines that contain both food and non-food components of household consumption expenditure:

- Food poverty line – R547 (in April 2018 prices) per person per month. This refers to the amount of money that an individual will need to afford the minimum required daily energy intake. This is also commonly referred to as the "extreme" poverty line;
- Lower-bound poverty line – R785 (in April 2018 prices) per person per month. This refers to the food poverty line plus the average amount derived from non-food items of households whose total expenditure is equal to the food poverty line; and
- Upper-bound poverty line – R1,183 (in April 2018 prices) per person per month. This refers to the food poverty line plus the average amount derived from non-food items of households whose food expenditure is equal to the food poverty line.

Table A.3. South Africa: Percent of Poor Households in Each Wave-Group of the NIDS

Poverty line (percent population below)	Wave 1 2008	Wave 2 2010/11	Wave 3 2012	Wave 4 2014/15	Wave 5 2017
Total	19%	26%	25%	19%	19%
By education					
up to 9th grade	28%	37%	35%	29%	31%
secondary	17%	27%	27%	22%	22%
tertiary	2%	7%	8%	5%	6%
By population group					
Black African	22%	30%	28%	21%	21%
Coloured	8%	15%	11%	8%	11%
Whites	1%	0%	0%	0%	0%
By living area					
traditional	29%	38%	39%	31%	30%
rural	17%	26%	19%	17%	23%
urban	10%	16%	13%	9%	9%

Source: NIDS and authors' calculations. Note: The table reports the percent of the population below the food poverty line (see above for definition) in each group.

Table A.4. South Africa: Frequency of Transition in and out of Poverty

Groups:	**All**	**Education**			**Population**			**Geographic**		
Average population shares in wave-pairs		<9th grade	primary	secondary	Black African	Coloured	White	Traditional	Rural	Urban
poor in t and t-1	53%	58%	50%	33%	55%	38%	0%	58%	53%	42%
poor in t, non poor in t-1	47%	42%	50%	67%	45%	62%	100%	42%	47%	58%
non poor in t, poor in t-1	13%	22%	13%	4%	15%	8%	0%	22%	14%	8%
non poor in t and t-1	87%	78%	87%	96%	85%	92%	100%	78%	86%	92%

Source: NIDS and authors' calculations. Note: Average percent of the population above and/or below the food poverty line (see above for definition) in a period and the period before for all consecutive period-pairs.

Table A.5. South Africa: Public and Private Transfers by Group

	Education group					
Transfers -	less than 9th grade		secondary		tertiary	
- receives any / median income share	beneficiaries	median	beneficiaries	median	beneficiaries	median
Government transfers	78%	59%	74%	36%	41%	19%
Private transfers	15%	26%	20%	21%	17%	18%
Number of observations	6,296		7,264		4,247	

	Population group					
Transfers -	African		Coloured		White	
- receives any / median amount	beneficiaries	median	beneficiaries	median	beneficiaries	median
Government transfers	70%	49%	68%	30%	23%	17%
Private transfers	19%	24%	12%	14%	7%	8%
Number of observations	15,337		2,482		649	

	Education group					
Transfers -	Traditional		Rural		Urban	
- receives any / median amount	beneficiaries	median	beneficiaries	median	beneficiaries	median
Government transfers	83%	59%	58%	31%	58%	31%
Private transfers	21%	26%	10%	20%	15%	18%
Number of observations	7,786		1,481		9,406	

Source: NIDS and authors' calculations. Note: For every group, the first percentage indicates the share of beneficiaries while the second percentage indicates the median amount received as a share of total income.

Table A.6. South Africa: Impact of Employment Transitions on Total and Labor Income

Dependent variable:	Log changes in the total real income per capita				Log changes in the real labor income per capita			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TRANSITIONS								
from formal employment								
to self or informal employment		-0.190***		-0.226***		-0.389***		-0.466***
		(0.0273)		(0.0266)		(0.0363)		(0.0348)
to no employment		-0.696***		-0.671***		-7.688***		-7.585***
		(0.0278)		(0.0284)		(0.0369)		(0.0372)
from self or informal employment								
to formal worker		0.0990***		0.121***		0.289***		0.343***
		(0.0252)		(0.0246)		(0.0336)		(0.0323)
to self or informal employment		-0.0261		-0.0305		-0.0775**		-0.0773**
		(0.0272)		(0.0263)		(0.0361)		(0.0345)
to no employment		-0.434***		-0.388***		-6.769***		-6.642***
		(0.0287)		(0.0295)		(0.0382)		(0.0387)
from no employment								
to formal worker		0.654***		0.635***		7.332***		7.240***
		(0.0260)		(0.0265)		(0.0346)		(0.0347)
to self or informal employment		0.403***		0.363***		6.504***		6.372***
		(0.0290)		(0.0293)		(0.0385)		(0.0384)
to no employment		-0.00877		-0.00278		-0.206***		-0.219***
		(0.0163)		(0.0169)		(0.0217)		(0.0222)
WAVE FIXED EFFECTS								
Wave 3	0.0959***	0.105***	0.0503**	0.0468**	0.239***	0.198***	0.281***	0.110***
	(0.0200)	(0.0189)	(0.0199)	(0.0190)	(0.0867)	(0.0251)	(0.0790)	(0.0249)
Wave 4	0.0969***	0.0922***	0.0378**	0.0459***	0.190**	0.0698***	-0.0563	-0.00751
	(0.0188)	(0.0178)	(0.0186)	(0.0177)	(0.0819)	(0.0236)	(0.0736)	(0.0232)
Wave 5	-0.000185	0.0188	-0.0619***	-0.0406**	-0.0845	0.0527**	-0.242***	-0.0428*
	(0.0191)	(0.0181)	(0.0190)	(0.0181)	(0.0831)	(0.0240)	(0.0752)	(0.0238)
Constant	0.0554***	0.0553***	0.0766***	0.0832***	-0.0158	0.0181	-0.0253	0.0683***
	(0.0146)	(0.0164)	(0.0147)	(0.0164)	(0.0635)	(0.0218)	(0.0582)	(0.0215)
Observations	15,597	15,597	14,679	14,679	15,597	15,597	14,679	14,679
R-squared	0.004	0.119	0.119	0.202	0.001	0.917	0.260	0.927
Residual square of errors	10,255	9,069	8,715	7,897	193,600	16,030	137,294	13,589
Partial R-square		11.6%		9.4%		91.7%		90.1%
+ controls	no	no	yes	yes	no	no	yes	yes

Source: NIDS and authors' calculation. Note: The default transition category is "staying in formal employment". Controls, when included, consist of change in the number of all adults, change in the number of working-age adults, change in the number of children, change in the number of females, change in the square of these variables, and change in the average age and years of education of working-age adults. All specifications include region-time fixed effects and the standard errors in parentheses are clustered at the region and household level. *** p<0.01, ** p<0.05, * p<0.1

Table A.7. South Africa: Baseline Difference-in-Difference Estimation

Dependent variable:	(1) Pre-transfer income		(2) Government transfers		(3) Remittances		(4) Total income		(5) Total consumption		(6) Poverty indicator	
	coef	se	coef	se	coef	se	coef	se	coef	se	coef	se
formal borrowing (dummy)	0.146***	(0.0258)	0.0471	(0.0538)	0.0599	(0.0765)	0.120***	(0.0162)	0.184***	(0.0197)	-0.0661***	(0.00809)
lag formal borrowing	-0.110***	(0.0261)	-0.0677	(0.0561)	-0.0803	(0.0799)	-0.108***	(0.0162)	-0.231***	(0.0232)	-0.0136**	(0.00669)
employment loss (dummy)	-0.263	(0.189)	0.581	(0.426)	-0.0442	(0.371)	0.0942	(0.139)	-0.169	(0.136)	0.00406	(0.0384)
- the lag of formal borrowing							**0.0233**	**(0.0480)**	**0.154*** **	**(0.0511)**	**-0.0464****	**(0.0211)**
- the number of adults	-0.139***	(0.0422)	0.111*	(0.0613)	0.0692	(0.0867)	-0.0243	(0.0236)	0.0520**	(0.0210)	-0.000545	(0.00997)
- the number of children	-0.0392	(0.0312)	-0.0917	(0.0716)	0.0171	(0.0792)	-0.00896	(0.0169)	-2.63e-05	(0.0192)	-0.00604	(0.0104)
- the number of female	-0.000286	(0.0380)	-0.0829	(0.0701)	-0.244**	(0.0953)	0.0190	(0.0212)	-0.0226	(0.0205)	0.0169	(0.0104)
- the nb. of working-age adults	0.273***	(0.0263)	-0.176**	(0.0659)	-0.127	(0.0841)	0.0754***	(0.0153)	-0.0206	(0.0209)	0.00928	(0.0109)
- an urban area dummy	0.165*	(0.0948)	0.0594	(0.187)	-0.0558	(0.187)	-0.0135	(0.0591)	-0.0187	(0.0447)	0.0138	(0.0231)
- a rural area dummy	0.172*	(0.0909)	-0.442	(0.279)	-0.135	(0.268)	0.00897	(0.0660)	0.0431	(0.0845)	0.0434	(0.0394)
- a secondary education dummy	-0.0826	(0.0850)	-0.101	(0.166)	0.234	(0.158)	-0.175***	(0.0472)	-0.0564	(0.0460)	0.00646	(0.0241)
- a tertiary education dummy	-0.0192	(0.102)	-0.128	(0.243)	0.267	(0.183)	-0.268***	(0.0554)	-0.0897	(0.0568)	0.00240	(0.0249)
- an African dummy	-0.878***	(0.152)	0.355	(0.337)	1.065***	(0.271)	-0.496***	(0.112)	-0.0569	(0.128)	0.0212	(0.0267)
- a Coloured dummy	-0.592***	(0.153)	0.209	(0.351)	0.616**	(0.275)	-0.327***	(0.107)	-0.0383	(0.125)	0.0260	(0.0305)
secondary education (dummy)	0.0186	(0.0224)	-0.107*	(0.0549)	-0.0910	(0.0658)	0.0125	(0.0169)	-0.0241*	(0.0142)	-0.0767***	(0.0111)
tertiary education (dummy)	0.0731***	(0.0241)	-0.231***	(0.0620)	-0.253***	(0.0651)	0.0835***	(0.0140)	0.00946	(0.0161)	-0.116***	(0.0128)
urban area (dummy)	-0.0394	(0.0296)	0.0615	(0.0559)	-0.0877	(0.0863)	0.0275	(0.0242)	0.0321**	(0.0149)	-0.0613***	(0.0120)
rural area (dummy)	0.0296	(0.0379)	0.0653	(0.0875)	-0.0238	(0.0985)	0.0809**	(0.0330)	-0.0140	(0.0240)	-0.0202	(0.0176)
African population group (dummy)	0.228***	(0.0389)	-0.0104	(0.0969)	-0.227**	(0.0987)	0.179***	(0.0342)	0.0816**	(0.0360)	-0.00896	(0.0126)
Coloured population group (dummy)	0.152***	(0.0457)	0.112	(0.120)	-0.215**	(0.0998)	0.129***	(0.0398)	0.0227	(0.0417)	-0.0406**	(0.0178)
lag number of workers	-0.308***	(0.0175)	0.114***	(0.0387)	0.119**	(0.0463)	-0.170***	(0.0105)	-0.0301***	(0.0100)	-0.0337***	(0.00490)
number of adults	0.0814***	(0.0119)	0.0189	(0.0303)	-0.0446	(0.0314)	0.0163**	(0.00764)	-0.0152*	(0.00858)	0.0494***	(0.00502)
number of children	-0.000233	(0.00901)	0.0754***	(0.0255)	-0.0743***	(0.0248)	-0.0140**	(0.00558)	-0.0160***	(0.00585)	0.0384***	(0.00373)
number of female	-0.0140	(0.0109)	0.00866	(0.0247)	0.125***	(0.0249)	-0.00376	(0.00673)	0.0115	(0.00718)	0.00809*	(0.00406)
number of working-age adults	-0.00138	(0.0146)	-0.0181	(0.0414)	0.0483	(0.0453)	0.0354***	(0.00964)	0.0190*	(0.0112)	-0.00602	(0.00697)
working-age adults average age	0.0255***	(0.00221)	0.00725	(0.00715)	-0.0302***	(0.00674)	0.0167***	(0.00143)	0.00847***	(0.00164)	-0.000615	(0.000621)
w.-a. adults avg. years of education	0.0757***	(0.00934)	-0.0412	(0.0252)	0.0168	(0.0265)	0.0426***	(0.00609)	0.0347***	(0.00540)	0.00718**	(0.00293)
Lag poverty indicator											0.213***	(0.0128)
Changes in												
- the number of adults	-0.328***	(0.0284)	0.351***	(0.0868)	-0.106	(0.0686)	-0.163***	(0.0198)	-0.156***	(0.0180)	-0.0117	(0.00853)
- the number of children	-0.137***	(0.0271)	0.128**	(0.0586)	0.0674	(0.0718)	-0.121***	(0.0170)	-0.117***	(0.0149)	-0.00822	(0.00710)
- the number of female	-0.233***	(0.0295)	0.581***	(0.0732)	-0.350***	(0.0888)	-0.179***	(0.0209)	-0.181***	(0.0238)	0.0295***	(0.00698)
- the number of working-age adults	0.416***	(0.0315)	-0.226***	(0.0485)	-0.211**	(0.0852)	0.171***	(0.0203)	-0.0246	(0.0187)	0.00954	(0.00801)
- the square number of adults	0.204***	(0.0292)	-0.302***	(0.0962)	0.130	(0.0878)	0.0894***	(0.0201)	0.100***	(0.0186)	0.00537	(0.00932)
- the square number of children	0.0601	(0.0368)	-0.179***	(0.0659)	0.124	(0.106)	0.0727***	(0.0196)	0.0718***	(0.0154)	-0.0105	(0.00939)
- the square number of female	0.161***	(0.0328)	-0.378***	(0.0576)	0.126	(0.0967)	0.145***	(0.0202)	0.116***	(0.0266)	-0.00867	(0.00830)
- the square number of w.-a. adults	-0.333***	(0.0541)	0.278***	(0.0850)	0.311*	(0.156)	-0.130***	(0.0305)	0.0460	(0.0321)	-0.0151	(0.0139)
Constant	0.242***	(0.0485)	-0.0595	(0.107)	0.287*	(0.157)	0.116***	(0.0414)	0.162***	(0.0379)	0.121***	(0.0187)
Observations	12,066		12,314		12,314		12,314		12,314		12,314	
R-square	0.321		0.073		0.062		0.214		0.180		0.344	
average % gain or loss	**-0.602*** **		**0.577*** **		**0.570*** **		**-0.332*** **		**-0.172*** **		**0.074*** **	
average % change without credit access							**-0.336*** **		**-0.206*** **		**0.091****	
average % change with credit access							**-0.320*** **		**-0.073*** **		**0.041****	
difference between changes w./w.o credit access							**0.016**		**0.132*** **		**0.050****	

Source: NIDS and authors' calculation. Notes: All specifications include region-time fixed effects and standard errors are clustered at the region and household level. Households where the main income earner retires are excluded to focus on unexpected transitory employment shocks. The bottom part of the table in bold facilitates the interpretation of the average net gains in the presence of multiple interaction terms. It provides estimates of the average loss for specific groups of households and tests for significant differences across these group averages (using STATA's *margins* command).

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Table A.8. South Africa: Difference in the Magnitude of Mitigation Across Groups: Triple Difference-in-Difference Estimation Results

	(1)		(2)		(3)		(4)		(5)		(6)	
	Education groups (1: up to 9th grade; 2: secondary; 3: tertiary)				Population groups (1: White; 2: African 3: Coloured)				Geographic groups (1: traditional area; 2: rural area, 3: urban area)			
Dependent variable:	Non-food consumption		Government transfers		Non-food consumption		Government transfers		Non-food consumption		Government transfers	
	coef	se	coef	se	coef	se	coef	se	coef	se	coef	se
formal borrowing (dummy)	0.336***	(0.0326)	0.0471	(0.0538)	0.337***	(0.0321)	0.0471	(0.0538)	0.335***	(0.0323)	0.0468	(0.0537)
lag formal borrowing	-0.417***	(0.0654)	-0.0677	(0.0561)	-0.209	(0.130)	-0.0677	(0.0561)	-0.395***	(0.0570)	-0.0676	(0.0560)
" interacted with group 2	-0.00820	(0.0730)			-0.232*	(0.132)			-0.0835	(0.136)		
" interacted with group3	-0.0214	(0.0851)			-0.210	(0.149)			-0.0434	(0.0641)		
employment loss (dummy)	-0.311	(0.229)	0.581	(0.426)	0.265	(0.435)	0.581	(0.426)	-0.300	(0.224)	0.585	(0.426)
" interacted with:												
- lag borrowing and group 1	0.184	(0.167)			-0.596	(0.458)			0.214	(0.160)		
- lag borrowing and group 2	0.281*	(0.157)			0.218	(0.161)			0.288***	(0.0960)		
- lag borrowing and group 3	0.218*	(0.112)			0.271***	(0.0921)			-0.343	(0.219)		
- the number of adults	0.0674**	(0.0266)	0.111*	(0.0613)	0.0682**	(0.0266)	0.111*	(0.0613)	0.0673**	(0.0267)	0.111*	(0.0613)
- the number of children	0.00706	(0.0379)	-0.0917	(0.0716)	0.00651	(0.0375)	-0.0917	(0.0716)	0.00753	(0.0373)	-0.0918	(0.0717)
- the number of female	-0.0556	(0.0392)	-0.0829	(0.0701)	-0.0556	(0.0391)	-0.0829	(0.0701)	-0.0577	(0.0389)	-0.0826	(0.0702)
- nb. of working-age adults	0.0122	(0.0333)	-0.176**	(0.0659)	0.0113	(0.0332)	-0.176**	(0.0659)	0.0132	(0.0335)	-0.175**	(0.0659)
- a rural area dummy	-0.0506	(0.0886)	0.0594	(0.187)	-0.0565	(0.0871)	0.0594	(0.187)	0.0899	(0.172)	-0.444	(0.278)
- an urban area dummy	-0.0255	(0.145)	-0.442	(0.279)	-0.0352	(0.144)	-0.442	(0.279)	-0.0752	(0.104)	0.0594	(0.187)
- a secondary edu. dummy	-0.0469	(0.0965)	-0.101	(0.166)	-0.0436	(0.0809)	-0.101	(0.166)	-0.0445	(0.0813)	-0.103	(0.166)
- a tertiary edu. dummy	-0.0709	(0.137)	-0.128	(0.243)	-0.0508	(0.0939)	-0.128	(0.243)	-0.0461	(0.0946)	-0.129	(0.244)
- an African dummy	-0.0309	(0.218)	0.355	(0.337)	-0.617	(0.436)	0.355	(0.337)	-0.0408	(0.219)	0.353	(0.338)
- a Coloured dummy	-0.0760	(0.220)	0.209	(0.351)	-0.646	(0.427)	0.209	(0.351)	-0.0795	(0.217)	0.209	(0.350)
secondary education (dummy)	-0.0202	(0.0264)	-0.107*	(0.0549)	-0.0200	(0.0229)	-0.107*	(0.0549)	-0.0215	(0.0228)	-0.106*	(0.0549)
tertiary education (dummy)	0.0259	(0.0342)	-0.231***	(0.0620)	0.0209	(0.0256)	-0.231***	(0.0620)	0.0182	(0.0256)	-0.230***	(0.0621)
urban area (dummy)	0.0397	(0.0420)	0.0615	(0.0559)	0.0417	(0.0417)	0.0615	(0.0559)	0.0721	(0.0646)	0.0660	(0.0877)
rural area (dummy)	0.0583	(0.0567)	0.0653	(0.0875)	0.0591	(0.0564)	0.0653	(0.0875)	0.0445	(0.0440)	0.0602	(0.0562)
African population group (dummy)	0.106*	(0.0544)	-0.0104	(0.0969)	0.261***	(0.0938)	-0.0104	(0.0969)	0.101*	(0.0552)	-0.00944	(0.0972)
Coloured population group (dummy)	0.0564	(0.0546)	0.112	(0.120)	0.203*	(0.106)	0.112	(0.120)	0.0526	(0.0548)	0.114	(0.120)
lag number of workers	-0.0468***	(0.0158)	0.114***	(0.0387)	-0.0471***	(0.0158)	0.114***	(0.0387)	-0.0471***	(0.0156)	0.112***	(0.0388)
number of adults	-0.0238	(0.0163)	0.0189	(0.0303)	-0.0238	(0.0163)	0.0189	(0.0303)	-0.0236	(0.0163)	0.0193	(0.0303)
number of children	-0.0175*	(0.0101)	0.0754***	(0.0255)	-0.0173*	(0.0101)	0.0754***	(0.0255)	-0.0178*	(0.0101)	0.0755***	(0.0255)
number of female	0.0190	(0.0127)	0.00866	(0.0247)	0.0188	(0.0127)	0.00866	(0.0247)	0.0190	(0.0127)	0.00832	(0.0248)
number of working-age adults	0.0164	(0.0186)	-0.0181	(0.0414)	0.0165	(0.0187)	-0.0181	(0.0414)	0.0167	(0.0187)	-0.0178	(0.0415)
Working-age adults average age	0.0124***	(0.00305)	0.00725	(0.00715)	0.0123***	(0.00311)	0.00725	(0.00715)	0.0124***	(0.00301)	0.00708	(0.00712)
W.-a. adults years of education	0.0499***	(0.0106)	-0.0412	(0.0252)	0.0497***	(0.0106)	-0.0412	(0.0252)	0.0498***	(0.0105)	-0.0407	(0.0253)
Change in												
- the number of adults	-0.168***	(0.0278)	0.351***	(0.0868)	-0.168***	(0.0277)	0.351***	(0.0868)	-0.169***	(0.0277)	0.351***	(0.0868)
- the number of children	-0.115***	(0.0271)	0.128**	(0.0586)	-0.115***	(0.0271)	0.128**	(0.0586)	-0.116***	(0.0273)	0.128**	(0.0587)
- the number of female	-0.135***	(0.0346)	0.581***	(0.0732)	-0.135***	(0.0346)	0.581***	(0.0732)	-0.136***	(0.0347)	0.582***	(0.0730)
- the number of working-age adults	0.0237	(0.0292)	-0.226***	(0.0485)	0.0227	(0.0293)	-0.226***	(0.0485)	0.0229	(0.0293)	-0.227***	(0.0485)
- the square number of adults	0.123***	(0.0263)	-0.302***	(0.0962)	0.123***	(0.0263)	-0.302***	(0.0962)	0.124***	(0.0262)	-0.303***	(0.0962)
- the square number of children	0.0607**	(0.0237)	-0.179***	(0.0659)	0.0615**	(0.0235)	-0.179***	(0.0659)	0.0612**	(0.0240)	-0.179***	(0.0663)
- the square number of female	0.0869**	(0.0390)	-0.378***	(0.0576)	0.0861**	(0.0389)	-0.378***	(0.0576)	0.0884**	(0.0392)	-0.377***	(0.0574)
- the square number of w.-a. adults	0.00214	(0.0437)	0.278***	(0.0850)	0.00401	(0.0437)	0.278***	(0.0850)	0.00263	(0.0438)	0.279***	(0.0850)
Constant	0.209***	(0.0666)	-0.0595	(0.107)	0.0574	(0.109)	-0.0595	(0.107)	0.212***	(0.0687)	-0.0600	(0.108)
Observations	12,314		12,314		12,314		12,314		12,321		12,321	
R-square	0.123		0.073		0.123		0.073		0.124		0.073	
A: group 1 % net gains (without credit)	**-0.256*** **		**0.705*** **		**0.323**		**0.142**		**-0.257*** **		**0.585*** **	
B: group 1 % net gains with credit access	**-0.106**	**(B-A=0)***			**-0.271***	**(B-A=0)**			**-0.0796**	**(B-A=0)**		
C: group 2 % net gains (without credit)	**-0.290*** **		**0.541*** **		**-0.286*** **		**0.628*** **		**-0.187**		**0.0161**	
D: group 2 % net gains with credit access	**-0.0599**	**(D-C=0)***			**-0.113**	**(D-C=0)**			**0.0843**	**(D-C=0)*** **		
E: group 3 % net gains (without credit)	**-0.307*** **		**0.501** **		**-0.307*** **		**0.407** **		**-0.311*** **		**0.682*** **	
F: group 3 % net gains with credit access	**-0.138**	**(F-E=0)** **			**-0.0913**	**(F-E=0)*** **			**-0.511*** **	**(F-E=0)**		
test for group differences (p-value)	0.193	(B-A=D-C=F-E)	0.796	(A=C=E)	0.113	(B-A=D-C=F-E)	0.476	(A=C=E)	0.00***	(B-A=D-C=F-E)	0.134	(A=C=E)

Source: NIDS and authors' calculation. Note: All specifications include region-time fixed effects and standard errors are clustered at the region and household level. Households where the main income earner retires are excluded to focus on transitory employment shocks. The bottom part of the table in bold facilitates the interpretation of the average net gains in the presence of multiple interaction terms. It provides estimates of the average loss for specific groups of households and tests for significant differences across these group averages (using STATA's *margins* command).

Table A.9. South Africa: Alternative Difference-in-Difference Estimation Results

Dependent variable: non-food consumption	(1)		(2)		(3)		(4)	
Measure of financial acces:	Formal borrowing		Informal borrowing		Formal saving		Formal borrowing now and before	
VARIABLES	coef	se	coef	se	coef	se	coef	se
financial access (dummy)	0.336***	(0.0321)	0.183***	(0.0391)	0.338***	(0.0460)		
lag financial access	-0.429***	(0.0348)	-0.303***	(0.0615)	-0.296***	(0.0387)		
employment loss (dummy)	-0.310	(0.227)	-0.197	(0.217)	-0.300	(0.222)	-0.345	(0.227)
" interacted with lag financial access	**0.230*** **	**(0.0803)**	**0.200*** **	**(0.115)**	**-0.00780**	**(0.0704)**	**0.0233**	**(0.0480)**
" interacted with the number of adults	0.0675**	(0.0265)	0.0739***	(0.0263)	0.0723***	(0.0261)	0.0636**	(0.0265)
" interacted with the number of children	0.00674	(0.0376)	0.00733	(0.0374)	0.00261	(0.0383)	0.00510	(0.0374)
" interacted with the number of female	-0.0554	(0.0391)	-0.0613	(0.0389)	-0.0579	(0.0389)	-0.0526	(0.0391)
" interacted with the nb. of working-age adults	0.0126	(0.0332)	0.0165	(0.0329)	0.0148	(0.0335)	0.00997	(0.0331)
" interacted with an urban area dummy	-0.0520	(0.0877)	-0.0393	(0.0891)	-0.0383	(0.0921)	-0.0623	(0.0883)
" interacted with a rural area dummy	-0.0280	(0.144)	-0.0371	(0.147)	-0.0481	(0.150)	-0.0288	(0.143)
" interacted with a secondary education dummy	-0.0427	(0.0811)	-0.0262	(0.0828)	-0.0259	(0.0858)	-0.0483	(0.0809)
" interacted with a tertiary education dummy	-0.0424	(0.0943)	-0.00725	(0.0947)	-0.0328	(0.0951)	-0.0628	(0.0934)
" interacted with an African dummy	-0.0387	(0.215)	-0.172	(0.204)	-0.00478	(0.210)	-0.00174	(0.218)
" interacted with a Coloured dummy	-0.0844	(0.215)	-0.213	(0.209)	-0.0551	(0.214)	-0.0477	(0.221)
secondary education (dummy)	-0.0211	(0.0228)	-0.0292	(0.0240)	-0.0313	(0.0240)	-0.0209	(0.0229)
tertiary education (dummy)	0.0200	(0.0256)	0.000247	(0.0267)	0.00377	(0.0255)	0.0230	(0.0258)
urban area (dummy)	0.0398	(0.0418)	0.0379	(0.0421)	0.0307	(0.0416)	0.0412	(0.0417)
rural area (dummy)	0.0587	(0.0564)	0.0566	(0.0563)	0.0609	(0.0545)	0.0583	(0.0564)
African population group (dummy)	0.108**	(0.0522)	0.155***	(0.0489)	0.0989**	(0.0485)	0.105*	(0.0531)
Coloured population group (dummy)	0.0586	(0.0530)	0.0933*	(0.0521)	0.0503	(0.0510)	0.0562	(0.0542)
lag number of workers	-0.0469***	(0.0158)	-0.0571***	(0.0154)	-0.0516***	(0.0156)	-0.0470***	(0.0157)
number of adults	-0.0238	(0.0163)	-0.0232	(0.0161)	-0.0266	(0.0164)	-0.0239	(0.0163)
number of children	-0.0175*	(0.0101)	-0.0206**	(0.00980)	-0.0183	(0.0110)	-0.0173*	(0.0101)
number of female	0.0190	(0.0127)	0.0226*	(0.0126)	0.0213	(0.0133)	0.0188	(0.0127)
number of working-age adults	0.0164	(0.0186)	0.0177	(0.0191)	0.0138	(0.0195)	0.0173	(0.0187)
Average age of working-age adults	0.0124***	(0.00303)	0.0140***	(0.00308)	0.0125***	(0.00310)	0.0124***	(0.00304)
Average years of education of working-age adults	0.0499***	(0.0106)	0.0537***	(0.0107)	0.0483***	(0.0105)	0.0499***	(0.0106)
change in the number of adults	-0.168***	(0.0277)	-0.148***	(0.0273)	-0.170***	(0.0279)	-0.167***	(0.0278)
change in the number of children	-0.115***	(0.0272)	-0.105***	(0.0275)	-0.119***	(0.0274)	-0.115***	(0.0271)
change in the number of female	-0.135***	(0.0347)	-0.144***	(0.0341)	-0.134***	(0.0341)	-0.135***	(0.0346)
change in the number of working-age adults	0.0237	(0.0292)	0.0240	(0.0293)	0.0171	(0.0297)	0.0231	(0.0292)
change in the square number of adults	0.123***	(0.0262)	0.105***	(0.0258)	0.119***	(0.0260)	0.123***	(0.0263)
change in the square number of children	0.0608**	(0.0237)	0.0517**	(0.0241)	0.0652***	(0.0237)	0.0608**	(0.0238)
change in the square number of female	0.0868**	(0.0390)	0.0924**	(0.0378)	0.0835**	(0.0371)	0.0867**	(0.0390)
change in the square number of w.-a. adults	0.00225	(0.0437)	0.00400	(0.0455)	0.0178	(0.0452)	0.00267	(0.0437)
new formal borrower (dummy)							0.329***	(0.0419)
" interacted with employment loss							0.153*	(0.0843)
borrowed formally but not anymore (dummy)							-0.415***	(0.0352)
" interacted with employment loss							0.221**	(0.0904)
continuing formal borrower (dummy)							-0.107***	(0.0344)
" interacted with employment loss							0.317***	(0.111)
Constant	(0.0665)	0.165**	(0.0634)	0.175***	(0.0641)	0.211***	(0.0667)	(0.0414)
Observations	12,314		12,303		12,219		12,314	
squared	0.123		0.109		0.120		0.214	
							average % gains or loss for	
average % gains or loss	**-0.237*** **		**-0.258*** **		**-0.240*** **		**never borrower**	**-0.300*** **
average % loss without financial access	**-0.349*** **		**-0.261*** **		**-0.256*** **		**new borrower**	**-0.184** **
average % loss with financial accesswithout financ	**-0.180*** **		**-0.098*** **		**-0.262*** **		**no more borrower**	**-0.126* **
difference between the above losses	**0.169*** **		**0.163*** **		**-0.006**		**continuous borrower**	**-0.039**

Source: NIDS and authors' calculation. Note: All specifications include region-time fixed effects and standard errors are clustered at the region and household level. Households where the main income earner retires are excluded to focus on transitory employment shocks. The bottom part of the table in bold facilitates the interpretation of the average net gains in the presence of multiple interaction terms. It provides estimates of the average loss for specific groups of households and tests for significant differences across these group averages (using STATA's *margins* command).

B. Tanzania: Data Details, Descriptive Statistics, Further Analysis

Table B.1. Households Demographic Summary Statistics by Wave

	Wave 1 2008/09	Wave 2 2010/11	Wave 3 2012/2013	Wave 4 2014/2015
Mean no. of household members	5.13	5.30	5.25	4.74
Mean no. of working age adults	2.97	3.07	3.07	2.70
Mean no. of children	2.16	2.22	2.18	2.04
Mean age of adults in households				
15-29	36%	33%	28%	37%
30-39	44%	47%	49%	42%
40-64	19%	20%	23%	21%
Education of head				
Below primary	42%	42%	42%	40%
Primary	48%	48%	48%	45%
Secondary or above	10%	10%	11%	15%
Main income source				
Agricultural	40%	40%	40%	30%
Non-agricultural	60%	60%	60%	70%

Source: LSMS and authors' calculations.

Table B.2. Household Summary Statistics on Annual Consumption and Income

	25th percentile	50th percentile	75th percentile	Mean	% of HHs with > 0
Consumption					
Total	1,260	2,034	3,328	2,842	100%
Food	813	1,263	1,868	1,564	98%
Health & Education	33	87	242	273	87%
Other non-food	193	477	1,258	1,053	100%
Income					
Total	498	1,304	2,932	3,211	100%
Wages	702	1,353	2,787	3,617	51%
Agriculture	107	253	590	723	70%
Self-Employment	321	798	1,927	1,934	47%

Source: LSMS and authors' calculations.

Note: All waves are pooled, and values are deflated to 2010 prices with the national CPI. The rows relating to sub-component of consumption and income only include households for which that sub-component is positive. The last column reports the fraction of households with a positive value for a given sub-component, averaged across waves.

Poverty Definition

We use the consumption-based definition of poverty proposed by the World Bank for the study of living standards in the LSMS. There was not methodological break over the sample period. As calculated in the Tanzania LSMS Wave 2 Final Report, the poverty line is 847 Tsh. per adult equivalent of weekly consumption in 2010 prices[22]. Despite its complexity and limited cross-country comparability relative to traditional metrics, for our analysis this measure of poverty has the advantage of being directly linked to household consumption dynamics.

Table B.3. Tanzania: Percent of Poor Households in Each Wave

	Wave			
	1	2	3	4
Household group	2008/09	2010/11	2012/2013	2014/15
All	12%	16%	18%	15%
Non-Agricultural	11%	12%	14%	13%
Agricultural	14%	22%	24%	19%

Source: LSMS and authors' calculations. Note: The definition of the consumption-based poverty line is explained in Appendix B.

Table B.4. Tanzania: Transition Probabilities in and out of Poverty

Groups:	**All**	**Main Income source**	
Average population shares in wave-pairs		Agricultural	Non-Agricultural
poor in t and t-1	42%	43%	41%
poor in t, non poor in t-1	58%	57%	59%
non poor in t, poor in t-1	13%	19%	9%
non poor in t and t-1	87%	81%	91%

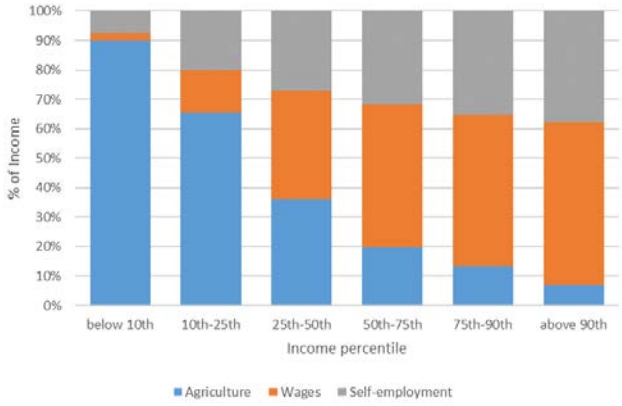
Source: LSMS and authors' calculations. Note: For a given t-1 state (i.e. not poor or poor), each entry shows the fraction of workers who were in each state in period t. These fractions are hence interpreted as transition probabilities. Time periods correspond to waves of the survey.

[22] See NBS (2013) for details on its computation. This value is expressed in W2 prices adjusted for regional price differences. In order to compute the poverty line in W1, W3, and W4, the values of consumption in those waves - already adjusted for cross-sectional variation in prices across regions- must be adjusted by the aggregate change in prices. For this exercise only, we use the Fisher index of prices produced by the compilers of the LSMS. To compute the adult-equivalent household size we use the scale suggested in the NBS (2013) Final Report.

Computation of Agricultural Income and Definition of Agricultural Households

In each wave, households report income from self-employment or household owned enterprises, wage-paid labor, and agricultural sales. Using the information contained in the agriculture section of the survey, we further impute the value of non-sold agricultural production, including agricultural byproducts.[23] Summing these sources of income, we impute households' total income, taking into account the value of non-sold products. Based on this variable, in each wave we compute the share of total income originating from each source. We define as "agricultural" those households where agricultural production constitutes the largest average share of income across the three waves. Based on this definition, approximately 40 percent of households in the Waves 1-3 sample classify as agricultural. The value is 10 percentage points lower for Wave 4. As this wave is not part of the panel, the lower share of agricultural households comes from the fact that we code the variable using the income shares for Wave 4 only, rather than the average across multiple waves. Note also that there is a difference between our definition of agricultural and that of a "rural" household, where the latter only has a geographical interpretation but does not imply that the household primarily relies on agricultural income. Figure B.1 reports the share of agricultural income for different quantiles of the income distribution.

Figure B.1. Tanzania: Composition of Income by Source Across Income Percentiles



Source: LSMS and authors' calculations.
Note: Each bar shows the average fraction of total income originating from each source for households in a given income percentile group. Percentiles are computed separately for each survey wave. Averages are then taken across waves. See Appendix B for details on the computation of agricultural income.

[23] Households report the total quantity and total value (in Tsh.) of each crop they produced in the year previous to the survey. To intelligibly describe the contribution of fluctuations in quantities and prices of crops, we impute the average price across the long and rainy season and across all plots on which a crop is produced. We also impute prices from the self-reported value of total harvest for each crop instead of differentiating between the sale price and the imputed price of the unsold produce. The process is slightly different for fruits, because households only report the value of the sold stock but do not report the value of the total product. Therefore, whenever a household reports a sale, we back out the price and use it to impute the value of the unsold portion of the produce. For households who produce a given fruit but do not report a sale, we impute the price using median prices. For the analysis we only select crops and fruits that have at least 40 price observations per wave.

Agricultural Income Volatility in Detail

Focusing on agricultural production for Waves 1 to 3, we decompose fluctuations in the total value of harvest across waves into its components. In a given wave, each household produces a set of crops, possibly in multiple plots, and sells part of the produce. We focus only on the crops and fruits that are more commonly produced by households and we exclude byproducts from crops and animals and the sale of seeds.

In a given period, a household produces quantity Q_j of product *j*, which is valued at price P_j, which is household-specific. Hence the total value of harvest at time *t,* Y(t) is

$$Y\ \ (t) = \sum_{j \in \mathbb{J}} Q_j\ (t) * P_j\ \ (t)$$

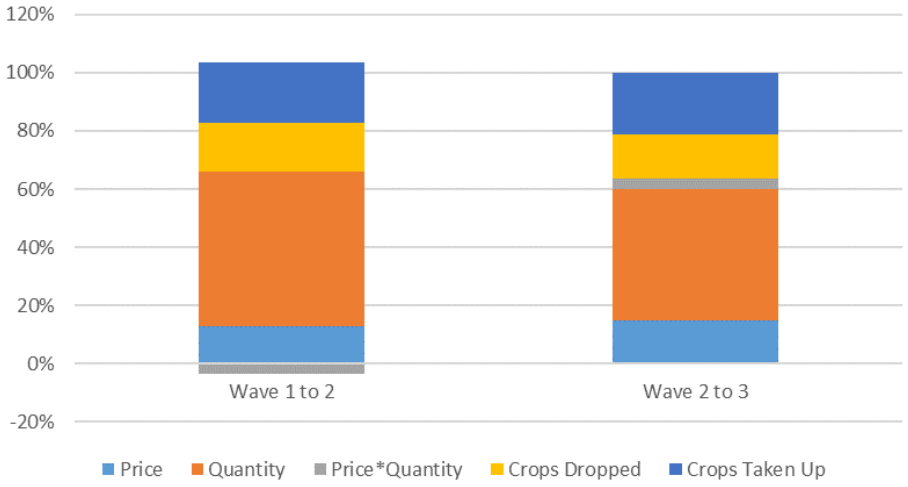
The level difference in agricultural output across two periods can be decomposed into the change in quantities and prices for each product. However, across two periods, the basket of crops may also vary, implying that some price changes cannot be observed. Part of the fluctuations in value therefore originate from the changing basket composition. Denoting $\mathbb{J}_t$ and $\mathbb{J}_{t+1}$ as the baskets of products in each period, a full decomposition can be done as follows:

$$\Delta Y(t+1) = Y(t+1) - Y(t)\ = \sum_{j \in \mathbb{J}_{t+1}} Q_j(t+1)P_j(t+1)\ - \sum_{j \in \mathbb{J}_t} Q_j(t)P_j(t)$$

$$= \sum_{j \in (\mathbb{J}_{t+1} \cap \mathbb{J}_t)} \Delta Q_j\ (t+1)P_j(t) + \sum_{j \in (\mathbb{J}_{t+1} \cap \mathbb{J}_t)} \Delta P_j(t+1)Q_j(t) + \sum_{j \in (\mathbb{J}_{t+1} \cap \mathbb{J}_t)} \Delta \mathrm{P_j}(t+1)\Delta Q_j(t+1\ )$$
$$+ \sum_{j \in\ (\mathbb{J}_{t+1} \cap \mathbb{J}_t^C)} Q_j(t+1)P_j(t+1)\ - \sum_{j \in (\mathbb{J}^C{}_{t+1} \cap \mathbb{J}_t\ )} Q_j(t)P_j(t)$$

The first term embodies the contribution of the change in quantities within the constant basket $(\mathbb{J}_{t+1} \cap \mathbb{J}_t)$ for given price, the second term comprises the contribution of the change in prices in the constant basket, and the third term captures the interaction of the two. Finally, the last two terms represent the change due to the newly grown crops $(\mathbb{J}^C{}_{t+1} \cap \mathbb{J}_t\ )$ and the discontinued ones $(\mathbb{J}^C{}_{t+1} \cap \mathbb{J}_t\ )$. With this decomposition, the contribution of each term relative to the total change can be computed dividing the term by $\Delta Y(t+1)$. Taking averages across all households *h,* we can obtain the average contribution of each term to agricultural income fluctuations. Figure B.2 shows this decomposition for changes across waves 1-2 and 2-3. Price changes account on average for a small fraction of agricultural income volatility. Quantities account for the bulk of volatility, both in terms of crops that are in the basket in both periods and of crop "turnover".

Figure B.2. Average Contribution of Different Factors to Changes in the Value of Total Agricultural Production across Waves at the Household Level



Source: LSMS and authors' calculations.

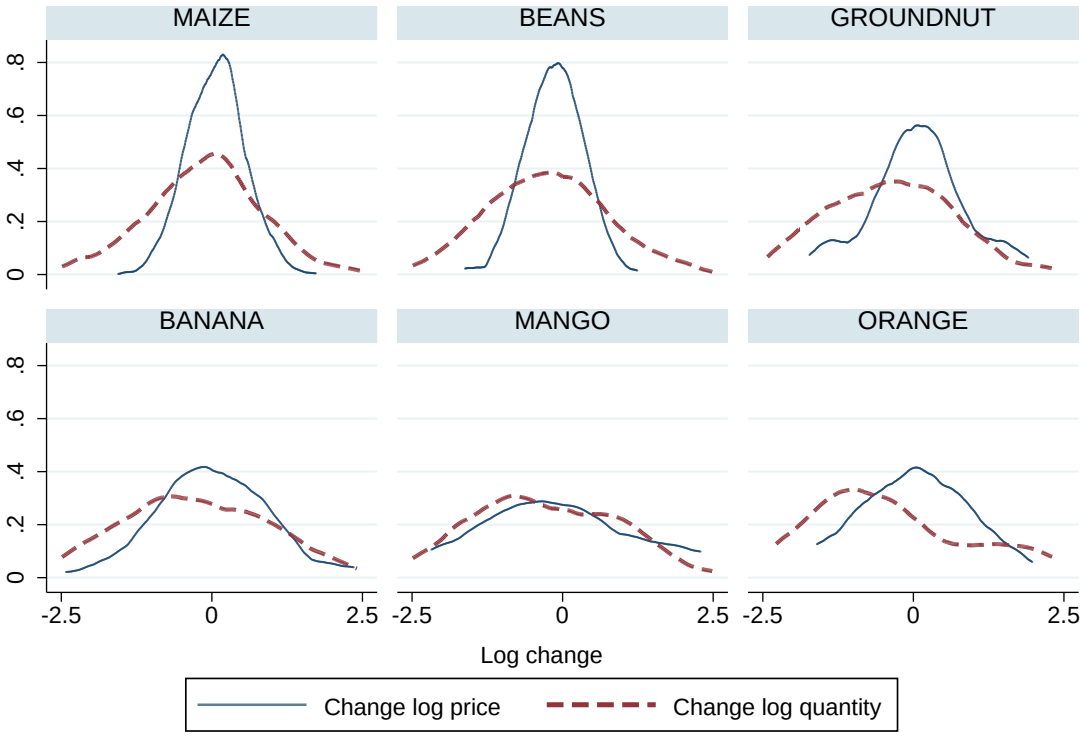
Further on this point, the Figure B.3 below plots the nonparametric distribution of log changes in prices and quantities for the most common crops at the household level (pooling the two waves together). It is evident that, with the exception of three fruit crops (banana, mango, and orange), for all other crops the volatility of prices is much smaller than that of quantities.

Deriving Price and Quantity Shocks

We create two proxies for agricultural income shocks based on the changes in price and quantity for the primary agricultural crop produced by each household in a given wave. For each household-wave observation, we select the crop representing the largest share of agricultural production. As Figure B.4 shows, on average the main crop accounts for 70 percent of total agricultural production.

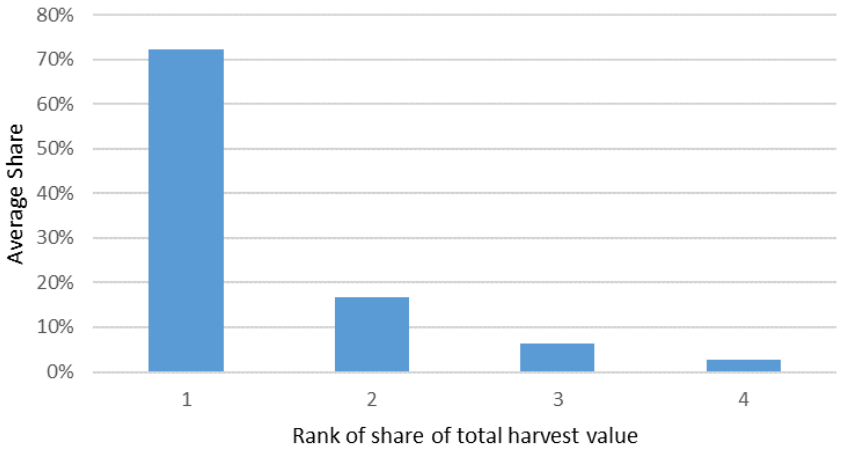
We then code a "price shock" as a change in price (at the household level) from one wave to the other that is below the 25th percentile of the distribution of all log changes in price (pooling all waves). Similarly, we code a "quantity shock" as a change in quantity produced from one wave to the other that is below the 25th percentile of the distribution of log changes in quantity or an instance in which the production of the primary good is discontinued in the second wave.

Figure B.3. Non-Parametric Distribution of Wave-to-Wave Log Changes in Quantity and Price of Each Crop across Households



Source: LSMS and authors' calculations.

Figure B.4. Average Share of Total Harvest Value by Crop Rank



Source: LSMS and authors' calculations. Note: Each bar represents the average share of the value of a household's total agricultural production for crops that are either the primary crop (Rank 1), or that constitute the second, third, and fourth largest share of total production (in monetary terms) for a household (Ranks 2 to 4).

C. Both Countries: Data Details, Descriptive Statistics, Further Analysis

Table C.1. Survey-based Poverty Rates in South Africa and Tanzania

Poverty line	Wave 1	Wave 2	Wave 3	Wave 4	Wave 5
(percent population below)	2008	2010/11	2012	2014/15	2017
South Africa	19%	26%	25%	19%	19%
	2008/09	2010/11	2012/13	2014/15	
Tanzania	12%	16%	18%	15%	

Source: NIDS, LSMS and authors' calculations.

Note: The table reports the headline poverty rate in each country across the waves of the surveys. The country-specific poverty lines, based on consumption levels, are explained in detail in Appendices A and B.