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The Consumption, Income, and Wealth of the Poorest:
An Empirical Analysis of Economic Inequality in Rural and Urban Sub-Saharan Africa for Macroeconomists*

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Abstract

We provide new empirical insights on the joint distribution of consumption, income, and wealth using cross-sectional and panel household-survey data from three of the poorest countries in the world—Malawi, Tanzania, and Uganda—all located in Sub-Saharan Africa (SSA). Our main contribution is to establish the co-existence of two phenomena in SSA: (i) a low transmission from income inequality to wealth inequality (i.e., low accumulation); and (ii) a low transmission from income inequality to consumption inequality (i.e., high consumption insurance). The variation between rural and urban areas in SSA—and between SSA and the U.S.—reveals a negative relationship and, potentially, a trade-off between accumulation and consumption insurance.

JEL: O10; O55; I32; E21

Keywords: Macroeconomy, Consumption, Income, Wealth, Sub-Saharan Africa, Inequality, Cross-Sectional Data, Panel Data, Accumulation, Insurance

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1 Introduction

Facts on the distributions of consumption, income, and wealth (CIW) are readily available for a large set of modern industrialized economies (Krueger et al., 2010; Díaz-Giménez et al., 2011; Piketty, 2014). These facts have been extensively used to build and test macroeconomic theories that incorporate heterogeneous household behavior with some degree of market incompleteness for the study of, almost invariably, rich economies.[1] To understand whether these macroeconomic frameworks are useful also for poor countries they need to be fully contextualized and informed by the behavior of households in these countries. In this paper we provide a careful and systematic dissection of the CIW behavior of rural and urban households in three of the poorest countries in the world—Malawi, Tanzania, and Uganda. To this end we use new and unique nationally representative data from the Integrated Surveys of Agriculture (ISA). Unlike most of the previous Living Standards Measurement Studies (LSMS), ISA not only includes cross-sectional data but also a panel dimension that we exploit.[2,3]

The main contribution of this paper is to exploit the rare availability of the triplet CIW and use the variation across rural and urban areas in Sub-Saharan Africa (SSA), and across SSA and the US, to establish the coexistence of two main findings that has not been previously emphasized in the literature: (i) a low transmission from income to wealth and (ii) a low transmission from income to consumption. We provide both cross-sectional evidence (e.g., conditional distributions) and panel-data evidence (e.g., complete markets tests à la Townsend (1994)) of these two findings. The two findings together imply that there is a negative relationship—and potentially a trade-off—between wealth accumulation and consumption insurance. Such potential trade-off is particularly important for rural areas where wealth accumulation is unambiguously low and consumption insurance is unambiguously high.

Our first main finding is a low transmission from income inequality to wealth inequality, i.e., a large and widespread inability to accumulate wealth conditional on income. This is the case in both rural and, to a lesser extent, urban areas of the three countries that we study in SSA.[4]

[1] See a recent review in Quadrini and Ríos-Rull (2015) and an earlier overview in Ríos-Rull (1995).

[2] The panel data are available in two waves for Malawi (2010/11 and 2013), four waves for Uganda (2005/6, 2009/10, 2010/11 and 2011/12), and two waves for Tanzania (2008 and 2010).

[3] To gain perspective on the relative poverty of the countries in this study, note that their average income per capita per day is close to US$1 (annually, US$359 in Malawi, US$524 in Tanzania, and US$471 in Uganda in 2010). Indeed, Malawi is the poorest world country in terms of income per capita according to the World Development Indicators (data retrieved in 2010). The rural population, where the overwhelming majority lives (84% in Malawi, 71% in Tanzania, and 85% in Uganda), has even lower levels of income per capita. In comparison, the poorest country studied in Krueger et al. (2010) is Mexico, which has an income per capita of US$8,920 and a rural population that is 22% of the total un 2010. In Thailand, a country extensively investigated in the development literature, these figures are respectively US$4,802 and 56% in 2010.

[4] For brevity, we refer to the three countries that we study as SSA. When we report a precise number for SSA,

We provide cross-sectional evidence of this phenomenon in four different ways. First, the ratio of wealth inequality to income inequality is much lower in SSA (1.5 in variance of logs) than in the US (4.5). This ratio is also lower in rural areas than in urban areas of SSA. These results hold for alternative measures of inequality. Second, the correlation of income and wealth is lower in SSA (0.29) than in the US (0.57), and lower in rural areas than in urban areas of SSA. Third, the lifecycle profile of wealth accumulation shows similar insights. While in the US wealth increases by a factor of 20 from age 25 to its peak, wealth increases by a much smaller factor in SSA: respectively 1.5 and 6 in rural and urban areas. The main component of household wealth, land holdings, largely explains this behavior with a lifecycle growth between age 25 and its peak of a factor of 1.5. The component of wealth that shows the strongest accumulation is livestock that grows by a factor of 3 over the lifecycle, a reminiscent of Rosenzweig and Wolpin (1993) for India.[5] Fourth, we study the wealth distribution conditional on income. Whereas the top 1% income-richest in the US hold 26% of total household wealth, the top 1% income-richest in SSA hold much less accumulated wealth: 4% of total rural wealth and 11% of total urban wealth.

Our second main finding is a high level of consumption insurance in SSA, particularly in rural areas (Townsend, 1994; Kinnan, 2014). We provide cross-sectional evidence of this phenomenon in four different ways. First, the ratio of consumption inequality to income inequality, a first pass to measure consumption insurance (Krueger and Perri, 2006; Morten, 2013), is much lower in SSA (0.43 in variance of logs) than in the US (0.81). Second, the correlation between income and consumption is lower in the SSA (0.53) than in the US (0.63), and lower in rural SSA (0.37) than in urban SSA (0.67). Our third form of evidence is the lifecycle behavior of consumption. In SSA, the pattern of lifecycle consumption shows a hump; as previously reported for other countries (Deaton and Paxson, 1994; Attanasio et al., 1999; Storesletten et al., 2004). The peak is twice larger in urban areas than in rural areas of SSA. This suggests a larger ability to smooth consumption over the lifecycle in rural areas (De Magalhães et al., 2017). Fourth, we explore distribution of consumption conditional on income and wealth. The consumption distribution conditional on income (or wealth) is more evenly distributed in SSA than in the US. Precisely, the bottom 20% of the land distribution accounts for 20% of total consumption and the top 20% accounts for 25% of total consumption. That is, land is likely to serve as an ex-ante redistribution mechanism that helps explain the high degree of consumption insurance suggested by the data.

Our analysis with panel data corroborates and extends our cross-sectional findings. First, income-rich households in SSA, despite having similar saving rates as the income-rich households in the US, are not income-rich for long enough, compared with their US counterparts, to accu-

that number relates to Malawi. Tanzania and Uganda show similar insights with details in the *Online Appendix*.

[5] However, despite this accumulation, livestock remains below 20% of total household wealth at age 65 while this proportion is 40% for land.

mulate similar wealth. That is, there is substantially more income mobility in SSA than in the US. Analogously, within SSA there is larger income mobility in rural areas than in urban areas, which helps explain the lower ability to accumulate wealth in rural areas compared with urban areas. This result arises from both income mobility matrices and the predicted income ranking of households. Both methods show larger upward as well as larger downward mobility in SSA than in the US. Second, using the joint panel of household-level consumption and income we compute insurance tests à la Townsend. These panel-based tests show higher consumption insurance in rural areas than in urban areas of SSA. In particular, we cannot reject the hypothesis of complete markets in rural areas when we define consumption as caloric intake, while this hypothesis is strongly rejected in urban areas.

The higher ability to insure in rural areas compared with urban areas is also apparent from self-reported information about shocks (e.g., weather, health, prices) and coping strategies (i.e, self-insurance, mutual insurance, or no response). Households in rural areas report using an informal insurance mechanism—conditional on having reported a shock—more often than urban households. This is suggestive, again, of a better ability to obtain insurance in rural areas than in urban areas. In terms of formal borrowing, we find that the success rate conditional on needing a loan is 17% in rural areas and 30% in urban areas. This way, the ability to formally borrow, proxied with conditional success rates on formal borrowing, is roughly twice larger in urban areas than in rural areas. However, this does not translate into higher consumption insurance in urban areas compared with rural areas. The reason is that formal borrowing in urban areas is 3.6 times more likely to be used for start-up capital (e.g., opening a business) than for consumption, while this ratio is 1.6 in rural areas. This suggests that urban households give up consumption insurance for accumulation (and growth) more often than rural households.

Our paper relates to a vast literature in growth and development economics. First, the patterns of low wealth accumulation in SSA relative to the US, which we study using micro data, are also present using aggregate data (Klenow and Rodríguez-Clare, 1997; Caselli, 2005). From a micro perspective, the facts that we document on the inability to accumulate wealth in SSA are directly related to the experimental work in Dupas and Robinson (2013a,b) for Kenya and in Brune et al. (2015) for Malawi. Both studies provide specific evidence of saving constraints that prevent accumulation. Second, the notion that the poor have strong institutions that preserve the ability to insure consumption is well-understood (Rosenzweig and Stark, 1989; Townsend, 1994; Attanasio and Ríos-Rull, 2000). We contribute to this literature by providing novel cross-sectional and panel evidence of a weaker transmission from consumption to income inequality in the rural areas than in the urban areas of SSA. The phenomenon of a differential ability to insure consumption in rural areas versus urban areas has been previously explored (Harris and

Todaro, 1970; Morten, 2013; Bryan et al., 2014; Munshi and Rosenzweig, 2016; Santaeulàlia-Llopis and Zheng, 2018). Finally, our paper relates to a growing literature that uses micro data to understand macro development (Hsieh and Klenow, 2009; Buera and Shin, 2011; Lagakos and Waugh, 2013; Gollin et al., 2014; Lagakos et al., 2016; Chen et al., 2017). Our contribution is to empirically study the joint behavior of the distributions of CIW in a manner that we hope is informative to discipline heterogeneous agent versions of macroeconomic models of growth and development (Galor and Weil, 1999; Hansen and Prescott, 2002; Gollin et al., 2002; Herrendorf et al., 2014).

In Section 2, we describe the data construction of household consumption, income, and wealth. In Section 3, we study the transmission from income to wealth and from income to consumption separately for rural and urban areas in SSA. We also establish comparisons between SSA and the US. We investigate the univariate distributions of CIW in Section 3.1, the joint distributions in Section 3.2, the lifecycle behavior in Section 3.3 and the behavior of the top and bottom of the distributions in Section 3.4. We provide detailed insights from panel data studying income mobility and consumption insurance tests in Section 4. We also investigate self-reported risks, insurance mechanisms, and formal borrowing. We conclude in Section 5.

2 ISA Data and Measurement Issues

The Integrated Surveys on Agriculture (ISA) allow us to recover—for any practical purpose—the entire deseasonalized budget constraint of a household in the poorest countries of SSA.[6] The budget constraint offers a simple way to organize the data for the study of CIW inequality,

$$c + k' = y_a + y_l + y_b + y_k + k + t_a + t_m, \tag{1}$$

where c is consumption, y_a is agricultural production, y_l is labor income, y_k is capital income, y_b is business income, t_a are food transfers, t_m are monetary transfers, k represents wealth today and k' wealth tomorrow. All this information regarding CIW is fully available in our data set, an availability that is very scarce even in rich countries with few notable exceptions (Krueger and Perri, 2011; Krueger et al., 2017).[7]

[6] The Integrated Surveys on Agriculture (ISA) are conducted under the umbrella of the Living Standards Measurement Study (LSMS). See a comprehensive introduction to ISA in the *Online Appendix* A.

[7] The availability of consumption, income, and wealth (CIW) in one single dataset is a rarity in the US and other rich countries. For example, in the US, the consumption expenditure survey (CEX) is widely used to study the joint dynamics of consumption and income (but without wealth data) (Krueger and Perri, 2006) and the Survey of Consumer Finances (SCF) is commonly used to study the joint dynamics of income and wealth (but without consumption data) (Díaz-Giménez et al., 2011). Since year 2000 the Panel Survey of Income Dynamics (PSID) extends its collection of household consumption data (beyond food) capturing a larger basket, which together with income and wealth data allows study the joint dynamics of CIW in the US (Krueger et al., 2017).

Due to the economic structure of the poor countries that we study, caution should be exercised in some aspects of our analysis, in particular, related to the income data. In this direction, we discuss in detail important measurement issues such as deseasonalization, units conversion of in-kind items, and the value of unsold agricultural production, as well as the implications of potential data limitations or sources of measurement error (e.g., underreporting and recall bias) on our main results; see our Appendix for details.

2.1 Household consumption

The main expenditure item is food that accounts for 62% of household expenditure. The ISAs record food consumption that is purchased, self-farmed, and received as gifts. Our measure of food expenditure includes food purchases, self-farmed consumption, and received food gifts. To construct this measure we attach consumption prices to the quantities of self-farmed food and food gifts. Food consumption is reported with a 7-day recall and is subject to seasonality (Paxson, 1993). We use the fact that the surveys are rolled out across the year (e.g., from March to March in Malawi 2004/05 and 2010/11) to construct seasonally-adjusted annual measures of food expenditure (see Appendix A).[8] Further, we use a new and simple price-unit conversion method to transform the reported amounts of self-farmed consumption and food gifts into a same baseline unit, kilograms (see Appendix B). This is useful to construct measures of caloric intake that we also use in our analysis.

Other nondurable expenditure classified under clothing (3%), health (i.e., prevention, treatment, hospitalization, and traditional healers—2%), education (2%), utilities (15%), housing (i.e, mostly self-reported rental value of dwelling or rent—2%), transportation (1%) and other nondurables (13%)[9]. Nondurable expenditure items (other than food) are collected monthly, quarterly, or annually. Analogously to food, we deseasonalize and annualize each of these nondurable items. This level of detail is similar in the Tanzania and Uganda ISA surveys.

2.2 Household Income

The main resource in rural areas is agricultural production. Production is reported by crops per plot and by season (rainy season, dry season, and permanent crop). We construct an annual measure of the entire agricultural production, sold and unsold, in monetary terms, which is

Another notable exception is the Italian Survey of Household Income and Wealth (Krueger and Perri, 2011).

[8] The Tanzania survey is also rolled out in 12 months. In Uganda the surveys are not rolled out throughout the year, but across all waves there are data for all months and we are able to deseasonalize the data.

[9] For example: fuel, newspaper and paper products, milling fees, hygiene and cleaning products, cooking and cleaning utensils, repair costs, cell phones, carpets and rugs, mats and linen, mosquito nets, rubber, plastics, construction and repair materials, mortgage payments, marriage and funeral costs and bridewealth costs.

household agricultural income. We use consumption prices to assign a monetary value to unsold agricultural production; alternatively, using the price-at-the-gate underestimates the value of unsold production (see Appendix C). In our computations, we use net measures of income and subtract the full set of production costs from intermediate inputs (seeds and fertilizers), rental cost of plots, rental costs of capital equipment and structures, hired labor, and transportation costs associated with inputs purchases and production sales.[10] Note that in net agricultural income we include the contribution of household labor to agricultural production.[11] Livestock sales and animal produce are also reported for the past 12 months, and we include this in agricultural income after netting out their associated costs (e.g., animal feed, vaccinations, veterinary services, and hired labor).

Other sources of household income include labor, businesses, capital and net transfers. Labor income is reported by occupation including main, secondary, and informal (e.g., *ganyu*). The survey has specific question on remuneration and number of hours worked per occupation that we use to compute annual labor income. In terms of business income, for each enterprise we compute net business income as total annual sales minus costs. Capital income includes net interest income, pension income, rental of property and durables, asset sales, inheritance etc. Despite the level of detail, household capital income is negligible compared with other sources of income. Finally, net transfers are defined as income transfers/gifts received from rural areas/urban areas/other countries minus income transfers/gifts given in the past 12 months. We also include food gifts from the consumption questionnaire (deseasonalized and annualized) in our definition of disposable income. In Malawi, food gifts represent approximately 6% of total disposable income and dwarfs the 1% contribution of net (cash) transfers in Malawi.

Underreporting of Income The underreporting of income is a recurrent issue in household surveys in both rich and poor countries (Deaton, 1997; Piketty, 2014). Tax avoidance is one reason for underreporting. This does not seem a major issue in the SSA countries that we study. For instance, we find it is reassuring that among rural households that can categorize as autarkic (i.e, with no production sales) the reported agricultural production (agricultural module) and the reported annualized self-farmed consumption (consumption module) yield very similar quantities (see Appendix C). Moreover, in Malawi less than 10% of the population is actually eligible to pay income tax,[12] a similar figure to that of the US in the 1930s (Piketty, 2014). What is perhaps

[10] In Malawi, the majority of households receive seed and fertilizer subsidies by the Farm Inputs Subsidy Program. We use the subsidized (coupon) prices reported by each household.

[11] This is innocuous for our purposes of measuring household income because the labor income generated by household members in agricultural production is also part of household income. Under some assumptions, this labor income can be separated from net profits, but this is beyond the scope of our paper.

[12] See the Malawi Revenue Authority: http://www.mra.mw/.

more relevant for our analysis is that the effect of the underreporting bias is well understood (e.g., Banerjee and Piketty (2005) for India, Alvaredo and Londoño (2013) for Colombia, and Heathcote et al. (2010) and Meyer et al. (2015) for the US). Any correction of the bias would simply increase the income of households at the top of the distribution. For example, Alvaredo and Gasparini (2013) compare the share of income accrued to the top 1% according to household-survey data and the tax records from actual register data. The share from tax records is higher than the share from household-survey data by a factor of 1.52 in Argentina, 1.74 in Uruguay, and 1.47 in Colombia.[13] In Malawi the top 1% earns 20% of total income, a share that increases to 31% if we apply the average correction estimated in Alvaredo and Londoño (2013) to Malawi. That is, corrections of underreporting imply a higher income inequality. This reinforces our argument in Section 3 for a low transmission from income inequality to consumption and wealth inequality.

2.3 Wealth and Its Portfolio

Our measure of household wealth is net worth which includes land, housing, livestock, agricultural equipment and structures (e.g., tools and barns), fishing equipment, other durables (e.g, cars, furniture, and household electrical appliances), minus debt. The underreporting of wealth is also potentially important, but perhaps less of a concern than the underreporting of income for three reasons. First, there are no taxes on assets or property in Malawi. Second, note that the two main assets held by these households are directly observable: (i) the dwelling is immediately seen by the surveyor and; (ii) the land holdings are measured by GPS. Third, one of the methodological improvements of the LSMS-ISA is the internal consistency checks (Carletto et al., 2010) that help further decrease measurement error in assets (e.g., GPS mapping, ability to sketch map of the plots, digital photography).[14] Three additional remarks are in order. First, the value of each asset refers to the self-reported current selling price, which adjusts for asset quality and is preferred to the standard use of the purchasing price (subject to recall bias) plus ad-hoc estimates of depreciation. Second, the value of savings (or other forms of liquid) is not collected but other studies suggest it is negligible (Beck et al., 2008; Brune et al., 2015). Third, loans only cover the last 12 months, but we note that long-term household debt such as mortgages and student loans which account for 90% of household debt in the US, are almost nonexistent in Malawi.

Finally, we note that the survey for Uganda does not report the value of outstanding debt, whereas Malawi and Tanzania do so. While debt is a minor component of net worth in Malawi and Tanzania, Uganda's wealth measure is likely to be overestimated for this reason. Also, the

[13] Precisely, the household survey and tax records shares of income accruing to the top 1% are respectively 8.8% to 13.4% in Argentina, 8.2% to 14.3% in Uruguay, and 13.9% ti 20.4% in Colombia.

[14] Carletto et al. (2013) show that the Gini indexes for self-estimated land size and for GPS-measured land size are extraordinarily similar: respectively 0.399 and 0.395 for Malawi.

Table 1: World Development Indicators and LSMS-ISA (Current USD, 2010)

(a) Macro Data: World Development Indicators, 2010

	Malawi	Tanzania	Uganda	Thailand	Mexico	US
Income per capita	359	524	471	4,802	8,920	48,377
Agricultural share (% Income)	29	28	25	12	3	1
Consumption per capita	257	328	376	2,577	6,023	32,783
Rural population (%)	84	71	85	56	22	19
Life expectancy	53	59	57	73	77	79

(b) Micro Data: LSMS-ISA, 2010

	Malawi	Tanzania	Uganda
Income per household	1,398	1,610	1,618
	[1,323; 1,472]	[1,470; 1,750]	[1,197; 2,040]
Income per capita	306	303	296
	[289; 322]	[278; 330]	[218; 375]
Agricultural share (% Income)	43	34	23
Consumption per household	1,566	1,920	2,350
	[1,532; 1600]	[1,854; 1,987]	[2,198; 2,503]
Consumption per capita	343	364	430
	[335; 350]	[351; 376]	[401; 459]
Rural households (%)	82	69	77
Sample size	12,015	3,014	2,337

Notes: Statistics in panel (a) are provided by the World Development Indicators at the World Bank and are based on national accounts data - Gross National Income in current dollars (data retrieved in 2010). Statistics in panel (b) are produced from the ISA household surveys data provided by the World Bank and adjusted as described in Section 2. Brackets denote 95% confidence intervals.

survey for Tanzania does not report the value of housing and other durables; thus, the monetary value of wealth reported for Tanzania is clearly underestimated, particularly for urban areas.

2.4 Household Survey Data vs. National Accounts

It is important to compare household survey data versus national accounts as they potentially yield different estimates of consumption and income level and growth (Krueger et al., 2010). Table 1 compares our household survey data from ISAs with the national accounts data for 2010 from the World Development Indicators at the World Bank database. The national accounts

figures are reported in panel (a), and the mean income and consumption per capita computed with the ISA household survey data adjusted as described in this Section are reported in panel (b). Focusing on Malawi, we find that the mean income per capita from our household survey data is US$306, which is lower than the measure reported in the national accounts number of US$359.[15] Income per capita from national accounts is also larger than that from the ISA data in Tanzania and Uganda.

Focusing on Malawi, note that the composition of income as estimated by the household survey implies that agricultural output represents 43% of total income, while this figure is solely 29% in the national accounts. This implies that national accounts and household survey data show similar levels of agricultural income. Further, if the national accounts are doing a good job in measuring nonagricultural income, the household survey is potentially underestimating (or not observing) some component of nonagricultural income. For example, we already discussed that there may be some underreporting in business income and that the share of income accrued to the top 1% is on average higher by a factor of 1.5 if measured with tax receipts (Alvaredo and Gasparini, 2013); also, illegal income from the diversion of international aid (e.g., in the form of bribes) could potentially account for some of this discrepancy (Deaton, 2005).[16]

The observation that income is lower than consumption from household survey data is likely due to the underreporting of income, which is common in household survey data. The idea is that consumption is in general better measured than income (Grosh and Deaton, 2000). In large part, this is due to the fact that the consumption basket in poor countries consists mostly of food which is usually collected with 7-days recall. In contrast, income faces larger recall bias, in particular, if there is only one (or few) rainy seasons in a country. Indeed, the incorporation of a new and comprehensive agricultural questionnaire (i.e, ISA) to previous LSMS data aims at improving the collection of agricultural production (i.e., the main source of income in these countries) to reduce underreporting. We do not observe this issue in national accounts because consumption is largely computed as a residual.

The main disparity between the household survey and the national accounts estimates is

[15] We use the nominal exchange rate for 1US$ in March 2010: Malawi, 152. We transform nominal variables into real using official CPI measures from the National Statistics Office (NSO) in Malawi that differ across food and non-food items and across rural and urban areas. Spatial differences in prices might introduce additional biases in the comparison of expenditure across households within rural and urban areas, although this is more of a concern for larger countries (Deaton and Dupriez, 2011). We proceed similarly for the other countries with nominal exchange rates for 1US$ in March 2010 of 1,350 for and 2,110 for Uganda.

[16] The reason is that international aid shows up in national accounts but not necessarily in household survey data. See, for example, the cashgate scandal covered by The Guardian, http://www.theguardian.com/global-development/2014/nov/11/malawi-official-jailed-cashgate-scandal-aid. This way, it is likely that the household survey will capture some, but not all, of the international aid, which according to WDI represents 26% of the total income in Malawi in 2010.

Table 2: Rural and Urban Levels: Cross-Country Comparison (ISA 2010)

	Malawi		Tanzania		Uganda	
	Rural	Urban	Rural	Urban	Rural	Urban
Consumption	1,318	2,951	1,547	2,875	1,796	4,904
" (p.c.)	287	662	280	623	319	1,048
▷ Nondurables	1,223	2,684	1,468	2,599	1,245	3,207
▷ Durables	40	143	4	76	328	1,060
Income	1,142	2,795	1,227	2,587	1,262	3,221
" (p.c.)	249	626	220	560	225	681
▷ Agriculture	662	245	690	204	426	132
▷ Labor	212	1,630	248	1,390	183	846
▷ Business	128	1,052	178	800	534	1,843
Wealth	1,309	3,976	3,361	1,757	6,148	10,256
▷ Assets						
Land	575	401	2,341	1,585	4,421	4,774
House	404	2,690	*n.a.*	*n.a.*	1,190	4,336
Land (acres)	1.7	0.4	6.0	2.5	4.7	1.5
▷ Debt	5	37	11	22	*n.a.*	*n.a.*
Sample size	9,820	2,195	2,067	945	1,809	528

Notes: All variables except land acres are in current USD. The construction of the measures of household consumption, income, and wealth is discussed in Section 2, with further details in the *Online Appendix*. Per capita variables are computed dividing by total household size.

found in consumption. The ISA estimates of consumption per capita are higher than the national accounts estimates for all three countries. This is consistent with other Sub-Saharan Africa countries (Deaton, 2005). For example, the national accounts are likely to underestimate the value of consumption from own agricultural production, which we estimate to be 20% of total consumption from the household survey data in Malawi. This suggests that national accounts might not only be underestimating consumption growth, as suggested in Young (2012), but also the level.[17] However, the ranking of consumption per capita across countries is maintained in the macro and the micro data: Malawi is the poorest, followed by Tanzania, then Uganda.

2.5 Rural-Urban Differences in Levels

The rural-urban gap in consumption and income within countries is at least an order of magnitude larger than the country differences across Malawi, Tanzania, and Uganda. In urban Malawi, mean per capita consumption and income is, respectively, US$648 and US$618, while these figures are

[17] However, note that our measure of consumption is different from that in Young (2012), who uses the ownership durables (and other education and health measures) to proxy for real consumption.

US$297 and US$245 in rural areas (Table 2). That is, consumption per capita in urban areas is 2.18 times higher than in rural areas, and income per capita in urban areas is 2.51 times higher than in rural areas. The magnitude of the difference between rural and urban areas is even higher for Tanzania and Uganda. Across rural areas in different countries, differences in consumption and income levels are no higher than 15%.

In terms of composition, and focusing on Malawi, we find that consumption in both rural and urban areas is dominated by nondurables that represent more than 95% of the total consumption basket. In terms of income, the major components in rural areas are agriculture income and labor income that respectively represent 60% and 19% of household income. In urban areas labor income represents 53% household income, while agriculture barely 10%. Business income represents 10% of household income in rural areas and 34% in urban areas. These proportions are similar for Tanzania and Uganda.

Finally, in terms of wealth, urban households hold 3.03 times more wealth than rural households in Malawi. In rural areas the main component is land, which represents 44% of household wealth, housing 30%, and livestock 13%. In urban areas the main component is housing, which represents 59% of household wealth, other durables 27%, and land 14%.

3 An Empirical Analysis of Consumption, Income, and Wealth Inequality in Rural and Urban Sub-Saharan Africa

Whether distributional differences in consumption, income, and wealth exist across rural and urban areas is a lesser-understood phenomenon. That is the focus of our study. For the sake of brevity, we focus on Malawi in the main text and relegate most of the results for Tanzania and Uganda to the *Online Appendix*. Malawi has the largest and arguably the highest quality data.[18]

3.1 Consumption, Income, and Wealth Inequality

In SSA, wealth inequality is larger than income inequality and, income inequality is larger than consumption inequality. In Malawi these numbers are (in variance of logs): 1.95 for wealth, 1.09 for income and 0.49 for consumption. This ordering also holds within urban and rural areas and for other measures of inequality (Table 3). Furthermore, we find that for consumption, income, and wealth, inequality is higher in urban areas than in rural areas. This can also be observed in Figure 1; the densities for wealth are flatter than those for income, and the densities for

[18] Malawi has a sample size that is roughly three times larger than Uganda and Tanzania, and has more detailed and comprehensive information for the triplet CIW as discussed in Section 2.

Table 3: Cross-Sectional Inequality: Rural and Urban Malawi (ISA 2010)

(a) Variance of Logs

	Malawi			U.S.		
	Rural	Urban	Full	SCF	PSID	CEX
Consumption	0.41	0.55	0.50	–	0.79	0.35
Income	0.98	1.56	1.09	0.99	0.97	0.55
Wealth	1.49	4.52	1.96	4.53	2.11	–
Inequality Ratios:						
▷ C/I	0.42	0.35	0.46	–	0.81	0.64
▷ W/I	1.52	2.90	1.80	4.58	2.18	–

(b) Gini

	Malawi			U.S.		
	Rural	Urban	Full	SCF	PSID	CEX
Consumption	0.36	0.42	0.41	–	0.41	0.32
Income	0.53	0.70	0.60	0.58	0.44	0.38
Wealth	0.60	0.84	0.70	0.82	0.79	–
Inequality Ratios:						
▷ C/I	0.68	0.60	0.68	–	0.93	0.84
▷ W/I	1.07	1.20	1.17	1.41	1.80	–

Notes: All variables are in current USD. For Malawi, all computations are done by the authors. The inequality ratios divide a measure of inequality for the variable in the numerator by the same inequality measure for the variable in the denominator. The measures of inequality that we study are the variance of logged variables (panel (a)) and the Gini index (panel (b)). For the US, we compare three data sources. First, we simply borrow the 2007 SCF estimates from Díaz-Giménez et al. (2011); second, we compute the 2006 PSID statistics using data kindly provided by Krueger et al. (2017); and, third, we compute the CEX statistics using the data publicly available from Krueger et al. (2010). Note that the CEX consumption and income data are top coded, which helps explain its lower dispersion. The construction of the measures of household consumption, income, and wealth is discussed in Section 2, with further details in the *Online Appendix*.

consumption are more concentrated that those of income in both rural and urban areas.[19]

In rural areas wealth and income inequality is respectively 1.48 and 0.98 (in variance of logs) and 4.51 and 1.56 in urban areas (panel (a) Table 3). Thus, the ratio of wealth-to-income

[19]The distributions of CIW are not symmetric with skewness statistics different from zero. The asymmetry is larger for wealth than for income, and for income than for consumption. All distributions are skewed to the right, and more skewed in rural areas than in urban areas. In rural areas, the skewness values are 3.9, 18.6 and 19.9 for consumption, income, and wealth respectively. In urban areas, the skewness values are 2.9, 7.9, 9.1 for consumption, income, and wealth respectively. The CIW distributions also have heavier tails than the normal distribution as shown by the high kurtosis values in rural areas (34.4, 580.3 and 662.4. for consumption, income, and wealth respectively) and in urban areas (13.9, 86.9 and 95.1 for consumption, income, and wealth respectively). In logs, the distributions resembles the normal distribution (i.e., skewness zero and kurtosis three). In rural areas CIW have respective skewness values of 0.23, -0.18, -0.67 and kurtosis values of 3.2, 4.9, and 5.9. In urban areas CIW have respective skewness values of 0.22, 0.27, -0.31 and kurtosis values of 3.5, 4.4, and 3.4.

inequality is 1.51 in rural areas and 3.05 in urban areas which suggests that, for a given amount of income dispersion, there is a larger ability to generate wealth dispersion in urban areas than in rural areas. Comparing SSA with US inequality, we find that income dispersion transmits much less into wealth dispersion in SSA than in the US. Precisely, in terms of household income, the US has a log variance of 0.99 for the year 2010, as reported in Díaz-Giménez et al. (2011) using the Federal Reserve's Survey of Consumer Finances (SCF), and the variance of logs in income in SSA is roughly the same, 1.09 in Malawi. In contrast, in terms of wealth the US has a log variance of 4.53, which is more than twice larger than that of Malawi, 1.95.[20] That is, given similar income inequality, the US is able to generate 2.3 times more wealth dispersion than SSA.[21]

This lower transmission from income to wealth inequality in SSA compared with the US is present in both rural and urban SSA. Rural Malawi has income inequality similar to that of the US, with a variance of logs of 0.99, while wealth inequality in rural Malawi is 1.49, i.e., one-third of the US wealth inequality. That is, with roughly the same income dispersion as rural Malawi, the United States is able to generate three times the wealth dispersion of rural Malawi. Also, the US is able to generate the same amount of wealth dispersion as urban SSA with about 60% of its income dispersion. This is perhaps the first indication of a larger inability to accumulate wealth in rural SSA compared with urban SSA, and in the SSA compared with the US. Similar insights arise if we look at Gini indexes (panel (b) Table 3).

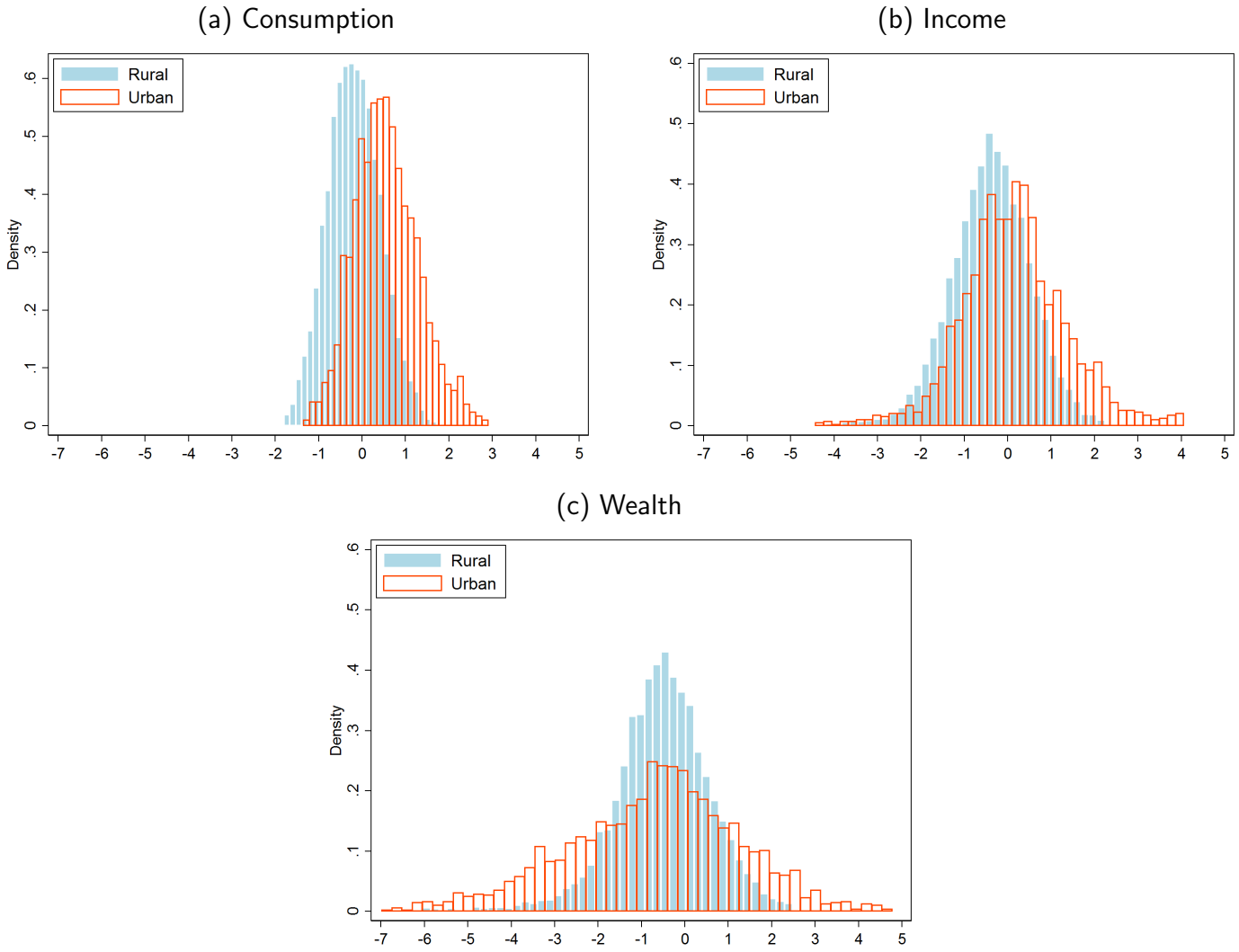
Focusing on consumption, inequality in rural areas is smaller than in urban areas with variance of logs of respectively 0.40 and 0.57 (panel (a) Table 3). That is, consumption is more unequal in urban areas than in rural areas by roughly a factor of 1.4 for Malawi. Urban and rural areas share a similar ratio of consumption-to-income inequality; a ratio that has been used as a first pass to understand consumption insurance (Krueger and Perri, 2006; Morten, 2013). However, Aguiar and Bils (2011) argue that there is a higher underlying consumption inequality than that inferred from consumption surveys with long recall due to a loss of quality data from goods that are mostly purchased by rich people.[22] In the SSA countries that we study this is more likely to occur in urban areas than rural areas, as non-food consumption (with a longer recall period than food) is more predominant for rich households in urban areas. Thus, any corrected measure of consumption would likely break the apparent tie in the ratio of consumption-to-income inequality between rural and urban areas. This tie breaking would be in the direction of a larger transmission from income to consumption in urban areas then in rural areas. Regardless of any correction, there

[20] The figures for Tanzania and Uganda are similar, see the *Online Appendix* B.

[21] Using PSID data the variance of log wealth is of 2.11 for the US, also larger than its counterpart in Malawi. The lower variance in the PSID data compared with the SCF data is explained by the inability of the PSID to recover the top of the wealth distribution which SCF does oversampling rich households (Krueger et al., 2017).

[22] Attanasio et al. (2007) argue that these differences in CEX data arise from interview data (monthly recalls) versus diary data (7-day recalls).

Figure 1: Density of Consumption, Income, and Wealth in Rural and Urban Malawi (ISA 2010)



Notes: The construction of household consumption, income, and wealth is described in Section 2. All variables have been logged.

is an already clear distinction between the ratio of consumption-to-income inequality between SSA and the US which is, respectively 0.43 and 0.81. That is, the consumption-to-income inequality ratio is much larger in the US than in Malawi.[23] This represents our first evidence suggesting lower transmission from income to consumption (i.e., higher consumption insurance) in poor SSA than in the US. Similar results are obtained with Gini indexes (panel (b) Table 3).

A recurrent theme in the inequality literature is the bias from the underreporting of income, in particular, from rich households (see Section 2.2). However, the correction of such bias simply

[23]This ratio for the US is 0.64 if we use CEX data in our computations. That is, CEX also implies a larger transmission from income to consumption in the US than in Malawi. An important difference between CEX and PSID data is that CEX data are top coded which can help explain why CEX tends to provide lower inequality measures (0.35 and 0.55 for the log variance of consumption and income respectively) than PSID data (0.79 and 0.97 for the log variance of consumption and income respectively).

implies an increase in income inequality (Banerjee and Piketty, 2005; Alvaredo and Londoño, 2013; Heathcote et al., 2010; Meyer et al., 2015), which would strengthen our results by making income even more unequal than consumption and wealth in SSA.

The use of cross-sectional data (e.g., Malawi, ISA 2010) to describe inequality patterns helps preserve a consistent comparison with previous studies in developed countries (Díaz-Giménez et al., 2011; Krueger et al., 2017), but it comes with caveats. In particular, it might be that part of the dispersion that we report with cross-sectional data is not all genuine variation (see our discussions on underreporting in Section 2.2 and on recall bias in the Appendix D). Note that these measurement issues are also acknowledged and relevant in the context of rich countries as well (Heathcote et al., 2010; Aguiar and Bils, 2011; Meyer et al., 2015). In order to explore this question in the context of SSA, we treat household averages across our panel as cross-sectional data. That is, we use the available panel data for Malawi (the 2010/11 wave and the 2013 wave) to compute household-specific averages of consumption, income, and wealth across waves and, then, we re-compute Table 3 with these measures. This implies measures of consumption, income, and wealth that are more permanent in nature. Our insights do not change with this panel-based analysis (see the *Online Appendix* B). Under these new panel-based variables it is still the case that income inequality is larger than consumption inequality and lower than wealth inequality within rural and urban areas. It is also the case that urban inequality is significantly larger than rural inequality by a similar factor. Similar insights arise for Uganda and Tanzania.

3.2 The Joint Cross-Sectional Behavior of Consumption, Income, and Wealth

A more direct measure of the transmission from income to wealth can be extracted from the joint densities. The correlation between income and wealth is lower in rural areas, 0.17, than in urban areas, 0.34 (panel (a) and (b), Table 4).This implies a stronger transmission from income to wealth in urban areas than in rural areas which is suggestive of a larger inability to accumulate in rural areas. In rural areas the correlation is stable throughout the income distribution, whereas in urban areas we find a slightly opened L-shaped joint density (Figure 2). For the bottom 80% of the income distribution the correlation between income and wealth is 0.06, while this correlation is 0.30 for the top 20% of income earners. Thus, only the income-rich households in urban areas seem able to accumulate wealth. For the whole sample there is a weaker link between income and wealth in SSA, where the correlation of these two variables is 0.29, than in the U.S., where this correlation is almost twice larger, 0.57 (panel (c) and (d), Table 4).[24]

The correlation of consumption and income is also lower in rural areas, 0.37, than in urban

[24]The correlation between income and wealth is even smaller in Tanzania and Uganda, respectively 0.06 and 0.20. Note that the ISA wealth data for Tanzania and Uganda is not as good as that for Malawi, Section 2.3.

Table 4: Correlation Matrix of Consumption, Income, and Wealth (ISA 2010)

(a) Rural Malawi

	C	I	W
Consumption (C)	1.00	–	–
Income (I)	0.37	1.00	–
Wealth (W)	0.30	0.17	1.00

(b) Urban Malawi

	C	I	W
Consumption (C)	1.00	–	–
Income (I)	0.60	1.00	–
Wealth (W)	0.44	0.40	1.00

(c) Malawi

	C	I	W
Consumption (C)	1.00	–	–
Income (I)	0.49	1.00	–
Wealth (W)	0.39	0.31	1.00

(d) United States

	C	I	W
Consumption (C)	1.00	–	–
Income (I)	0.68	1.00	–
Wealth (W)	0.20	0.57	1.00

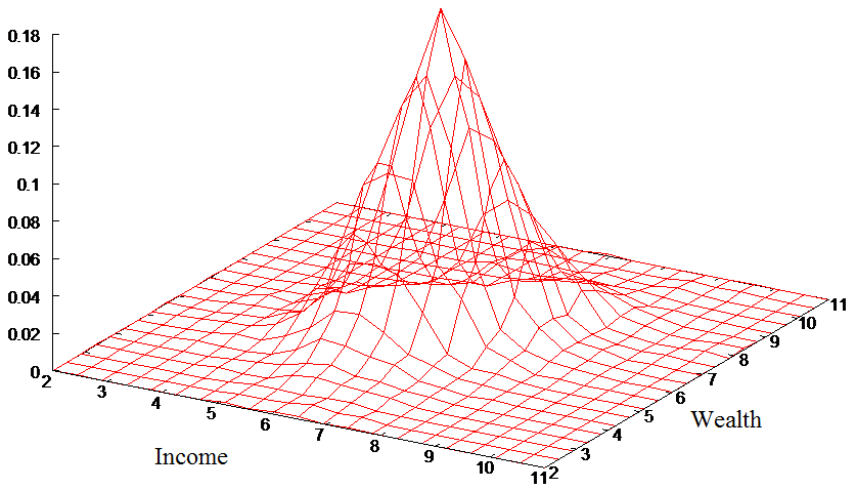
Notes: All variables are in current USD. For Malawi, all computations are done by the authors. For the US, the correlation between income and wealth is directly borrowed from (Díaz-Giménez et al., 2011) that use 2007 SCF data; we use CEX data publicly available from Krueger et al. (2010) to compute the correlation between consumption and income; and the correlation between consumption and wealth is directly borrowed from (Krueger et al., 2017) using 2006 PSID data. The construction of the measures of household consumption, income, and wealth is discussed in Section 2, with further details in the *Online Appendix*.

areas, 0.62 (Table 4). This suggests a lower transmission from income to consumption, i.e., more consumption insurance, in rural areas than in urban areas in SSA. This correlation is fairly stable across the income distribution (Figure 2). Finally, notice that this correlation is smaller in SSA than in the US, respectively, 0.53 and 0.68 (Table 4). These results suggest a larger ability to insure consumption in rural SSA then in urban SSA, and in SSA than in the US.

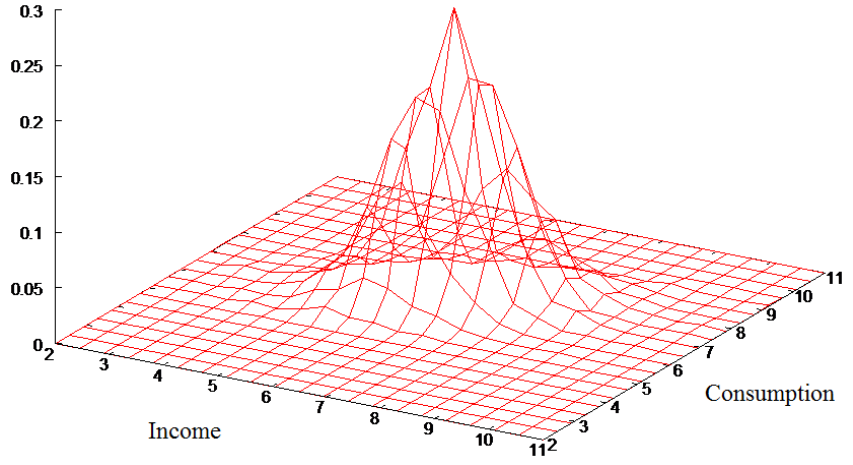
Finally, note that in both rich and poor countries if we summarize the transmission from wealth to consumption with their correlation, this transmission is lower than from income to consumption (panel (c) and (d) Table 4). While merely indicative, a stronger relation between income and consumption than between wealth and consumption suggest that shocks to wealth have potentially a lesser effect on consumption than income shocks. This is also the case for rural and urban areas in Malawi where the correlation between wealth and consumption is 0.31 and 0.43, respectively (panel (a) and (b) Table 4). That is, this correlation is lower in rural areas than in urban areas pointing to a large ability to insure consumption in rural areas independently of the type of shock (income or wealth) compared with urban areas.[25]

[25] Our results remain unchanged using panel data for Malawi (the 2010/11 wave and the 2013 wave) to construct household-specific averages of consumption, income, and wealth across waves, see the *Online Appendix*.

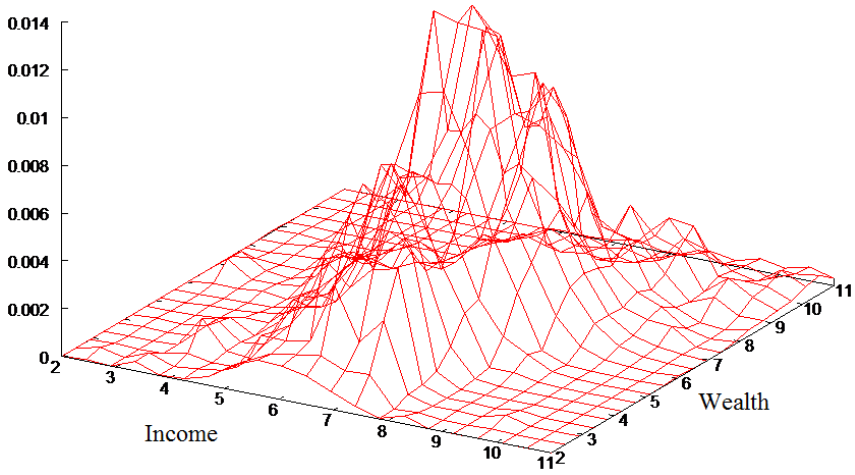
Figure 2: Joint Densities of Consumption, Income, and Wealth in Rural and Urban Malawi (ISA 2010)



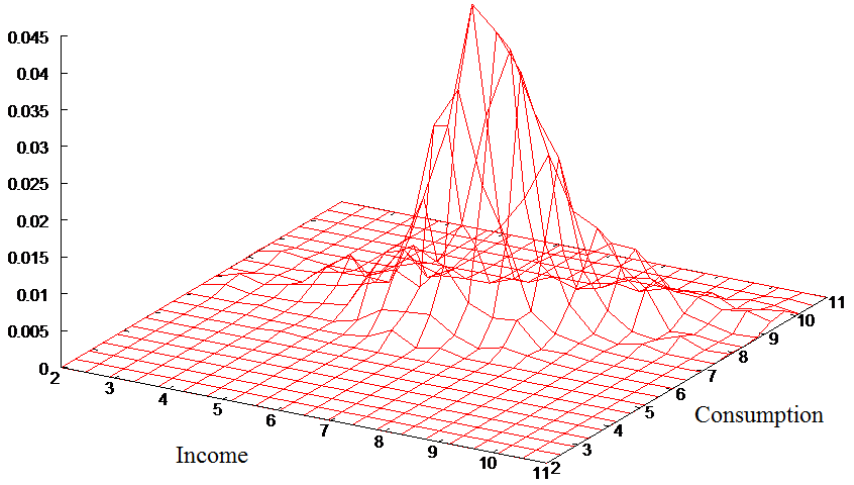
(a) Income and Wealth, Rural



(b) Income and Consumption, Rural



(c) Income and Wealth, Urban



(d) Income and Consumption, Urban

Notes: The construction of household consumption, income, and wealth is described in Section 2. All variables have been logged.

3.3 Consumption, Income, and Wealth Over the Life Cycle

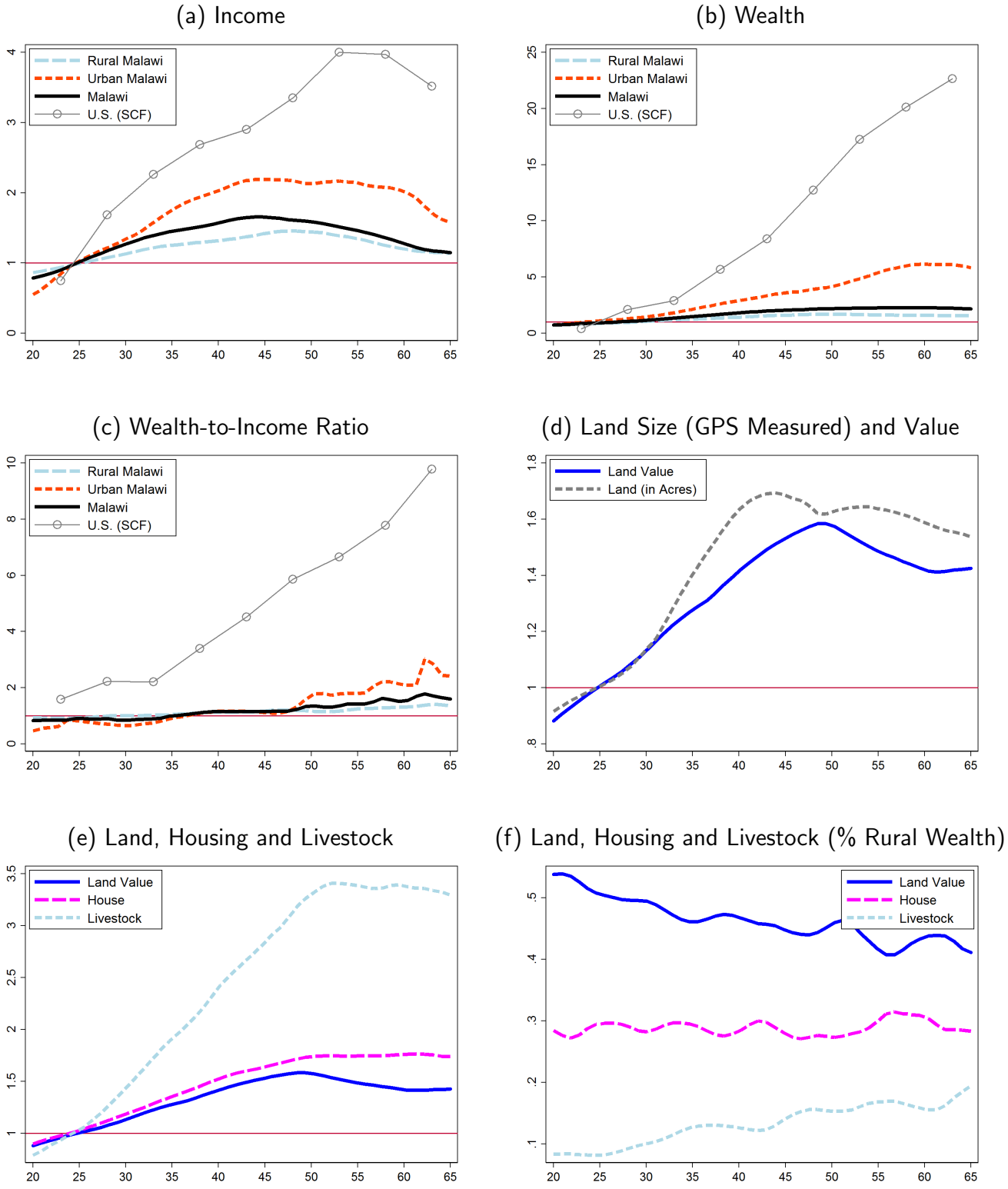
To gain a better understanding of accumulation we describe lifecycle behavior of income and wealth. We plot the life cycle profiles of income normalized to 1 at age 25 (panel (a), Figure 3), where the age is that of the household head..[26] The age profile of income in Malawi shows a hump in both rural and urban areas that peaks around age 45. The hump is less salient in rural areas. In rural areas income is about 1.5 times larger at its peak than at age 25, while in urban areas income is about twice as large at its peak than at age 25. This implies a nationwide income age profile for Malawi that is roughly 1.75 times larger at its peak than at age 25. With non top-coded income data from the SCF, Díaz-Giménez et al. (2011) find that income in the US grows over the lifecycle by a factor of 4. This implies that household income grows roughly four times less over the lifecycle in SSA than in the US. This way, flatter nationwide life cycle profiles of income in SSA countries may be the result of a composition effect driven by the larger share of rural households in SSA than in rich countries.[27]

The differentials in the accumulation of wealth over the lifecycle are more sizable than the differentials of income. In the rural areas of SSA, as it is the case of income, wealth accumulates less over the lifecycle than urban areas (panel (b), Figure 3). Rural wealth peaks at the age of 50 with a value that is less than 1.5 times the rural wealth at age 25. This implies that wealth accumulates roughly at the same pace as income grows in rural areas, which is consistent with a relatively constant lifecycle wealth-to-income ratio in rural areas(panel (c), Figure 3). In contrast, in urban areas wealth rises more rapidly than income, which suggests a higher ability to accumulate wealth conditional on income. In urban areas, wealth shows a peak at age 60 that is roughly 6 times higher than the urban wealth at age 25. This implies that the urban wealth-to-income ratio grows by roughly four times from a ratio of 0.5 at age 25 to a ratio of 2 at age 65. Nationwide, the wealth-to-income ratio in Malawi grows from 1 at age 25 to 1.5 at age 65, which implies a lifetime growth of roughly 50%. In the US, the wealth-to-income ratio grows from 2 at age 25 to 10 at age 65—a lifetime growth of 400%. This suggests that the ability to accumulate wealth (relative to income) is eight times larger in the US than in Malawi, and two times larger in the US than in urban Malawi.

[26] To preserve the comparison with the non-top coded cross-sectional lifecycle profiles of income and wealth in Díaz-Giménez et al. (2011), we focus on reporting the estimated age profiles using the ISA 2004/05 and 2010/11 cross-sectional data. In our estimation we controlling for time effects only. Although not reported here, our results stand robust to controlling for cohorts effects only.

[27] Our results for income relate to those in Bils and Klenow (2000) and Lagakos et al. (2016) that document flatter age profiles for wages in poor countries than in rich countries. Note that we focus on household total income to take into account that in the SSA countries that we investigate there is a large rural population (approximately 80%) for whom own agricultural production (rather than wages) is the main source of income.

Figure 3: Lifecycle Household Income and Wealth in Rural and Urban Malawi (ISA 2010)



Notes: The construction of household income and wealth (and its subitems) is described in Section 2. The age of the household is the age of the household head. All variables have been normalized to 1 at age 25, except for the wealth-to-income ratio in panel (c) and the share of rural wealth in panel (f). Panel (d), panel (e), and panel (f) refer to the rural areas only. We discuss these results in Section 3.3. In all graphs we show the estimated age dummies of the variable of interest after controlling for time dummies. The data are the ISA 2004/05 and the 2010/11 cross-sections

The inability to accumulate assets over the lifecycle is particularly strong in rural areas of SSA. This is consistent with most of rural wealth being land holdings together with land barely growing over the lifecycle (a factor of 1.5). This is true whether we use land value or GPS-measured land size (panel (d), Figure 3). The low accumulation of land over the lifecycle is perhaps not surprising given the low amount of available marketed land (Restuccia and Santaeulàlia-Llopis, 2017). The component of wealth that shows the strongest accumulation is livestock, which is a reminiscent of Rosenzweig and Wolpin (1993) for India. In Malawi, livestock grows by a factor of three over the lifecycle (panel (e), Figure 3). However, despite this accumulation, livestock remains below 20% of total household wealth at age 65 while this proportion is 40% for land (panel (f), Figure 3).

Lastly, it is important to note that this large inability to grow wealth over the lifecycle coexists with a large ability to smooth consumption over the lifecycle. First, lifecycle consumption is flatter in rural areas than in urban areas of SSA, suggesting a higher ability to smooth consumption in the rural areas of SSA than in the urban areas. Although not reported here, this is true for both total expenditure and food consumption measured in caloric intake (De Magalhães et al., 2017).[28] Second, compared with the US, consumption profiles are smoother in SSA than in the US. These results also stand after controlling for household structure à la Deaton and Paxson (1994). The smoother lifecycle consumption profiles in SSA than the in US convey the presence of powerful mechanisms that help better insure consumption over the lifecycle in rural Malawi compared to urban Malawi, and better in SSA compared to the US. Again, this result adds evidence to a relatively large ability to preserve consumption over the lifecycle in poor countries, in particular rural areas of poor countries, with respect to the US.

3.4 The Top and Bottom of the Consumption, Income, and Wealth Distributions

There is a growing interest in the behavior of the top (and bottom) of the distributions of income and wealth in particular (Piketty, 2014). For the case of poor countries, such as those in SSA, it is also interesting to study consumption given the importance of informal redistribution mechanisms that determine welfare (Kinnan, 2014). Recent macroeconomic studies on welfare in developed countries also incorporate consumption (of wealth-poor households) to the discussion of inequality (Krueger et al., 2017).[29]

[28] In De Magalhães et al. (2017) we investigate these lifecycle patterns of consumption in more detail, and associate this ability to smooth consumption to an increase in self-farm production in old age which comes at the cost of less children schooling and lower nutrient quality for households with elderly heads.

[29] It is relevant to note that the studies of income and wealth inequality typically use non-top coded data from the SCF (Díaz-Giménez et al., 2011) (that excludes the FORBES 400) or administrative data Piketty (2014). While our data is not top-coded, the LSMS-ISA sampling strategy does not oversample the rich households and might be missing the very rich of the income distribution. In this context, it is important to note that a resolution to this potential caveat (e.g., à la Alvaredo and Gasparini (2013)) would simply increase income inequality in the

The marginal distributions are consistent with the measures of inequality reported earlier. Urban areas are more unequal than rural areas, and there is less inequality in consumption than in income, and less inequality in income than in wealth (Table 5). Ranking households by consumption, the top 10% of the distribution consumes 22% of the total consumption in rural areas (panel (a1), Table 5) and 36% in urban areas (panel (b1), Table 5). The top 1% consumes 7% and 9% in rural and urban areas, respectively. In terms of income, the top 10% of the income distribution earns 43% and 62% of the total income in rural and urban areas, respectively. The top 1% of the income distribution earns 14% and 25% of total income in rural and urban areas, respectively. In terms of wealth, we find that the top 10% of the wealth distribution holds 49% of total wealth in rural Malawi and 73% in urban areas. Further, the top 1% of the wealth distribution holds 17% and 32% of total wealth in rural and urban areas, respectively.

Nationwide, the marginal distribution of income in Malawi (panel (c1), Table 5) is strikingly similar to that of the US (panel (d1), Table 5). In Malawi, the top 20% of the income distribution earn 62% of total income, while this is 61% in the US. The top 10% and 1% of the income distribution earn respectively 50% and 20% of total income in Malawi and 47% and 21% in the US (Díaz-Giménez et al., 2011). Despite similar inequality in income between Malawi and the US, wealth dispersion is higher in the US. The top 10% and top 1% of the wealth distribution in the US hold, respectively, 71% and 34% of total wealth (Díaz-Giménez et al., 2011). These shares are lower for Malawi, respectively, 58% and 25%. This wealth differential is larger when we look at the rural areas of Malawi where 85% of the population lives and where the top 10% and top 1% of the wealth distribution hold, respectively, 40% and 17% of total rural wealth, i.e., almost half of its US counterparts. This suggests a much lower transmission from income to wealth in Malawi than in the US.

An additional measure of the transmission of income inequality to wealth inequality is the ratio between the share of total income held by the top 10% of the income distribution and the share of total wealth held by the top 10% of the wealth distribution. This ratio is not ideal as it has the caveat of not necessarily using the same set of households—an issue that we resolve below by studying the conditional distributions for Malawi and the US—but has the advantage that we can compute it for a larger set of countries for which only marginal distributions are available from Piketty (2014). We show the top 1% and top 10% of the income and wealth distributions for our SSA countries and a set of rich countries in Table 6.[30]

SSA countries that we study and hence reinforce our results of a lower transmission from income to consumption and wealth in SSA (see Section 2.2).

[30] Piketty (2014) also provides top income shares for a set of emerging countries, but top wealth shares are not available for those countries which implies that we cannot compute these ratios for these countries.

Table 5: Shares of Total Consumption, Income, and Wealth by Rural and Urban Residency, Malawi (ISA 2010)

(a) Rural Malawi

(a1) Marginal Distributions:	Bottom(%)			Quintiles					Top(%)			All
	0-1	1-5	5-10	Q1	Q2	Q3	Q4	Q5	10-5	5-1	1	0-100
	Shares of Total (%)											
Consumption	0	1	2	7	11	16	23	43	10	14	6	100
Income	-0	0	1	3	8	12	20	57	11	18	15	100
Wealth	-0	0	0	2	6	11	18	63	11	21	17	100

(a2) Income Partition:	Bottom(%)			Quintiles					Top(%)			All
	0-1	1-5	5-10	Q1	Q2	Q3	Q4	Q5	10-5	5-1	1	0-100
	Shares of Total (%)											
Consumption	1	2	3	12	15	19	22	32	7	10	3	100
Wealth	0	2	2	10	12	15	21	41	10	14	4	100

(b) Urban Malawi

(b1) Marg. Dist.:	Bottom(%)			Quintiles					Top(%)			All
	0-1	1-5	5-10	Q1	Q2	Q3	Q4	Q5	10-5	5-1	1	0-100
	Shares of Total (%)											
	0	1	1	6	10	15	21	48	11	17	6	100
	0	0	0	2	5	9	15	69	12	26	19	100
	-0	0	0	0	1	4	10	85	12	26	35	100

(b2) Inc. Part.:	Bottom(%)			Quintiles					Top(%)			All
	0-1	1-5	5-10	Q1	Q2	Q3	Q4	Q5	10-5	5-1	1	0-100
	Shares of Total (%)											
	1	3	3	13	13	16	19	40	9	14	4	100
	1	1	1	5	11	9	12	62	10	29	13	100

(c) Malawi

(c1) Marginal Distributions:	Bottom(%)			Quintiles					Top(%)			All
	0-1	1-5	5-10	Q1	Q2	Q3	Q4	Q5	10-5	5-1	1	0-100
	Shares of Total (%)											
Consumption	0	1	1	6	10	15	22	47	10	16	8	100
Income	-0	0	1	3	7	11	18	61	10	20	18	100
Wealth	-0	0	0	2	5	9	15	70	11	22	25	100

(c2) Income Partition:	Bottom(%)			Quintiles					Top(%)			All
	0-1	1-5	5-10	Q1	Q2	Q3	Q4	Q5	10-5	5-1	1	0-100
	Shares of Total (%)											
Consumption	1	2	3	12	14	17	21	36	8	12	5	100
Wealth	1	1	2	9	11	14	18	48	9	15	12	100

(d) U.S.

(d1) Marg. Dist.:	Bottom(%)			Quintiles					Top(%)			All
	0-1	1-5	5-10	Q1	Q2	Q3	Q4	Q5	10-5	5-1	1	0-100
	Shares of Total (%)											
	0	1	1	5	11	16	23	45	11	12	6	100
	-0	0	1	3	5	11	18	61	10	16	21	100
	-0	-0	-0	-0	1	5	11	84	11	27	33	100

(d2) Inc. Part.:	Bottom(%)			Quintiles					Top(%)			All
	0-1	1-5	5-10	Q1	Q2	Q3	Q4	Q5	10-5	5-1	1	0-100
	Shares of Total (%)											
	0	1	2	8	13	17	24	38	9	9	4	100
	1	1	0	4	5	8	14	70	11	23	26	100

Notes: All variables are averages in current USD. The construction of the measures of household consumption, income, and wealth is discussed in Section 2, with further details in the *Online Appendix*. The numbers for the US are results directly borrowed from Díaz-Giménez et al. (2011) who use the 2007 SCF for the study of income and wealth, and whenever consumption is involved (its marginal distribution and its joint distribution with income) we show our results from the 2006 PSID data kindly provided by Krueger et al. (2017).

Table 6: Cross-Country Comparison: Top of the Income and Wealth Distributions (2010)

	Micro Data						Macro Data
	Income		Wealth		W-to-I Shares Ratio		Inc. (USD)
Countries	Top 1%	Top 10%	Top 1%	Top 10%	Top 1%	Top 10%	WDI
Sub-Saharan Africa:							
Malawi	18	46	25	56	1.4	1.2	359
Tanzania	14	49	24	70	1.7	1.4	524
Uganda	31	63	28	67	0.9	1.1	471
Average:	*22*	*55*	*26*	*66*	*1.2*	*1.2*	451
Piketty (2014):							
US	20	48	34	71	1.7	1.5	48,377
Britain	15	42	28	70	1.9	1.7	38,363
France	9	33	24	62	2.7	1.9	40,706
Sweden	7	28	20	59	2.9	2.1	52,076
Average:	*12*	*37*	*27*	*66*	*2.3*	*1.8*	44,880

Notes: The construction of the micro measures of household income and wealth for all SSA countries is discussed in Section 2, with further details in the *Online Appendix*. The figures for rich and emerging countries are retrieved from Piketty (2014). All numbers refer to 2010, except for Argentina, which refers to 2005. The macro measures of income per capita in current USD retrieved directly from the World Development Indicators (WDI)

Taking the ratio of the share of total wealth held by the top 10% of the wealth distribution to the share of the total income earned by the top 10% of the income distribution we find a ratio of 1.2 in Malawi, 1.4 in Tanzania, and 1.1 in Uganda. This implies an average ratio for our SSA countries of 1.2. Because we lack housing wealth in Tanzania (which is more equally distributed than non-housing wealth) the ratio for Tanzania is likely to be an upper bound. In any case the ratios for the top 10% of the marginal distributions of wealth and income in SSA countries are lower than those in rich countries: 1.5 in the US, 1.7 in Britain, 1.9 in France, and 2.1 in Sweden. Focusing on the comparison between Malawi and the US, there is (1.5-1)/(1.2-1)=2.5 times more transmission from income to wealth in the US than in Malawi. On average, the ratio for rich countries is 1.8 which compared to 1.2 in SSA implies that there is four times more transmission from income to wealth in rich countries than in SSA using the top 10% of the marginal distributions of income and wealth. Focusing on the top 1%, the marginal distributions imply that the transmission from income wealth in rich countries is more than six times larger in rich countries than in SSA.

The transmission from income to wealth can be important for aggregate development (Galor and Moav, 2004). If high levels of wealth inequality are a necessary part of the growth process at early stages of aggregate development, then it seems that none of the three SSA countries

that we study is ready to experience a growth takeoff yet. To see this, note that the current concentration of wealth at the top of the distribution in the SSA countries that we study is much lower than that attained by developed countries when these economies were experiencing growth takeoffs and industrialization. In 1810 Britain the top 10% and top 1% of the wealth distribution held 82% and 53%, respectively, of the total wealth; in 1810 France these figures were 80% and 46%, and in 1810 Sweden 83% and 57% (Piketty, 2014).

As noted earlier, inference from the marginal distributions is limited by the fact that households at the top of the consumption, income, and wealth distributions are not necessarily the same. To overcome this caveat we study the wealth distributions conditional on the income distribution. We find that the top 10% income-rich households hold 27% of total wealth in the rural areas of Malawi and 49% in the urban areas (panel (a2) and (b2), Table 5). In contrast, the top 10% of the income distribution holds 60% of total wealth in the US (Díaz-Giménez et al., 2011). This implies a substantial difference in the ability to accumulate wealth, given income, between Malawi and the US, particularly for rural Malawi. This differential is largest for the top 1% income-rich households, who hold 26% of total wealth in the United States, but merely 4% of total wealth in rural Malawi and 11% in urban Malawi, which implies a nationwide average of 5% for Malawi. The top income-richest 1% households in Malawi hold a share of total wealth that is one-fifth of its US counterpart. This implies that the transmission from income to wealth is five times larger in the US than in Malawi, a number that is twice the one obtained using the ratio of top 10% shares of income and wealth from the marginal distributions.

Regarding the joint distribution of consumption and income. The top 10% income-rich households account for 21% of total consumption in rural Malawi (panel (a2), Table 5), while the top 10% income-rich households account for 30% of total consumption in urban Malawi (panel (b2), Table 5). Similar insights arise if we focus on the top 1% of the income distribution which account for 3% of total consumption in rural areas and 6% of total consumption in urban areas. That is, again, using the top shares of the income distribution, we find evidence of less transmission from income to consumption in rural Malawi than in urban Malawi.

Finally, an important aspect of the distribution of welfare in rich countries is that while the wealth-poor households barely contribute to aggregate savings, they hold a large share of total consumption (Krueger et al., 2017). We find that this is also the case in SSA countries. In SSA, the distribution of consumption conditional on wealth is even less dispersed than in the US (panel (a), Table 7). The top (bottom) 20% of the wealth distribution consume 35% (15%) of total consumption in Malawi and 37% (11%) in the US. Focusing on the bottom 40% of the wealth distribution, who barely hold any wealth in Malawi and the US (Table 5), we find that they consume 29% of total consumption in urban Malawi, a similar share than the 23% obtained

Table 7: Consumption by Wealth and Land Partitions, Malawi (ISA 2010)

	Bottom(%)			Quintiles					Top(%)			All
	0-1	1-5	5-10	Q1	Q2	Q3	Q4	Q5	10-5	5-1	1	0-100
(a) Cons. by Wealth Partition:				Shares of Total (%)								
Malawi: ▷ Rural	1	3	4	15	15	18	21	31	8	10	2	100
▷ Urban	1	2	2	11	15	17	19	38	9	12	4	100
▷ Nationwide	1	3	4	15	14	16	20	34	8	11	4	100
US	1	3	3	11	12	17	22	37	9	8	3	100
(b) Cons. by Land Partition (Rural):				Shares of Total (%)								
Unconditional	16	-	-	21	16	17	20	26	6	8	2	100
If Land>0	1	3	4	17	16	19	22	27	6	8	2	100

Notes: All variables are averages in current USD. The construction of the measures of household consumption, income, and wealth is discussed in Section 2, with further details in the *Online Appendix*. The results for the US quintiles are directly borrowed from Krueger et al. (2017) using 2006 PSID data, and we added our results for the top and bottom 10% of the wealth distribution using their data.

for the US. In rural Malawi, the wealth-poor (the bottom 40%) consume an even larger share of consumption, 31%. Indeed, we find a strikingly uniform distribution of consumption conditional on land, the main asset in rural areas (panel (b), Table 7), with the bottom 40% of the land distribution accounting for 36% of total consumption. This is true whether we condition on positive land assets or not. This suggests that the ex-ante distribution of nonmarketed land is likely to be used to partly mitigate consumption inequality.

4 Further Insights

First, using panel data, we study whether the current patterns of income mobility can help explain the inability to accumulate wealth in SSA, in particular in rural areas. Second, we use the consumption and income panel data to conduct consumption insurance tests in rural and urban areas. Third, we provide direct empirical evidence of informal ex-post redistribution mechanisms that are stronger in rural areas than in urban areas through food gifts and self-reported copying strategies. We also discuss the ex-ante redistribution of land as consumption insurance mechanism. Fourth, we show the availability of more formal borrowing in urban areas than in rural areas. Formal borrowing is largely devoted to productive activities (e.g., start a business) rather than for consumption insurance purposes.

4.1 Insights from Income Mobility

We have seen that the top 10% income earners hold 39% of total wealth in rural Malawi and 59% in urban Malawi, which yields a nationwide average for Malawi of 49%. This figure is much larger, 70%, in the US (Díaz-Giménez et al., 2011). The savings rate for the top 10% of income earners, computed as one minus the expenditure rate of disposable income, is 30% in rural Malawi and 35% in urban Malawi, which is similar to the saving rate for the top 20% of income earners in the US, 37.5% (Krueger et al., 2017). In this context, why are the top income earners in SSA not able to accumulate wealth despite high saving rates? Note that wealth accumulation is the result of past saving behavior and, hence, at saving rates similar to those of the US, the top income earners in SSA will accumulate sizable wealth only if they remain at the top for a period of time comparable with their US counterparts. This implies that the study of income mobility can help, at least partially, reconcile these two facts—high saving rates but relatively low wealth accumulation for the top income earners in SSA.

We compare SSA income mobility to the US in Table 8. The SSA sample pools the panel data from three countries: ISA data for Malawi 2010-13, Tanzania 2008-10, and Uganda 2009-11 (see the *Online Appendix* C for a country-by-country analysis). Before pooling the data we divide each country-year sample by its sample mean. This implies a total sample of 6,640 households for SSA. The bottom panels (b) refer to the US. The US sample is the 2004-06 PSID with a size of 5,649 households. There are several findings to note. First, there is substantially more persistence at the top of the income distribution in the US than in SSA with 76.17% of households in the top quintile remaining in that quintile after 2 years in the US and 52.41% in SSA. That is, the chances of remaining at the top quintile of the income distribution after two years are roughly 50% higher in the US than in SSA. There is also larger downward mobility in SSA than in the US with 4.52% of households in the top quintile moving to the bottom quintile in SSA, and barely 0.62% in the US. That is, the chances of moving from the top to the bottom quintile of the income distribution are roughly 6 times larger in SSA than in the US. Second, there is substantially more persistence in the bottom of the income distribution in US than in SSA as 73.19% of households in the bottom quintile remain in that quintile after two years in US while this figure is 41.87% in SSA. That is, the chances of remaining at the bottom of the income distribution after two years are roughly 75% higher in the US than in SSA. There is also larger upward mobility in SSA than in the US with 5.27% of households in the bottom quintile moving to the top quintile in SSA, and barely 0.18% in the US. That is, the chances of moving from the top to the bottom quintile of the income distribution are almost 30 times larger in SSA than in the US.[31] Focusing on the diagonal elements of the transition matrix SSA and the US both show

[31] The mobility of top and bottom 1% and 10% show similar relative movements.

Table 8: Income Mobility Matrices: Sub-Saharan Africa vs. the US

(a) Sub-Saharan Africa

	Bottom		Quintiles					Top	
t \ t+1	0-1	0-10	Q1	Q2	Q3	Q4	Q5	90-100	99-100
0-1	2.99	29.85	34.33	20.90	17.91	14.93	11.94	2.99	0.00
0-10	1.36	26.05	46.39	24.25	13.10	10.69	5.57	2.11	0.15
Q1	1.43	23.95	41.87	26.51	15.81	10.54	5.27	2.03	0.23
Q2	1.13	11.60	25.98	27.71	23.64	15.89	6.78	2.11	0.15
Q3	1.13	8.28	17.7	21.31	26.51	23.12	11.37	4.22	0.23
Q4	0.90	3.99	9.94	16.64	21.54	27.71	24.17	10.02	0.30
Q5	0.45	2.18	4.52	7.83	12.5	22.74	52.41	31.63	4.07
90-100	0.30	1.81	3.16	5.42	9.49	18.83	63.10	45.18	7.23
99-100	0.00	4.55	4.55	3.03	13.64	12.12	66.67	60.61	25.76

(b) U.S.

	Bottom		Quintiles					Top	
t \ t+1	0-1	0-10	Q1	Q2	Q3	Q4	Q5	90-100	99-100
0-1	22.81	75.44	87.72	7.02	1.75	0.00	3.51	3.51	0.00
0-10	6.90	61.24	82.83	12.39	3.89	0.53	0.35	0.35	0.00
Q1	3.81	41.59	73.19	20.53	4.78	1.33	0.18	0.18	0.00
Q2	0.88	6.02	20.35	53.27	20.18	5.13	1.06	0.53	0.00
Q3	0.18	1.68	4.07	20.27	52.57	18.85	4.25	1.50	0.18
Q4	0.00	0.35	1.77	3.89	18.58	57.43	18.32	4.16	0.09
Q5	0.18	0.35	0.62	2.04	3.90	17.27	76.17	43.58	4.69
90-100	0.18	0.35	0.89	1.95	2.30	7.45	87.41	69.86	8.69
99-100	1.79	1.79	1.79	0.00	3.36	3.57	89.29	83.93	51.79

Notes: The top panel (a) refers to SSA. The SSA sample pools panel data from three countries: the ISA data for Malawi 2010-13, Tanzania 2008-10, and Uganda 2009-11. Before pooling the data we divide each country-year sample by its sample mean. This implies a total sample of 6,640 households for SSA. The bottom panel (b) refer to the US. The US sample is the 2004-06 PSID with a size of 5,649 households.

an inverted-U shaped pattern. There is an asymmetry: the top 20% are more persistent than the bottom 20% in both SSA and the US. That is, there is more upward mobility than downward mobility in both economies, althouhg more prominently in SSA than in the US.

The large sample size allows us to also explore the mobility of the top and bottom 10% and 1% of the distribution in both SSA and the US. In SSA, 25.76% of households at the top 1% of the income distribution remain at the top 1% after two years, while this figure is more persistent, 51.79%, in the US. Chances of moving from the top 1% to the bottom quintile are also larger in SSA (4.55%) than in the US (1.79%), suggesting again larger downward mobility in SSA than in the US. The top 10% of the income distribution shows similar insights, higher persistence in the US and larger downward mobility in SSA. Focusing on the bottom of the distribution, 2.99%

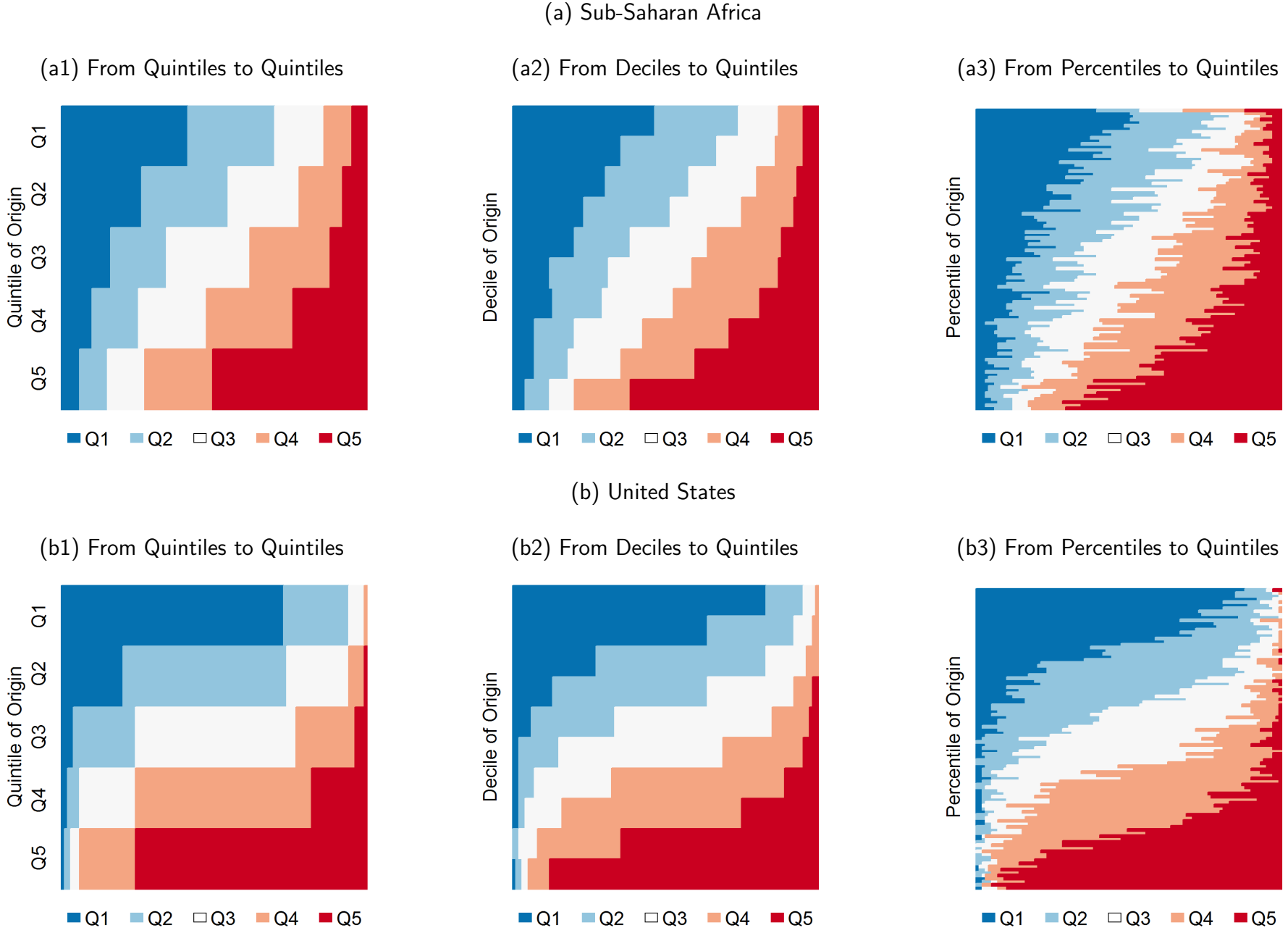
of households at the bottom 1% of the income distribution remain at the bottom 1% after two years, while this figure is much more persistent, 22.81%, in the US. Chances of moving from the bottom 1% to the top quintile are also larger in SSA (11.94%) than in the US (3.51%), suggesting again a larger upward mobility in SSA than in the US. The top 10% of the income distribution also shows higher persistence in the US and larger downward mobility in SSA.

An isomorphic representation of the income mobility matrix is in the conditional transition probabilities depicted Figure 4. The vertical axis refers to the quintile of origin in the transition and the horizontal axis shows the conditional transition probability to a destination quintile identified with the colors labeled at the bottom of each figure. The left panels show the transition probabilities using the quintiles of the income distribution as origin, the center panels use the income deciles as origin, and the right panels use the income percentiles as origin. The top panels refer to SSA and the bottom panels to the US. In all cases there is clearly more income persistence in the US than in SSA across the entire income distribution. For example, the chances of being in the bottom quintile of the income distribution after two years (blue color in all panels) are more skewed to the top of the original distribution of income in SSA than in the US. That is, there is a nontrivial chance of ending up in the bottom quintile from the entire origin distribution of income in SSA (roughly 5% from the top decile, 10% from the median of the distribution, 40% from the bottom decile, and 45% from the bottom 5%), while these transitional probabilities are much smaller for the US from the top of the original distribution of income (less than 0.5% from the top decile, less than 1% from the median of the distribution) and much larger from the bottom of the original distribution of income (85% from the bottom decile, and 90% from the bottom 5%). The opposite occurs for the chances of being at the top quintile of the income distribution after two years (red color in all panels) as the conditional probability is more skewed to the bottom of the original distribution of income in SSA than in the US.

Finally, there are important income mobility differences in rural and urban areas. We find a higher persistence of income in urban areas than in rural areas along the entire income distribution for Malawi, (see the *Online Appendix* C). This is evident from the diagonal elements in the mobility matrix that accumulate larger mass in urban areas than in rural areas, except for the bottom quintile of the distribution. Focusing on the bottom (i.e., first) quintile of the distribution, we find similar levels of persistence in rural and urban areas, 33.88% and 34.58% respectively. However, conditional on leaving the bottom quintile of the distribution there is larger upward mobility in rural areas than in urban areas as 8.84% of those who leave the bottom quintile in rural areas move to the top quintile, while this figure is almost half 4.72% in urban areas.[32]

[32] In the *Online Appendix* C, we show analogous income mobility matrices for Tanzania and Uganda. We also show an alternative measure of mobility based on the predicted future income ranking of households given the current income ranking. We find similar insights as those from mobility matrices and transition probability plots.

Figure 4: Income Transition Probability Plots: Sub-Saharan Africa vs. the US



Notes: The top panels (a) refer to SSA. The SSA sample pools the panel data from three countries: ISA data for Malawi 2010-13, Tanzania 2008-10, and Uganda 2009-11. Before pooling the data we divide each country-year sample by its sample mean. This implies a total sample of 6,640 households for SSA. The bottom panels (b) refer to the US. The US sample is the 2004-06 PSID with a size of 5,649 households. The vertical axis refers to the quintile of origin in panels (a1) and (b1), the decile of origin in panels (a2) and (b2), and the percentile of origin in panels (a3) and (b3). In all panels the horizontal axis shows the conditional transition probability to each destination quintile identified with the colors labeled at the bottom of each figure.

4.2 Complete Markets Tests

Panel data on consumption and income allows for the computation of insurance tests à la Townsend. In particular, we can test the idea that there is more consumption insurance in rural areas than in urban areas. Therefore supporting the cross-sectional evidence in Section 3. To this end, we conduct complete markets tests, as proposed in Townsend (1994), using the following econometric specification: $\Delta lnc_{it} = \beta \Delta lny_{it} + \Theta x_{it} + \varepsilon_{it}$, where consumption growth is the log difference $\Delta lnc_{it} = lnc_{it+1} - lnc_{it}$, income growth is $\Delta lny_{it} = lny_{it+1} - lnc_{it}$, and x_{it} includes a wide range of household controls such as age, dummies for education, regions, sex, marital status, and household size. The idea is that if the Townsend-β is significantly different from zero, we reject the hypothesis of complete markets, and accept it otherwise. Our results are in Table 9.

First, we use growth in total nondurable consumption as the endogenous variable for urban and rural areas respectively in Columns (1) and (2). In both cases, urban areas and rural areas significantly violate complete markets. This feature is more salient in urban areas than in rural areas as 12.3% of income growth translates into consumption growth in urban areas and 9.8% in rural areas. Quantitatively, it is not clear what it means that one Townsend-β is larger than the other, besides suggesting that rural areas are closer to complete markets (hence, full insurance) than urban areas. Second, our measure of household nondurable consumption can mask the presence of insurance as it includes variation in prices as well as non-food items that are perhaps harder to measure correctly. To help overcome this difficulty the last four columns (3)-(6) use growth in caloric intake as the endogenous variable. In this case 5.1% of income growth significantly transmits to caloric intake growth in urban areas when we use the full sample of households, Column (3). In sharp contrast, we cannot reject complete markets in rural areas with a nonsignificant transmission of 0.5% from income to caloric intake, Column (4). Rural households seem to be able to perfectly insure caloric intake against idiosyncratic income risk. This result is even starker if we focus on the most vulnerable households defined as those where income growth is less than median growth. In this case 10.5% of income growth significantly transmits to caloric intake growth in urban areas (Column (5)), while again we cannot reject complete markets in rural areas.

Our results add value to the notion that there is more consumption insurance in rural areas than in urban areas in poor countries, which is not new in other settings. For example, this is consistent with the idea that migrating the city implies a loss of insurance due to higher unemployment risk as in Harris and Todaro (1970) or the loss of casts networks as in Munshi and Rosenzweig (2016). Recently, Santaeulàlia-Llopis and Zheng (2018) also find higher levels

Table 9: Complete Markets Tests: Insurance in Rural and Urban Areas, Malawi ISA 2010-13

	Nondurables		Calories		Calories ($< p_{50}$)	
	Urban	Rural	Urban	Rural	Urban	Rural
Consumption Growth:	(1)	(2)	(3)	(4)	(5)	(6)
Income Growth (β)	0.123***	0.098***	0.051***	0.005	0.105***	-0.020
Household Controls	✓	✓	✓	✓	✓	✓
Observations	515	1,767	550	1,808	270	885

Notes: Columns (1) and (2) use growth in total nondurable consumption as endogenous variable separately for urban and rural areas, respectively. The last four columns (3)-(6) use growth in caloric intake as endogenous variable where columns (3) and (4) use the full sample, and columns (5) and (6) use only the sample of households where income growth is less than its median growth. Our econometric specification is $\Delta lnc_{it} = \beta \Delta lny_{it} + \Theta x_{it} + \varepsilon_{it}$, where consumption growth is the log difference $\Delta lnc_{it} = lnc_{it+1} - lnc_{it}$ and income growth is $\Delta lny_{it} = lny_{it+1} - lnc_{it}$. The household controls include age, dummies for education, regions, sex, marital status, and household size. We denote significance at 1% level with ***, 5% with **, and 10% with *.

of consumption insurance in rural areas than in urban areas in growing China. To the best of our knowledge, our results are the first showing empirical evidence of higher consumption insurance in rural areas than in urban areas in SSA countries. In particular, we cannot reject the presence of complete markets in rural areas when we define consumption in terms of caloric intake.

4.3 Informal Redistribution Mechanisms

We study two types of informal redistribution mechanisms, ex-post and ex-ante. First, we study self-reported copying strategies (mutual insurance versus self-insurance) in response of adverse income shocks. Second, we study the distribution of land in rural areas which is achieved through non-market channel and can be interpreted as an ex-ante redistribution mechanism.

4.3.1 Ex-Post Redistribution: Self-Reported Insurance

During the 12 months of the Malawi survey, in rural areas, 43% of households have suffered an aggregate shock, 6% an idiosyncratic shock, and 22% both types of shocks, leaving 29% of the population without shocks. The most common aggregate shock in rural areas is rain, 43% of households report a rain shock (too little or too much), followed by agricultural costs (33%) and food prices (26%).[33] In urban areas, 15% of households have suffered an aggregate shock, 13% an idiosyncratic shock, and 11% both types of shocks in the past 12 months, leaving 61% of

[33]Here we define rain as a type of aggregate shock, but we acknowledge there is rainfall dispersion across households. If we redefine rain as an idiosyncratic shock, then we find that in rural areas 14% of households have suffered only an aggregate shock, 25% only an idiosyncratic shock, and 31% both types of shocks in the past 12 months. The planting of maize needs to be timely. Rains that come too early or too late are as problematic as droughts and floods. Our measure of shock includes all these possibilities.

the population without shocks (basically twice as much as in rural areas). The most common aggregate shock in urban areas is unexpected high food prices, reported by 18% of households, which highlights the tight link between rural and urban areas. In both rural and urban areas, health shocks are the most important idiosyncratic shocks, followed by death and theft.

We group insurance mechanisms into "no insurance", "self-insurance", and "mutual insurance".[34] We focus on what households declared as their main coping strategy. The items "no insurance", "mutual insurance", and "self-insurance" do not sum to 100%; instead, they sum up to the percentage of households that reported having a shock. Precisely, in rural areas, where 71% of households reported suffering a shock: 35% of total rural households reported using no insurance to deal with that shock, 28% reported some form of self-insurance, and 7% reported some form of mutual insurance. In urban areas, where 39% of households reported suffering a shock: 22% of total urban households report using no insurance, 15% reported some form of self-insurance, and 2% reported some form of mutual insurance. That is, in rural areas, 35/71=49% of households report not using an insurance mechanism conditional on having reported a shock, while this figure is slightly higher (22/39=56%) in urban areas. This is suggestive, again, of a worse ability to provide insurance in urban areas than in rural areas.[35]

4.3.2 Ex-Ante Redistribution: Acquired vs. Inherited Land

The somewhat uniform distribution of consumption conditional on land in rural areas (Section 4.1) suggests that the distribution of land helps reduce consumption inequality. If the wealth-rich are land-rich, then limitations to accumulate wealth at the top of the distribution (Section 3.4) are potentially mirrored by limitations to accumulate land. For example, the ability to accumulate wealth can be limited by access to land markets. Thus, it is important to distinguish between land that is acquired through the market, and land that is distributed outside the market, i.e., through inheritance or other mechanisms.[36]

The share of the rural population that owns land is 87%. This number increases with wealth from 60% for the bottom quintile of the wealth distribution to 95% for the top quintile. That

[34] Self insurance includes savings, dietary restrictions, market labor, own labor (working in the family-owned farm), credit and selling of assets. Mutual insurance is almost exclusively family/friends help within the village; the percentage of households that report receiving mutual insurance from children living elsewhere or from government and nongovernmental organizations (NGOs) is negligible in both rural and urban areas.

[35] Across the CIW distributions we find that households that self-report "mutual insurance" as a coping strategy tend to be at the bottom of the income distribution, while those that report "self-insurance" populate the top of the income distribution. This is consistent with our results on the larger ability to accumulate wealth in the top of the income distribution than in the rest of the economy, see our the longer version of this paper (De Magalhães and Santaeulàlia-Llopis, 2015).

[36] Restuccia and Santaeulàlia-Llopis (2017) find that land markets are related to the degree of misallocation. If determined by markets, the allocation of land is several times more efficient than otherwise.

is, the wealth-rich are indeed land-rich. Conditional on owning land, we find that the share of land value that has been inherited represents 81% of the total value of land holdings. This figure is similar to the proportion of inherited wealth in the total wealth for France in the nineteenth century (Piketty, 2014). This proportion barely declines as we move from the bottom quintile of the wealth distribution, 84%, to the top 1%, 75%. The low amount of marketed land at the top of the wealth distribution suggests that merit plays little role on the accumulation of land (and wealth) in SSA. Similar insights arise if we focus on a broader measure of nonmarketed land that includes inherited land, land granted by the chief, and land acquired as bride price. The proportion of nonmarketed land represents 97% of the total value of land (i.e., only 3% of land is bought or rented in the market). This proportion barely changes with wealth, from 98% in the bottom quintile of the wealth distribution to 95% at the top 1% of the wealth distribution. This is a key mechanism that prevents households to accumulate wealth in SSA: the main source of household wealth, land, is simply not for sale.[37]

4.4 Formal Borrowing, Need and Self-Selection

An alternative mechanism to insure consumption is formal borrowing (e.g loans). However, this argument strictly depends on whether households use loans to insure consumption. In contrast, if loans are used to finance risky investments/growth (e.g., start a business), then the effects of formal borrowing on consumption insurance are less obvious. In ISA, households are first asked whether they have applied or not applied for a loan in the past year. Second, whether they succeeded in receiving the loan and the amount borrowed. Third, whether or not a loan was needed. This allows us to construct direct measures of how many household are credit constraint (households that were turned down after applying for a loan) controlling for self-selection (households that did not apply for a loan, even when needing one, because they thought they would not get it).

Only a small proportion of total households report receiving a loan: 13% in rural areas and 20% in urban areas. Nevertheless, a large part of the population is in need of loans, in particular in rural areas. A slightly higher percentage of households report needing a loan in rural areas, 75%, than in urban areas, 67%. The main reasons for not applying for a loan when needing one are "not knowing any possible lender" and "having no collateral". The application rate conditional on needing a loan is 26% in rural areas and 40% in urban areas. Accordingly, the success rate

[37] For Tanzania and Uganda this also appears to be the case. In Tanzania there is a question on whether the household holds any documentation of ownership for their dwelling (not specifically land): 75% have no document, 25% do but these include inherited property, traditional occupancy, and allocation by village chief as well as property bought in the market. In Uganda the government encouraged the formalization of ownership, but this is not widespread as discussed in McAuslan (2003).

conditional on needing a loan are 17% in rural areas and 30% in urban areas. This way, the ability to borrow, proxied with success rates conditional on need, is roughly twice larger in urban areas than in rural areas.[38] The larger ability of urban households to borrow does not necessarily imply more consumption insurance in urban areas than in rural areas. To link credit to consumption insurance we must look into the reasons for borrowing. In the ISA survey there are 3.6 times more loans acquired for start-up capital than for consumption in urban areas. This ratio is much less, 1.6, in rural areas. This suggests that households formal borrowing is mostly used to target production activities rather than for consumption insurance, and this feature is more salient in urban areas than in rural areas.

5 Conclusion

From a macroeconomic perspective, the inequality and joint behavior of consumption, income, and wealth in the very poor countries that we study can be summarized by two findings: (i) a low transmission from income to wealth and (ii) a low transmission from income to consumption. These findings are stronger in the rural areas than in the urban areas of SSA. First, we relate the low transmission from income to wealth to a large inability to save and accumulate wealth in rural SSA compared with urban SSA, and in SSA compared with other world regions. Second, the low transmission from income to consumption suggests that despite being unable to persistently save—and hence, self-insure—SSA households are able to insure their consumption relatively well. Such a phenomenon requires the presence of powerful insurance arrangements, particularly in rural areas. The coexistence of these two findings (i)-(ii) reveals a negative relationship—and potentially a trade-off—between accumulation and insurance for SSA. In particular, it raises the question of whether the process of accumulation and growth potentially requires the disruption of consumption insurance for SSA.

A natural next step is to understand the causes and implications of this negative relationship between accumulation and consumption insurance along the growth path. In particular, a careful quantitative assessment could benefit from incorporating the dynamics of consumption, income, and wealth inequality that we document in macroeconomic models of poor countries. To this end, we hope that our empirical study is informative to discipline heterogeneous agent versions of

[38] We can compare these figures to the US. The SCF in the US asks two similar questions: First, households are asked if they are denied credit, and, second, they are asked if they did not apply for a loan for fear of being turned down (Bricker et al., 2014). The fraction of households that say "yes" to one or both of these questions is 27% percent in 2013 in the US while this figure is 63% in rural Malawi and 47% in urban Malawi. This indicates that there are roughly twice as many households credit constraint in Malawi as in the US. The composition is also very different. In the US there are 19% of households that report not applying for fear of being turned down, while this is 56% in rural Malawi and 40% in urban Malawi. Moreover, 16% of households in the US report being turned down for a loan, while this figure is 7% in both rural and urban Malawi.

macroeconomic models of growth and development (Galor and Weil, 1999; Hansen and Prescott, 2002; Gollin et al., 2002; Herrendorf et al., 2014).

This task faces some important challenges. First, in contrast to standard macroeconomic models with heterogeneous agents that focus on explaining the observed high concentration of wealth in rich countries (Castaneda et al., 2003; deNardi, 2004; Quadrini, 2000),[39] our study documents much lower wealth concentration for SSA, in particular, in its rural areas. Mechanisms that prevent accumulation (e.g., no land markets) can help explain this lower concentration. Second, the degree of consumption insurance provided in poor countries, in particular in rural areas, is larger than what is typically achieved in standard incomplete markets models with self-insurance (Carroll, 1997; Kaplan and Violante, 2010). For example, using caloric intake to proxy consumption we cannot reject the complete markets hypothesis in rural areas, while this is clearly rejected in urban areas. In addition, our evidence suggests that self-insurance (i.e., own savings) is not a major force at play. A natural alternative model would incorporate endogenously incomplete markets. Such models are typically used to assess mutual insurance in economically poor settings. However, these models fall short in replicating the consumption and income (hence wealth) distributions of village economies (Ligon et al., 2002). In this context, it is important to note that matching these distributions, in particular that of wealth, is crucial to provide valid macroeconomic inference on variables such as aggregate savings (Krusell and Smith, 1998) as well as assess macroeconomic social insurance policy (Conesa et al., 2009). Third, the study of heterogeneous-agent economies with idiosyncratic income shocks along the transition path is always computationally challenging (Buera and Shin, 2011). To this computational difficulty, we need to add the fact that the degree of market incompleteness is likely to change over the aggregate stage of development as growing economies become less rural and more urban.[40]

Appendix

A Seasonal Adjustments

The vast majority of African countries, including Malawi, have strong seasonal variations in income and consumption due to the fact that household consumption relies heavily on agricultural production. If data are not collected with an annual reference period (i.e., one year recall), seasonality biases potentially arise that jeopardize both representativeness and the study of inequality. This is usually the case of consumption because data on consumption items are collected with recalls of the past 3 months, past month, or even past week. One virtue of our Malawi LSMS-ISA data, with respect of previous LSMS data sets, is that data have been collected evenly across 12 rolled-over months during the years 2004-2005

[39] The high concentration of wealth is a puzzle for the typical Aiyagari-Bewley-Hugget-Imrohoruglu economies as these models imply lower shares of total wealth at the top of the distribution than what is observed in the data.

[40] Along these lines, and focusing on a one-sector model transition for the US, Krueger and Perri (2006) propose a model in which consumption insurance improves with aggregate output.

and 2010-2011. This helps keeping track of seasonal changes in consumption patterns. This way, the household survey average annualized consumption (i.e., the sum of monthly average consumption over the whole year) is not subject to aggregation biases due to seasonal variation and is directly comparable to aggregate annual consumption in national accounts. In contrast, inequality measures will still be subject to seasonal bias if these measures are not stationary over the year. For example, it is natural to think that household food consumption (that largely depends on agricultural production) differs largely between the pre- and post-harvesting periods. This seasonal difference creates artificial inequality across households simply generated by the fact the households are surveyed at a different month within a year. Indeed, we find that households asked in the lean period (November-February) consume (on average) about 2,626 (MKW) per week, while in the harvest season period average household consumption is 3,291 (MKW) per week. Given our focus on inequality, to deal with artificial seasonal biases we deseasonalize consumption items using a simple model that regresses period-average log-consumption on seasonal (months) dummies:

$$\overline{\log c}_{z,s,t} = \sum_{s} \gamma_s \mathbf{1}_s + \overline{v}_{z,s,t}, \tag{2}$$

where $\overline{\log c}_{z,s,t} = \frac{1}{N}\sum_{z}^{N} \log c_{z,s,t}$ is the average consumption across households in year t, and γ_s predicts the effect of seasonal dummies on (logged) average consumption. Precisely, this dummy captures the growth rate change in average consumption.[41] Here note that to identify γ_s we need observations for s in at least two calendar years. For Malawi, we use LSMS-ISA 2004-2005 and 2010-201. Then, annual household consumption for a household z that was interviewed in season s is constructed as

$$\widetilde{\log c}_{z,s,t} = \overline{v}_{z,s,t} * 12.$$

If the reference seasonal period for a given type of consumption is a quarter, we multiply by 4.

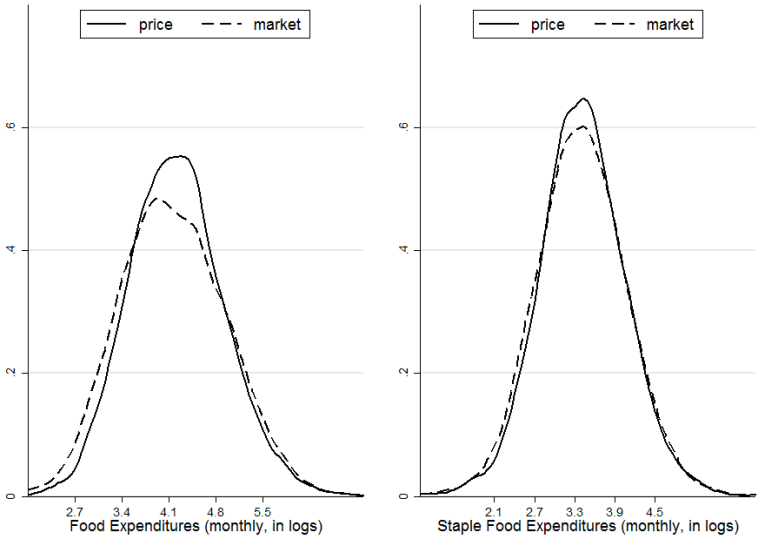
B Units Conversion of In-Kind Items: From Pails to Kilograms using Prices

In household surveys from poor countries it is standard to report amounts of consumption and agricultural production in units that are not standard nor harmonized across time nor space. For example, in the Malawi ISA, households are asked to report the amount they consume of a given item in any unit they wish (e.g. bags, dishes, bunches, pails, or kilograms). It is then necessary to deal with the measurement issue of converting all these reported units into a baseline unit, say kilograms. This is particularly important for poor countries, where 'self-farmed' and 'gift' consumption represent about half (or more) of the total value of food consumption. Once all items are converted to a baseline unit we can use prices to estimate their monetary value.[42] In our paper we have constructed a price-unit conversation rate to put all reported units into a baseline unit. In this section we compare our new price-unit conversion methodology with the standard physical-unit conversion methodology implemented by the World Bank. The World Bank physically measured conversation rates with an additional market survey in which field workers visited market-places across Malawi and physically measured the item specific unit-conversion rates. In contrast, our methodology to construct price-unit conversion rates does not require the collection of additional surveys.

[41] Attanasio and Weber (1993) offer an extensive discussion on why using the mean of the logs is preferable to using the log of the mean. The second alternative suffers from an aggregation bias while the first does not.

[42] For Tanzania unit-conversion rates are not necessary as in Tanzania all quantities are reported in kg.

Figure 5: Food expenditure: Price vs. Market conversion



Note: Density of estimated food expenditure using prices to convert units and using market weight measures.

We generate household-specific conversion rates using the information on prices by different households that bought the same item but reported purchased quantities in different units. We merge all household-specific conversion from for 2004/05 and 2010/11. We pick the median conversion rate (if there are at least 7) for each item-unit pair by subgroups of households. The subgroups are rural-north, urban-north, rural-centre, urban-centre, rural-south, and urban-south. For a minority of rare items, the subgroups are rural and urban. This is so in order to achieve at least 7 household-specific conversion rates. With the resulting conversion rates, items are first converted into the modal unit, and then into kg. The new price unit-conversion method that we suggest retrieves more item-unit pairs and allows for more food items to be converted in to kg and added up to total consumption. Using our price conversion rates we are able to retrieve 9,855 households with positive values of 'own' consumption, while the number using the market-place physical conversion rates is 9,398. Similarly, the price conversion retrieves 7,674 households with positive values for 'gift' consumption, while the number using the market-place physical conversion rates is 6,082.

To make the comparison between the physical-unit conversion rates and our price-unit conversion rates clear, we present the raw monthly value of consumption converted into dollars for the 2010 survey only.[43] In Figure 5 the solid line is the estimated food expenditure in logs when the price unit-conversion rates are used; and the dotted line is the estimated food expenditure when the market-place physical unit-conversion rates are used. In the right figure we plot the density of *staple* food expenditures only (all maize, rice, cassavas, potatoes, banana, beans, and groundnut). For these staple items the density generated by the price and market-place conversion units are virtually identical, except that the price conversion in able to retrieve information for a few more households. In the left figure, we can see that the density generated with the market-place rates has a slight leftward shift in relation to the density generated with the price conversion rates. Again this is due to the price conversion being able to pick up more item-unit specific conversion rates. There is little effect regarding inequality

[43]The food consumption values in this sub-section are not annualized, deseasonalized, or trimmed.

measures as the distributions are very similar. Respectively for price and market-place unit conversion: the average monthly consumption in US$ is 84.7 and 84.6, and the median is 62.8 and 58.7. Overall the densities are very similar, but it must be noted that the use of the market-place unit-conversion rates may underestimating consumption slightly.

C Measuring Unsold Agricultural Production

In agricultural economies such as the ones we study, assigning a monetary value to unsold agricultural production is essential to the measurement of household income. Unsold production represents the majority of total household production. We use maize in Malawi to illustrate this issue. First, we convert maize production into the same unit to find that maize represents 69% of the total agricultural production in kilograms. Most households produce maize as their main source of food and calorie intake, but few sell it. Of the 9,280 households in the Malawi survey who report producing maize, only 1,618 (17%) report selling any maize and this proportion grows with income. Among the top 20% of the income distribution in rural areas, 30% of households report selling maize; among the bottom 20%, only 6% sell maize. It is noteworthy that even the rich keep their own production for consumption. Also, sales among the poor may indicate desperation rather than a good business strategy (Manda, 2010).

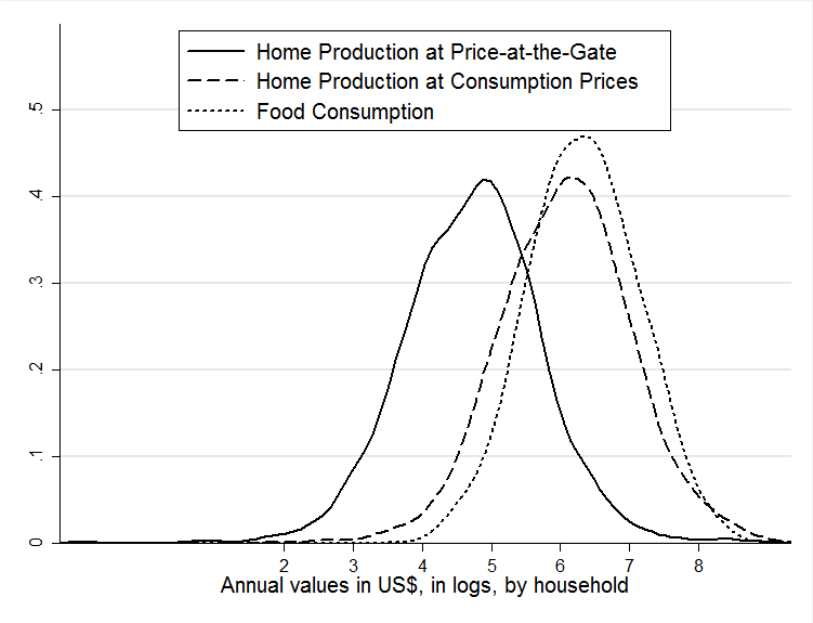
We need to assign prices to unsold production. The price at the gate is normally used for this purpose (Deaton and Zaidi, 2002). For valuing maize, this implies using the price of shelled maize reported by households mostly in the immediate post-harvest season. There are two reasons this price underestimates the value of unsold production. The shelled maize is a different good than what farmers produce, as farmers use the cobs, husks, and stems for other intermediate purposes such as fuel, animal feed, and as cover to protect soil from erosion. Such uses have an important monetary value in subsistence households. Further, maize prices are lowest immediately after harvest (Kaminski et al., 2014), whereas consumption takes place throughout the year. While the storage facilities are limited (only 9% of households have a dedicated storage structure; most crops are stored in the house or in open drums or sacks) almost all households report storing some maize for their own use later. This suggests that storage adds value to maize when prices are high, and this option value is not captured by the relatively low post-harvest price at the gate. For this reason, we use consumption prices to value unsold agriculture production and the price-at-the gate to value sold production.

The underestimation of the value of production by the use of the price at the gate can be illustrated by focusing on rural households that sell neither maize nor tobacco, tobacco being the main cash crop. These are the households closest to an autarkic model, in which the maize they consume is what they have produced. In this sample, the mean estimated quantity of maize produced is 124 kg and the mean estimated quantity of maize consumed is 130 kg.[44] Since the quantities of production and consumption are similar, it becomes clear that assigning prices at the gate to production and consumption prices to consumption can create an artificial wedge between their monetary values if these two prices differ. Indeed, the price of shelled maize at the gate for these households is approximately US$0.16 per kg, and the consumption price of green maize on the cob is approximately US$0.36 per kg. If we use the price at the gate, the average estimated production value is US$22, which is less than half of the average consumption value, US$47. That is, the price at the gate underestimates the value of unsold production.

In Figure 6 we compare the distribution of the monetary value in dollars of household total food consumption in logs (dotted line) with the value of household agricultural production valued with consumption prices (dashed line) and valued with the price at the gate (solid line). Since we are focusing

[44] For the entire sample of rural households these numbers are, respectively, 129 kg and 137 kg.

Figure 6: Agricultural Production: Consumption Prices vs. Prices at the Gate



Note: The sample includes 4,385 households that sell neither maize nor tobacco and report producing a positive value of maize and consuming a positive value of home-produced maize. These households represent 36% of the entire sample and 45% of all rural households.

on households that sell neither tobacco nor maize and these are rural households close to subsistence, one would expect the distribution of agricultural production and food to overlap. This is actually the case in raw quantities and, hence, also the case if we value home production with consumption prices. However, if we value production with prices at the gate, the total value of food production is estimated to be considerably lower than food consumption. Even if we value production with consumption prices, the distribution of the value of food production is slightly shifted left in relation to consumption. This is to be expected as these households may have other sources of income, albeit small, such as informal labor or received food gifts. In light of our results, it is our view that the shadow price of unsold agricultural production is best captured by consumption prices.

Finally, the remaining issue is how to value the part of agricultural production that is actually sold on the open market. We have chosen to use the price at the gate to value sold production as sold items lose their storage value for the producer household, but this is of relatively small consequence given the low share of sold production in the sample. The estimated average per capita value of maize production for the sample of all rural households is US$101 under our preferred measure — that is, if we use consumption prices for the unsold production and prices at the gate for the sold production. This figure is US$109 if we use the consumption price for all production, sold and unsold.

D Recall Bias and Trimming

Food consumption is the lion's share of household consumption in our settings and hence, this measurement is perhaps the most important aspect of consumption. The ISA collection of food consumption data is based on a 7-day recall questionnaire. These short-recall periods tend to yield better consumption

measures (Beegle et al., 2012),[45] but at a cost. Given that ISAs are spread over 12 months, the surveys will do a good job in recovering average food consumption in the population, but they will potentially do a poor job in measuring annual dispersion as part of this dispersion will be artificially due to seasonal variation that needs to be net out for our purposes. Indeed, Malawi, Tanzania, and Uganda have clearly demarcated lean and plenty seasons that largely determine food consumption. This shortcoming can easily be dealt with using standard deseasonalization techniques to recover monthly consumption dummies.[46] Measurement error for other types of consumption such durables (collected with 12 month recall) is still potentially present. We note, however, that durable consumption represents a minor share of total consumption (4% in rural areas and 6% in urban areas; see below).

Income is based on recall of the entire production per crop and plot for the past two harvests. The harvest referred to in the questionnaire may have taken place months earlier. We conduct robustness testing for potential recollection bias for production using measures of household income only for those households interviewed within 3 months after the rainy season harvest (which represents 93% of annual agricultural production) has been completed (May, June, July); the mean and median of total agricultural production in kilograms is virtually identical for these three months and for the yearly values.

Finally, our trimming strategy consists of two steps that mitigate the presence of outliers. As a first step, we exclude households with zero calorie consumption or with an intake per person above the maximum daily of 10,000 Kcal. As a second step, we trim clear outliers after a visual inspection by subitems and then by aggregated measures. We finalize with an implied trimming of 2% of households for Malawi and Tanzania and 4% for Uganda.[47] The final samples for Malawi, Tanzania, and Uganda include, respectively, 12,015, 3,012, and 2,337 households.

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[45] See also Gibson et al. (2014).

[46] The lean season in Uganda stretches from March to July; in Malawi and Tanzania the lean season stretches from October to February.

[47] The 2010 surveys for Tanzania and Uganda are the second waves of panel surveys. Splitter households were dropped to compute the tables in this paper and are not accounted for in the percentage of trimming reported.

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