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Leaving No One Behind:
Urban Poverty Traps in Sub-Saharan Africa

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Abstract

Despite considerable achievements in the reduction of poverty over the last decades, poverty remains conspicuously high and profound. While fast urban population growth, especially in Sub-Saharan Africa, has contributed to poverty reduction, new development challenges like the urbanisation of poverty emerge. This paper investigates the persistence of urban poverty within the theory of poverty traps among urban households in Nigeria and Tanzania. Using household panel data from the World Bank Living Standard Measurement Study, we test whether consumption-based poverty traps exist in these contexts. Our results show that initially poor households experience an increase in well-being over time, while richer households face a decline and remain vulnerable to falling back into poverty. However, a sticky consumption floor as well as divergence of the floor with the mean show that despite upward dynamics amongst the poor, some are being being left behind. Finally, we argue that improved urban data is needed to identify the vulnerable middle, and to design structural policies preventing them from falling back into poverty.

JEL Classification: I32; P25; E21

Keywords: urban poverty, poverty trap, Sub-Saharan Africa, consumption floor, social protection

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1 Introduction

Urbanisation is one of the demographic mega-trends which will influence development policy and practice over the next decades (United Nations, 2018). In 2021, 57% of the global population was living in urban areas (World Bank, n.d.-c), and by 2050 more than two thirds of the world's population is expected to be urban (United Nations, 2018). However, the levels and rates of urbanisation across the globe are heterogeneous, with particularly high urbanisation in Sub-Saharan Africa. Between 2015 and 2020, Sub-Saharan Africa's urban population increased by almost 4% per year (United Nations, 2018). By the end of the 21st century, 13 of the world's 20 largest urban agglomerations are projected to be in Africa. At around 80 million inhabitants, Lagos in Nigeria is expected to become the world's most populous city (Washington Post, 2021).

Due to economic opportunities, higher wages and attractive standards of living in cities, more and more people have migrated to urban centres over the past decades. Urban population growth is also considered a significant driver of poverty reduction in the Global South, as global poverty, measured at $1.90 per capita per day (2011 PPP), has decreased from over 40% in the 1980s to less than 9% in 2018 (World Bank, n.d.-b; Ravallion, 2007). Despite this remarkable progress, the speed of poverty reduction has recently slowed down, as countries seem to face difficulties in reaching the last few percent (Ravallion et al., 2020). On top of that, the poor are urbanising faster than the general population, raising the urban share of poverty (Ravallion, 2007; Cuesta et al., 2021). Chronic or persistent poverty is thus still a major concern to researchers and policy makers, as the most poor and vulnerable may be trapped.

The aim of this paper is to investigate the persistence of poverty within the theory of poverty traps. A poverty trap is a self-reinforcing mechanism causing poverty to persist, and occurs when current poverty increases the likelihood of being poor in the future (Kraay & McKenzie, 2014; Azariadis & Stachurski, 2005). In the face of a poverty trap, the poor will always remain below a critical level (or threshold) of well-being, and find themselves unable to accumulate the resources to trespass this threshold. The theory of poverty traps thus stands in sharp contrast to the narrative that anybody can make it through hard work, and eventually has important implications for how we think about poverty and development. If current poverty is a direct cause of poverty in the future, and the poor find themselves unable to exit poverty, understanding poverty traps can provide a foundation for policy and programme interventions.

There is a large body of literature on micro-level poverty traps which investigates asset- or income dynamics over time. Even though conclusions are mixed, there is evidence that poverty traps are at play under certain conditions and in sub-samples and among certain groups, for instance in rural China (Jalan & Ravallion, 2002), Bangladesh (Balboni et al., 2021) or Mozambique (Giesbert & Schindler, 2012). Other studies find no evidence of poverty traps, but instead show that the poor, on average, are able to move out of poverty over time (von Fintel, 2017; McKay & Perge, 2013). Furthermore, the literature suggests that policy interventions, mostly large-scale 'Graduation programmes' are able to induce sustained changes in outcomes, or an exit from poverty (Banerjee et al., 2022; Balboni et al., 2021). This may work in a remote, rural area with a focus on a single asset class, e.g., livestock, which has been the focus of the overwhelming share of poverty traps research. However, the underlying poverty trap dynamics may be different for people in urban areas. With increasing urban population growth, often in informal and peripheral settings, comes a rising share of urban poverty, and a potential risk for urban poverty traps. Still, the paucity of data on urban areas and urban poverty dynamics in the Global South results in a lack of understanding of the underlying socio-economic development processes and limits the effectiveness of policy responses (Tacoli et al., 2015; Cuesta et al., 2021).

In this paper, we aim to address this knowledge gap by analysing consumption-based poverty trap dynamics in urban areas in Sub-Saharan Africa between 2010 and 2012, using panel data from the Living Standard Measurement Study (LSMS) from Nigeria and Tanzania. The two countries are particularly relevant in the context of urban poverty analyses for several reasons. Both are among the largest in population size in Sub-Saharan Africa (211 million inhabitants in Nigeria, and 61 million in Tanzania as of 2021) (World Bank, n.d.-a), they both have large urban populations, fast population growth, and they both have substantial data coverage (approximately 25% urban observations) that allows conducting analyses on urban poverty dynamics. We extend the existing literature on poverty traps into urban settings and include new perspectives on distribution-sensitive poverty dynamics at the household level. Using different autoregression models such as parametric, non-parametric and Generalized Method of Moments (GMM) models, we estimate consumption dynamics across time in order to understand whether current poverty in fact increases the likelihood of being poor in the future. Our results do not provide evidence in favour of such poverty trap, but show that poor households are able to increase their level of well-being between 2010 and 2012, while initially richer households face a decline. Those initially richer households form a vulnerable middle with levels of well-being above the conventional poverty line of $3.20, but is vulnerable to falling back into poverty over time. Finally, a sticky consumption floor as well as divergence of the floor with the mean show that despite upward dynamics amongst the poor, some are being being left behind.

The paper is structured as follows. Section 2 provides an overview on the poverty traps literature, exploring theory and concepts of poverty traps. Sections 3 and 4 introduce the empirical strategy and data. The results will be presented in Section 5, and an in-depth discussion of the findings follows in Section 6. Section 7 concludes and provides avenues for future research.

2 Theory and Concepts

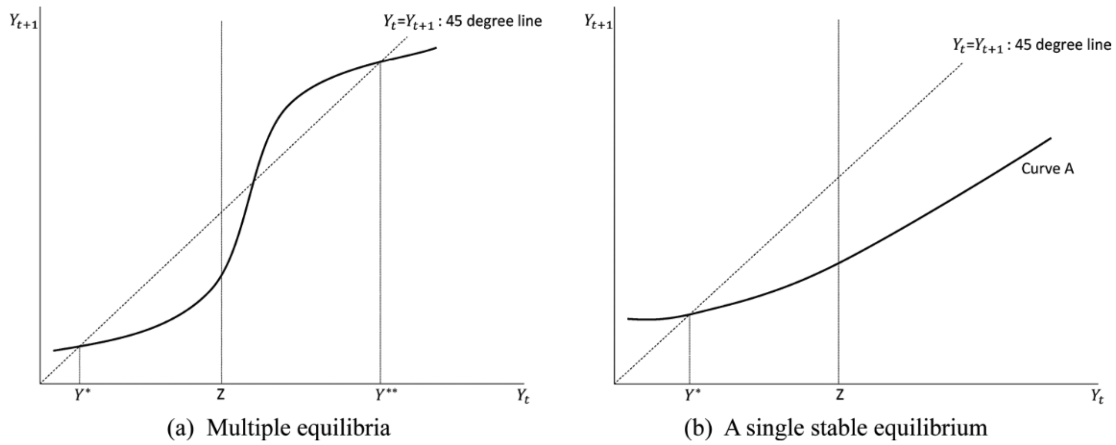
2.1 Theoretical Framework

Poverty traps are self-reinforcing mechanisms which cause poverty to persist, and keep the poor poor below a critical threshold of well-being (Barrett et al., 2016; Barrett, 2005; Carter & Barrett, 2006; Balboni et al., 2021; Kwak & Smith, 2013). While households with an initially low level of well-being find themselves unable to accumulate the necessary resources to escape poverty, those who are initially better off converge to a high steady-state of well-being. Thereby, the mechanisms leading to poverty traps are manifold. Households may find themselves trapped in poverty due to several, possibly interacting factors, such as an initial lack or loss of assets, the foregoing of high-return productive investments in human capital, as well as risk avoidance due to limited resources or a lack of access to credit and insurance (Carter & Barrett, 2006; Barrett et al., 2016; Barrett, Marenya, et al., 2006; Whitehead, 2006; Janzen et al., 2012).

Dominant poverty trap models in the literature revolve around dynamic traps with multiple equilibria. These occur when the relationship between well-being (proxied by assets, income or, as in our case, consumption) in period t and $t+1$ is S-shaped, with three distinct equilibria (see Figure 1(a)) (McKay & Perge, 2013; Barrett, Marenya, et al., 2006; Barrett & Swallow, 2006; Carter & Barrett, 2006; Quisumbing & Baulch, 2013). This theory predicts that households bifurcate away from the unstable equilibrium, either to a low or high stable equilibrium Y^* or Y^{**}, and their initial level of endowments determines the equilibrium to which they gravitate. Increases among the poor that do not lift above the unstable equilibrium of well-being are thus only of short-lived nature and vice versa, as equilibrium dynamics would pull them back into their respective steady state.

In some cases, well-being dynamics do however not follow an S-shaped curve, and there is only one single equilibrium (Figure 1(b)). In these cases, a non-poor outcome does not exist and all households converge to a single, low-level equilibrium of well-being (Barrett & Carter, 2013; Barrett et al., 2016). The most prominent example of single equilibrium poverty traps is the geographic poverty trap, when all households within a specific geographic location, for example a remote region, are unable to escape poverty (Jalan & Ravallion, 2002). Moreover, structural barriers related to unfavourable diseases or institutional factors that are beyond a household's control can lead to single-equilibrium poverty traps (Fitz & Gouri Suresh, 2021;

Figure 1: Multiple and single equilibria poverty traps



Source: Kwak & Smith (2013, p.957)
Note: Y^* shows the low-level equilibrium, Y^{**} the high-level equilibrium. Z is a set poverty line.

Acemoglu et al., 2001; Sachs & Malaney, 2002).

Against this backdrop, poverty traps are linked to the concept of (social) mobility. According to theory, small differences in initial asset or income endowments can lead to large differences in well-being. Where dynamic, multiple-equilibria poverty traps prevail, initially similar households around the unstable equilibrium can converge to different steady states, leading to inequality (Barrett & Carter, 2013). At the same time, the ultra poor who are stuck at the low-level equilibrium would not move out of poverty at all or much more slowly than those around and above the critical threshold (Ahmed et al., 2014). In addition, where single equilibrium poverty traps prevail, there is hardly any evidence for upward mobility. The theory of poverty traps thus stands in sharp contrast to mobility concepts such as the Prospect Of Upward Mobility (POUM) hypothesis, according to which individuals hold the view that they can make it through hard work (Benabou & Ok, 2001). The presence of poverty trap dynamics could even be an inhibitor of mobility, where the critical threshold or unstable equilibrium works as a sort of 'glass ceiling', preventing the poor from transcending without external intervention. Therefore, the presence of poverty trap dynamics provides a justification for policy and programme interventions, which can help poor households in moving beyond the critical threshold and onto the higher-level trajectory of well-being (Barrett & Swallow, 2006).

2.2 Evidence on Poverty Traps

The evidence on household-level poverty traps is mixed, and empirically identifying poverty traps remains challenging (McKay & Perge, 2013; Kraay & McKenzie, 2014; Barrett et al., 2016). Nonetheless, some important trends in the literature can be highlighted. First, while some studies find evidence for dynamic, multiple-equilibria poverty traps, others confirm single-equilibria poverty traps or even the absence of poverty trap dynamics overall. Second, most studies to date have used asset-based indicators, such as livestock, an index of various asset classes, or income-based measures to model poverty trap dynamics over time. Lastly, the overwhelming majority of poverty trap studies stem from rural, mostly remote areas.

In line with the poverty traps hypothesis, there is evidence that households with initially higher levels of assets from rural Bangladesh, Ethiopia, Kenya and Madagascar are able to accumulate assets and eventually move out of poverty, as measured by the ownership of productive assets, whereas those below a critical asset threshold are trapped in poverty (Balboni et al., 2021; Barrett, Marenya, et al., 2006; Van Campenhout & Dercon, 2012). While small transfers may increase consumption in the short term, a big-push intervention in the form of a large-scale asset transfer can push poor households out of poverty more sustainably, for instance in the case of Balboni et al. (2021) over a time frame of four years. However, in many other cases, the evidence does not support the dynamic multiple-equilibria poverty trap theory, and some studies show instead that asset, income or consumption accumulation paths generate a single-equilibrium. For instance, specific areas in rural China appeared to be so left behind that all households experienced continuous decline in consumption, while otherwise similar households in other rural areas enjoyed consumption growth (Jalan & Ravallion, 2002). In rural India as well as Mozambique, households find themselves trapped in a low-level equilibrium just below the poverty line (Dercon & Shapiro, 2005; Giesbert & Schindler, 2012). Any positive or negative shock, for instance a drought, is only of short-lived nature, after which they converge back to their initial steady state.

On top of that, there is some evidence for poverty dynamics which rather follow theories of (economic) convergence than single-equilibrium poverty traps as displayed in Figure 1(b). For example, households in South Africa experienced relatively steep income growth at the lower end of the distribution, after which structural income from assets remains persistent and there is hardly any upward mobility (von Fintel, 2017). Similarly, an analysis of asset accumulation on a collection of panel studies from low-income countries as well as an empirical study in rural Bangladesh showed that initially poorer households converge upwards (slowly) until a single equilibrium (McKay & Perge, 2013; Quisumbing & Baulch, 2013). Although those results do not confirm the presence of a poverty trap, there may be considerable heterogeneity across households. For instance, a recent study on asset dynamics among high- and low-caste households in rural India finds that asset accumulation is significantly different across these two groups (Mohapatra, 2021). While relatively well-off households from the low caste may experience a glass ceiling with limited upward mobility, households from the higher caste face a sticky floor, or a low-level poverty trap holding them behind. It remains important to recognise that a lack of evidence for poverty traps is not evidence for the lack of poverty traps or the absence of (chronic) poverty *per se*. Poverty might be transient, even if it may take longer to eradicate poverty eventually (Barrett et al., 2016). Furthermore, poverty may exist in sub-samples, so a lack of evidence may simply be a neglect of significant heterogeneity across households (McKay & Perge, 2013), or difficulties in the estimation of poverty trap dynamics.

As mentioned above, most evidence on poverty traps stems from remote, rural locations or low-productivity contexts with a limited asset base, for instance households relying solely on livestock (Barrett, Carter, & Little, 2006; McKay & Perge, 2013). However, this is little indicative of the persistence of poverty in urban areas. The evidence on urban poverty traps to date is rather scarce, and conclusions to be drawn are ambiguous. For example, initially poor households in urban Mexico are experiencing positive income growth over time, and converge to a stable income-equilibrium well above the poverty line (Antman & McKenzie, 2007). In contrast to that, urban households in Colombia from the first and second quintile find themselves in a poverty trap, and those in the third quintile are vulnerable to being trapped, too, as they decrease assets and incur debt to smooth consumption in the face of or after an adverse shock (Arbelaez et al., 2019). Beyond empirical estimations, there is growing recognition around the emergence of spatial urban poverty traps (Grant, 2010). Poverty is increasingly clustered in areas like slums or informal settlements with little to no formal labour opportunities nor public services. Unfortunately, such (informal) environments are to date under-represented in formal data collection efforts, and thus evidence to generate effective policy solutions is scarce (Grant, 2010; Lucci et al., 2018).

3 Methodology

To close this gap, we aim to establish whether poverty trap dynamics exist in urban Nigeria and Tanzania. For this, we first follow Giesbert & Schindler (2012) and McKay & Perge (2013) who analyse asset accumulation paths using a parametric model as well as a non-parametric kernel estimation, and then move on to system GMM models building on Jalan & Ravallion (2004). First, we apply nonparametric estimation techniques with Epanechnikov kernel weights according to the following transition equation:

$$C_{it} = f(C_{i,t-1}) + \epsilon_{it} \tag{1}$$

where $C_{i,t}$ is household consumption in year t, and ϵ_i is the error term, assumed to be normally and identically distributed with zero mean and constant variance. The advantage of non-parametric regressions is that they do not impose any functional form onto the relationship between two variables. Equation 1 investigates the relationship between real consumption in period t and *t-1*. We expect the coefficient β_1 to be positive and larger than 1, so that a one-unit increase in baseline consumption would lead to consumption growth in the follow-up period.

Secondly, we estimate the relationship between consumption growth and lagged consumption with a parametric estimation technique, an OLS regression with fixed effects adapted from Giesbert & Schindler (2012) as follows:

$$\Delta lnC_{it} = \beta_1 lnC_{i,t-1} + \beta_2 lnC^2_{i,t-1} + \beta_3 lnC^3_{i,t-1} + \boldsymbol{X'_{i,t-1}\gamma} + \eta_i + \epsilon_{it} \tag{2}$$

where consumption growth (in percent) $\Delta lnC_{i,t}$ of a household is a third-degree polynomial function of its consumption level in the previous period, X are baseline household characteristics, and η_i are district fixed effects, respectively. Standard errors are clustered at the primary sampling unit (enumeration area) level. All $C_{i,t-1}$ are transformed by taking their natural logarithm. Household characteristics include household size, the age dependency ratio of the household, the age and gender of the household head, his or her educational attainment (in years), and whether the household cultivates any land.

Since our main explanatory variable $C_{i,t-1}$ may be endogeneous (Dercon & Shapiro, 2005), we conclude our estimations of poverty trap dynamics using dynamic panel methods, following Lokshin & Ravallion (2004) and Dercon & Shapiro (2005). In theory, dynamic panel models have the advantage of allowing for unbiased analysis of dynamic relationships with a small number of time periods, where the lagged dependent variable is included as an explanatory variable (Bun et al., 2015). In line with the poverty traps literature, we estimate the differenced model with a two-step system GMM (Roodman, 2009; Blundell & Bond, 1998).

$$\Delta lnC_{it} = \gamma_1 \Delta lnC_{i,t-1} + \gamma_2 \Delta lnC_{i,t-1}^2 + \gamma_3 \Delta lnC_{i,t-1}^3 + \Delta \boldsymbol{X'_{it}} \boldsymbol{\beta} + \Delta \epsilon_{it} \tag{3}$$

For this, we use the second lag of the regressor $lnC_{i,t-2}$ as instrumental variable, which is uncorrelated with $\Delta lnC_{i,t} = lnC_{it} - lnC_{i,t-1}$. Based on Lokshin & Ravallion (2004), Jalan & Ravallion (2004), and Antman & McKenzie (2007), we use $lnC_{i,t-2}$, $lnC_{i,t-2}^2$ and $lnC_{i,t-2}^3$ as instruments for $\Delta lnC_{i,t-1}$, $\Delta lnC_{i,t-1}^2$ and $\Delta lnC_{i,t-1}^3$, respectively. We consider household characteristics to be endogenous, and use them as additional instruments in the GMM model. Year dummies are included as strictly exogenous variables and added as instruments as well. Assuming no measurement errors, we are able to obtain consistent estimates for $\hat{\gamma_1}$, $\hat{\gamma_2}$ and $\hat{\gamma_3}$ and determine whether there is non-convexity in consumption dynamics.

While all three different models have advantages and drawbacks, for instance with respect to the consistency of the estimators, we believe that utilising three different models can provide useful insights into the true underlying poverty trap dynamics and provide a robustness test for the validity of our results.

4 Data

Since we are interested in urban poverty traps, we place our study in particularly poor settings that experience rapid urbanization, as evidence in these and from these settings will be of increasing importance. To date, data on such urban settings is scarce. However, Nigeria and Tanzania, the largest and fourth largest countries in terms of population size in Sub-Saharan Africa in 2021, have the data that allow for conducting such analyses, and hence provide evidence for two key areas in Sub-Saharan Africa. We use representative household survey panel data from the Living Standard Measurement Study - Integrated Surveys on Agriculture (LSMS-ISA) project: the General Household Survey (GHS) from Nigeria as well as the National Panel Survey (NPS) from Tanzania, which contain approximately 25% urban observations, rendering them the only two LSMS countries suitable for conducting this analysis. Table 1 provides an overview of the data sets from both countries.

The Nigerian General Household Panel Survey is a sub-sample of the annual GHS cross-sectional survey, which collects data on amongst others household income, household expenditure and consumption (National Bureau of Statistics, 2016). It is a nationally representative panel survey of approximately 5,000 households, which are also representative of the six geopo-

Table 1: Data overview

	Nigeria			Tanzania		
	Wave 1	**Wave**	**Wave 3**	**Wave 1**	**Wave 2**	**Wave 3**
Survey	GHS	GHS	GHS	NPS	NPS	NPS
Year	2010-11	2012-13	2015-16	2008-09	2010-11	2012-13
Time Period	August-November 2010	September-November 2012, January 2013	August-October 2015	September 2008-October 2009	October 2010-November 2011	October 2012-November 2013
Observations	1,271	1,271	1,271	820	820	820

Note: Data for the GHS survey in Nigeria is obtained from the post-planting visit.

litical zones of Nigeria. Data for the GHS is collected twice a year, after the planting and the harvest seasons, respectively. For better alignment with the data structure from Tanzania, we use one data point per year from the post-planting survey[1] in Wave 1 (2010-11, hereafter referred to as GHS 2010), Wave 2 (2012-13, hereafter GHS 2012) and Wave 3 (2015-16, hereafter GHS 2015) (National Bureau of Statistics, n.d.-a,-b,-c). Attrition based on households that dissolve, decline to be interviewed or whose interview was incomplete for the dependent and explanatory variables (Alderman et al., 2001), was 16% among urban households between 2010 and 2012[2]. This also includes households who moved from an urban to a rural area between two interviews. Between waves two and three, so between 2012 and 2015, attrition among urban households amounted to only 5% in urban areas[3]. Overall, attrition in our sample is relatively low in comparison to other surveys conducted in Sub-Saharan Africa (Giesbert & Schindler, 2012; Alderman et al., 2001). We run a logit model where attrition is our binary dependent variable (taking the value 1 if the household remained in the sample, zero otherwise) to check for potential attrition bias, controlling for household-level variables (consumption, household size, dependency ratio, gender, age and education of household head, and whether the household cultivates land). Baseline geographic are (state) is included as fixed effects. We reject the joint orthogonality test with a p-value<0.01, and therefore use attrition-corrected survey weights in all our analyses. Finally, we create a balanced panel using 1,271 household observations from urban areas who were successfully interviewed and had complete consumption data in all three survey rounds. This represents 26% of the total GHS sample, or 32% of Nigerian households in 2010[4].

Similarly, the Tanzania National Panel Survey is a representative household panel survey

[1] Education expenditures (Wave 3) are only available from the post-harvest survey. However, as the reference period is 12 months, which includes the point of data collection of the post-planting visit, we use these components from the post-harvest visit instead.

[2] Attrition among the full sample (urban and rural households) was 9% between 2010 and 2012.

[3] Attrition for the full sample between 2012 and 2015 was 4%.

[4] In comparison, the urban population made up 43% of the total population in Nigeria in 2010 (World Bank, n.d.-c).

that gathers information on income generating activities, consumption expenditures, as well as a wealth of other socio-economic characteristics (National Bureau of Statistics, 2014). Like the GHS, it is representative at the national and regional level. We use Waves 1 (2008-09, hereafter referred to as NPS 2008), Wave 2 (2010-12, hereafter NPS 2010) and Wave 3 (2012-13, hereafter NPS 2012) (National Bureau of Statistics, n.d.-a,-b,-c). In the National Panel Survey sample, attrition based on households that dissolve, fail to be successfully re-interviewed or move away from urban areas was 26% between 2008 and 2010, and 8% between 2010 and 2012, respectively[5], whereby a large share of attrition is due to households moving from an urban to a rural area. As above, we estimate a logit model on the probability that a household remains in the sample, and reject the joint orthogonality test at the 1% level. Therefore, we also use attrition-corrected sampling weights. Eventually, we create a balanced panel of 820 urban households, representing 16% of the sample, as well as 16% of Tanzanian households in 2010[6].

4.1 Consumption as an Indicator of Well-Being

The majority of the poverty traps literature relies on asset-, and to a lesser extent income-based measures, mostly a single asset class or an asset index. Asset-based approaches are common in the study of well-being dynamics as they are perceived to be a forward- looking measure of poverty. Moreover, they are assumed to be free from temporary fluctuations, and representing structural well-being in the sense that future income can be derived from current assets (Carter & Barrett, 2006; Barrett & Carter, 2013; McKay & Perge, 2013).

Yet, our analyses of poverty dynamics are based on aggregate consumption, measured as daily per-capita consumption in 2011 International Dollars at Purchasing Power Parity (PPP), rather than asset- or income-based measures. We argue this is a more adequate measure of well-being for the following reasons. First of all, according to the permanent income hypothesis, current spending, or consumption, is determined by expected long-term (or structural) average income (Friedman, 1957). By using aggregate consumption, we therefore build on the asset framework: as a substantial improvement in structural assets would be reflected in consumption since current consumption is derived from long-term assets. As households smooth their consumption by borrowing and saving during and after short-term shocks, consumption is thought to capture long-run levels of well-being levels (Ngo & Christiaensen, 2019). Correspondingly, a transitory increase in income is saved rather than spent, which makes consumption less tied to short-term fluctuations in income and thus less variable and smoother than income

[5]Attrition among the full sample (urban and rural) is 3% both between waves one and two, and two and three.

[6]In comparison, 28% of the total population in Tanzania was living in urban areas in 2010 (World Bank, n.d.-c)

measures (Deaton & Zaidi, 2002). Income measures, especially in the context of developing countries, are often inadequate for the study of poverty dynamics due to a high frequency of reported zero-incomes[7]. While we acknowledge well-known issues with survey data (Beegle et al., 2012; Ravallion, 1996; Deaton, 2003), we use per capita consumption based on consumption aggregates as our preferred indicator of well-being. With this, we also follow the empirical literature on urban poverty, amongst others Jayamohan & Kitesa (2014), Cheng et al. (2002), Yenneti et al. (2017), and Wilson et al. (2022), as well as the methodology of national poverty estimations both in Nigeria and Tanzania which is based on consumption aggregates[8] (World Bank, 2022a,b).

The surveys have been conducted in different years and the consumption expenditures have been registered in local currency units in current prices. Hence, we convert all consumption data into 2011 constant local prices using Consumer Price Indices from each country, based on the months during which the interviews have been conducted. We then convert the resulting values into International Dollars using 2011 Purchasing Power Parity (PPP) exchange rates, and use log-transformed values in our regression models (see kernel density function in Figure 6, Appendix C). To derive meaningful comparisons of results between Nigeria and Tanzania, we perform some additional adjustments needed of the consumption aggregates to ensure maximum comparability, which are described in Appendix A.

4.2 Descriptive Statistics

Based on our sample of urban households, the large majority (46.8%) of the urban population in Nigeria lives in the South West geopolitical zone surrounding Lagos, the country's largest city as well as one of the fastest-growing cities worldwide (Faisal Koko et al., 2021). Around 17.5% lived in Lagos state in 2010. In Tanzania, 31% of the urban population lived in and around its capital city Dar Es Salaam.

Table 7 in Appendix B reports summary statistics for the baseline period 2010 for selected variables for Nigeria and Tanzania, and Table 8 outlines the questions and components for key variables in both contexts. All statistics have been calculated using sampling weights, and are thus representative of urban populations. For most demographic characteristics, as well as consumption measures, there are significant differences across the two countries. For instance, while average daily per capita consumption[9] was $4.31 in urban Nigeria in 2010, it was $5.39

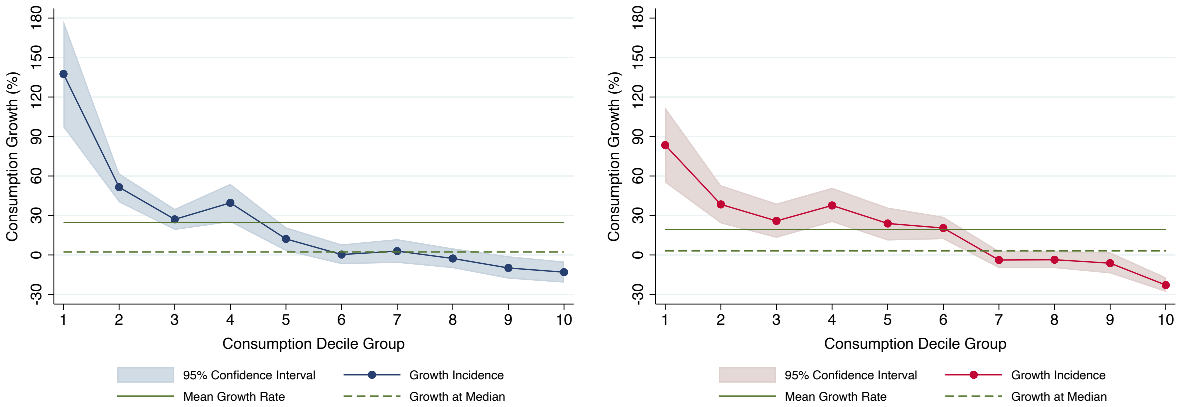
[7]In our study, consumption is preferred to reported income, as around 14% and 22% of urban households in our sample report no income in 2010 and 2012, respectively.

[8]Official poverty estimates for Nigeria are based on the General Household Survey (GHS) data from 2018/19 (National Bureau of Statistics, 2016). Official poverty estimates for Tanzania are based on per capita consumption from the Household Budget Survey (World Bank, 2022b).

[9]Per capita consumption is measured in International Dollars at 2011 Purchasing Power Parity (PPP), using

Figure 2: Growth incidence curves (GIC) (2010-2012)

(a) Nigeria **(b)** Tanzania



Note: Weighted mean of real consumption growth between 2010 and 2012. Consumption deciles are based on the year 2010 and have been calculated using real consumption values in International Dollars at 2011 PPP and survey weights from 2010.

in urban Tanzania. In both countries, reported household consumption averages are well above the International Poverty Line of $1.90, and the poverty line of $3.20 used for lower-middle income countries like Nigeria and Tanzania.

Before moving to the analysis of urban poverty trap dynamics, we calculate Growth Incidence Curves (GIC), displaying average growth in daily per-capita consumption (2011 PPP) per consumption decile between 2010 and 2012 (Figure 2). Growth incidence curves are a useful tool to assess whether growth is pro-poor (Ravallion & Chen, 2003). In both Nigeria and Tanzania, consumption growth in daily per capita consumption[10] is particularly high amongst the poorer deciles, meaning that growth has been relatively pro-poor (Kraay, 2006), or substantial redistribution has taken place. The level of consumption growth flattens off around the center at the distribution, however only around the seventh consumption decile in Tanzania, and the eighth in Nigeria, consumption growth becomes negative. These plots hint to somewhat different relationships than what a poverty trap with multiple equilibria would suggest. On the one hand, based on Figure 2 we observe that in general, very poor households (those in deciles 1 to 4, where mean consumption growth remains below the $3.20 poverty line) seem to experience steep consumption growth, and may thus be able to move out of poverty over time. On the other hand, those who are initially rich seem to face a contraction in consumption levels over time. These initial findings would not only contradict the multiple equilibrium hypothesis, but also the single equilibrium poverty trap hypothesis as described in Section 2. Furthermore, the

household size (no adult equivalents are applied).

[10] Consumption growth in daily per capita consumption is measured in International Dollars at 2011 Purchasing Power Parity (PPP), using household size (no adult equivalence scales are applied).

level of average consumption growth at the lower end of the distribution appears extremely high, reaching more than 120% in the case of Nigeria, and around 90% in Tanzania, albeit with rather large confidence intervals but robust to the inclusion of outlier values and trimming the data at the lower- and higher end (Figure 7 in Appendix C). However, at rather low baseline values (average daily per capita consumption of $1.10 in Nigeria and $1.30 in Tanzania in the first quintiles in 2010), even a small nominal increase in consumption results in a high rate of consumption growth. For example, a Nigerian household with an increase in daily per capita consumption of 50 cents, or from $1.10 to $1.60 would have experienced consumption growth of 45%, although its level of well-being is still below the extreme poverty line of $1.90 per day. To further investigate these findings, the following sections will provide a deeper examination of underlying consumption dynamics.

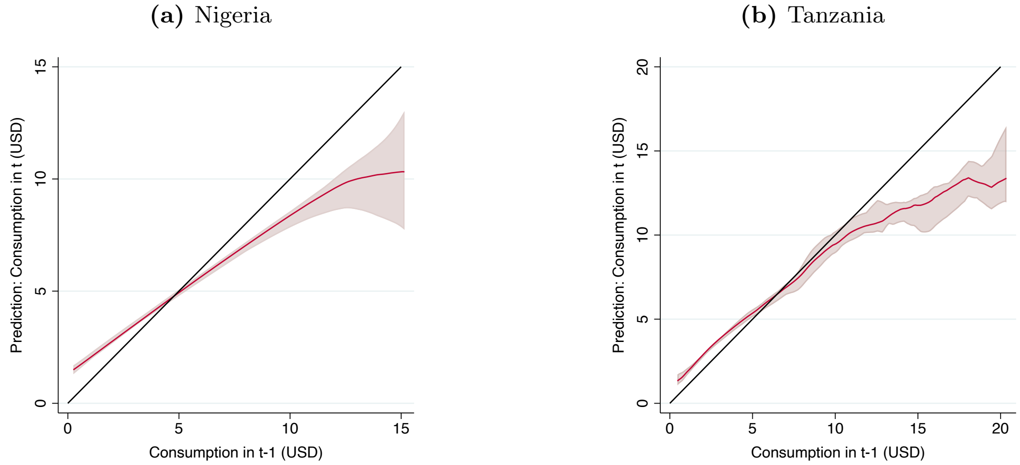
5 Results: Urban Poverty Traps

5.1 Main Results

We now move on to the poverty trap estimations as described in Section 3. Figure 3 shows the results from the nonparametric kernel regression of Equation 1, relating daily per capita consumption (2011 PPP) in 2010 to consumption in 2012. Generally, we do not seem to observe an S-shaped curve with multiple equilibria as hypothesised based on Figure 1 a). On the contrary, the function of predicted consumption lies above the 45-degree line for lower levels of initial consumption, and intersects with the 45-degree line at $4.75 in Nigeria, or $6.45 in Tanzania. Households with an initial per capita consumption below these thresholds experience a relative growth in consumption over time. Those around the centre of the distribution maintain their level of well-being (as predicted consumption is not statistically different from the 45 degree line), and initially richer households face a decline in consumption, both in Nigeria and Tanzania.

Next, we move to the results from the parametric regression in Equation 2, the relationship between consumption growth and consumption in *t-1* (2010) (Table 2). When interpreting the estimates, we are less interested in the exact size of the regression coefficients. Instead, we closely examine the significance of coefficients as well as predicted functions of consumption growth in order to gain a more general understanding of poverty trap dynamics, thresholds and their distributional differences in Nigeria and Tanzania. Across all models in Table 2, the coefficients on the linear term of consumption in *t-1* are negative and significant, confirming the relationship shown in Figure 2. In other words, the higher consumption in period *t-1*, the lower consumption

Figure 3: Predicted consumption (nonparametric regression)



Note: Time period: 2010-2012. Consumption reflects daily per capita consumption based on household size, and is measured in International Dollars at 2011 Purchasing Power Parity (PPP). For better visualisation, the graph only shows values of the consumption distribution until the 99$^{\text{th}}$ percentile for Tanzania.

growth in t. This relationship is robust to the inclusion of control variables (columns (2) and (4)). However, coefficients on the squared and cubic lags of consumption are small and not significant at conventional significance levels, meaning that the estimated relationships do not exhibit properties of an S-shaped function. Table 9 in Appendix B further shows that the coefficients on some demographic control variables, for instance household size and dependency ratio, are negative and significant, so these effects may be particularly pronounced among larger households, or households with many economically dependent members.

The results from Table 2 are visualised in Figure 4, which plots predictive margins of consumption growth from columns (2) and (4) in Table 2, and confirms that households with lower baseline consumption experience relatively higher consumption growth. More specifically, consumption growth is positive but decreasing until a baseline consumption level of approximately \$3.35 per person per day in Nigeria, and \$4.50 in Tanzania. While the overall relationship is in line with the results from the non-parametric regressions in Figure 3, the estimated thresholds here are slightly lower. The poorest of the poor seem to experience specifically high consumption growth, albeit with rather large confidence intervals at the bottom of the distribution. For households with initial consumption levels beyond \$3.35/\$4.50, average consumption growth is negative. In other words, poorer households are able to improve their level of well-being over time, while initially richer households experience a relative stagnation, or even decline in well-being. Accordingly, Figure 4 does not suggest the presence of multiple equilibria, but one single unstable equilibrium slightly above the \$3.20 poverty line. On the contrary, the results are rather in line with (economic) convergence, which will be discussed in detail in Section 6.

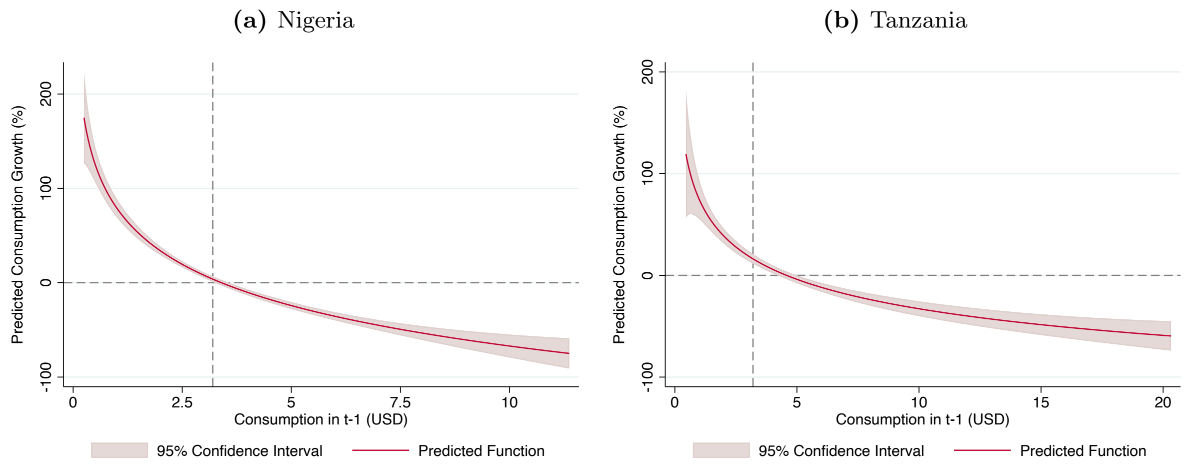
Table 2: OLS fixed effects regressions

	Nigeria		Tanzania		Both	
	(1) Δ Cons.	(2) Δ Cons.	(3) Δ Cons.	(4) Δ Cons.	(5) Δ Cons.	(6) Δ Cons.
Log Consumption (t-1)	-0.57***	-0.66***	-0.52***	-0.54***	-0.58***	-0.66***
	(0.06)	(0.07)	(0.17)	(0.19)	(0.06)	(0.07)
Log Consumption (t-1) Squared	0.04	0.02	0.07	0.03	0.04	0.01
	(0.06)	(0.07)	(0.11)	(0.12)	(0.05)	(0.06)
Log Consumption (t-1) Cubic	-0.00	-0.00	-0.01	-0.00	0.00	0.01
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
Household Controls	No	Yes	No	Yes	No	Yes
Missing Controls	No	Yes	No	No	No	Yes
Country FE	No	No	No	No	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.37	0.42	0.27	0.29	0.36	0.41
Observations	1271	1266	820	820	2091	2086

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

Note: Time period: 2010-2012. Dependent variable: Δ Consumption ($lnC_t - lnC_{t-1}$). Control variables are defined as baseline values. Standard errors are clustered at the primary sampling unit (enumeration area) level. Consumption reflects daily per capita consumption based on household size, measured in International Dollars at 2011 Purchasing Power Parity (PPP) and transformed into natural logarithms. For analyses using the pooled sample, we adjust the survey weight of each observation according to the population size of the respective country and year using the formula $weight\_adj_{it} = weight_{it} * population_t / sum(weight_{it})$.

Figure 4: Predicted consumption growth (OLS fixed effects regression)



Note: Consumption reflects daily per capita consumption based on household size, and is measured in International Dollars at 2011 Purchasing Power Parity (PPP). The vertical dashed line represents the poverty line of \$3.20 per person per day. For better visualisation, the graph only shows values of the consumption distribution until the 99th percentile for Nigeria, and between the 1th and 99th percentile for Tanzania.

Pooling the data from Nigeria and Tanzania and adding country fixed effects, we observe very similar results to the separate country analyses (columns (5) and (6) in Table 2. The magnitude and direction of the coefficient on consumption in *t-1* are aligned, and on top of

Table 3: OLS fixed effects regressions (extended time periods)

	Nigeria			Tanzania		
	(1) 2010-2012	(2) 2012-2015	(3) 2010-2015	(4) 2008-2010	(5) 2010-2012	(6) 2008-2012
Log Consumption (t-1)	-0.66***	-0.62***		-0.51**	-0.54***	
	(0.07)	(0.07)		(0.23)	(0.19)	
Log Consumption (t-1) Squared	0.02	0.06		0.05	0.03	
	(0.07)	(0.06)		(0.16)	(0.12)	
Log Consumption (t-1) Cubic	-0.00	-0.01		-0.01	-0.00	
	(0.03)	(0.02)		(0.03)	(0.02)	
Log Consumption (t-2)			-0.73***			-0.29
			(0.05)			(0.19)
Log Consumption (t-2) Squared			-0.01			-0.15
			(0.05)			(0.14)
Log Consumption (t-2) Cubic			0.01			0.03
			(0.02)			(0.03)
Houshold Controls	Yes	Yes	Yes	Yes	Yes	Yes
Missing Controls	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.42	0.42	0.49	0.35	0.29	0.37
Observations	1266	1266	1266	820	820	820

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

Note: Dependent variable: Δ Consumption ($lnC_t - lnC_{t-1}$). Control variables are defined as baseline values. Standard errors are clustered at the primary sampling unit (enumeration area) level. Consumption reflects daily per capita consumption based on household size, measured in International Dollars at 2011 Purchasing Power Parity (PPP) and transformed into natural logarithms.

that, country fixed effects (country dummy for Tanzania) remains insignificant 9 in Appendix B). Hence, we conclude that our results are consistent across countries between 2010 and 2012.

So far, we analysed urban poverty trap dynamics between 2010 and 2012. To exploit all three survey waves from our data set, we extend our analysis in the following ways. First, we run the regressions from Equation 2 on the remaining time periods (2012-2015 for Nigeria, and 2008-2010 for Tanzania, columns (2) and (4) in Table in Table 3) to compare these results to our base model (2010-2012, columns (1) and (5)) and see whether the results are consistent across time. Second, we investigate whether the effects are sustained over a longer period of time, using the first and third survey wave from each country, and thus daily per capita consumption in *t-2* as our independent variable (columns (3) and (6) in Table 3). The results show that the signs and sizes of coefficients are once again broadly in line with our base specifications. The only significant difference in regression coefficients of consumption occurs for the comparison of the short and medium-term periods in Tanzania (columns (5) and (6)). The coefficient on consumption in *t-2* is not significant at conventional significant levels, so our results may not hold for the period between 2008 and 2012 in Tanzania. Apart from that, there are no significant differences in coefficients across time periods, which means that our results thus far are robust

Table 4: Dynamic panel models (two-step system GMM)

	Nigeria		Tanzania	
	(1)	(2)	(3)	(4)
	Δ Cons.	Δ Cons.	Δ Cons.	Δ Cons.
Log Consumption (t-1)	-0.96***	-0.93***	-1.26***	-1.24***
	(0.10)	(0.09)	(0.27)	(0.27)
Log Consumption (t-1) Squared	0.05	0.04	0.30	0.28
	(0.09)	(0.09)	(0.19)	(0.19)
Log Consumption (t-1) Cubic	0.02	0.01	-0.05	-0.05
	(0.02)	(0.02)	(0.04)	(0.04)
Household Controls	No	Yes	No	Yes
Nr. of Instruments	8	16	8	15
Household Control Instruments	No	Yes	No	Yes
Year Instruments	Yes	Yes	Yes	Yes
Hansen J Statistic (Overidentification)	1.51	2.02	.40	.65
Prob > chi-squared	.68	.57	.94	.89
Observations	2542	2542	1640	1640

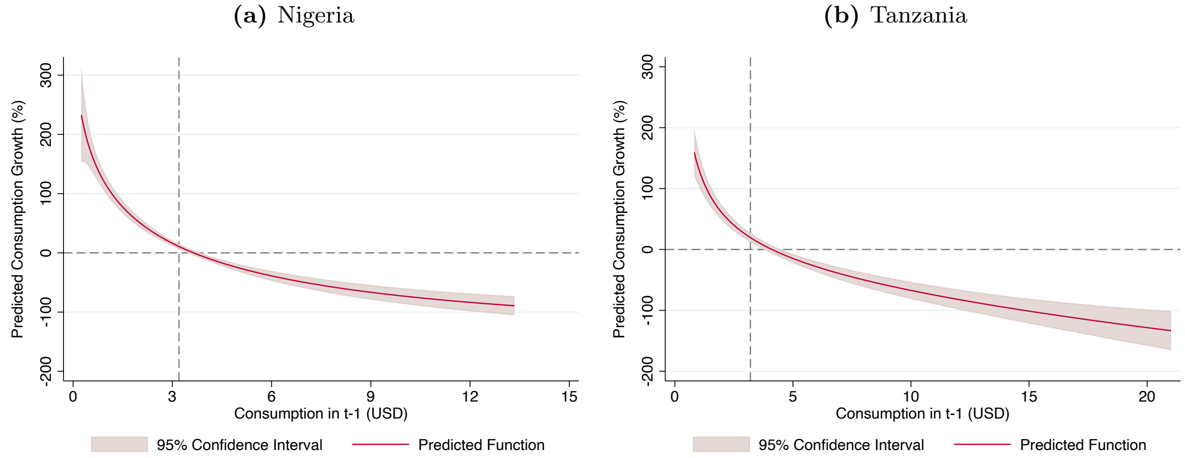
Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: Time period: 2012-2015 for Nigeria, 2010-2012 for Tanzania. Dependent variable: Δ Consumption ($lnC_t - lnC_{t-1}$). Control variables are defined as baseline values. Consumption reflects daily per capita consumption based on household size, measured in International Dollars at 2011 Purchasing Power Parity (PPP) and transformed into natural logarithms.

to the timing and length of the period of analysis, at least for Nigeria.

Lastly, we estimate the two-step system GMM, the results for which are shown in Table 4 and Table 10 in Appendix B (full output). Testing for S-shape, we estimate third-order polynomial models of consumption in period *t-1* on consumption in *t*. As described in Section 3, household characteristics are added as endogenous, and year dummies as exogenous instruments. The coefficients on the linear term of consumption in *t-1* are negative and significant across all models, so the higher consumption in *t-1* the lower consumption growth in *t*. Like in Table 2, the coefficients on the squared and cubic terms of consumption in *t-1* are insignificant. Across all models in Table 4, we fail to reject the Hansen test, and may therefore infer that our instruments are valid. However, the magnitude of coefficients differs across countries, which could largely be due to the different time periods on which this analysis draws. As the three survey waves do not overlap perfectly, the analysis is based on consumption growth between 2012 and 2015, using consumption 2010 as an instrument for Nigeria, while for Tanzania, we analyse consumption growth between 2010 and 2012, using consumption in 2008 as an instrument. The data for Tanzania also spans the global financial crisis in 2008/09, differential results may also be attributed to the adverse effects of the crisis on household's well-being. Given these time differences, we do not perform any pooled analyses based on the GMM model.

Figure 5: Marginal predictions of consumption growth (dynamic panel model)



Note: Consumption reflects daily per capita consumption based on household size, and is measured in International Dollars at 2011 Purchasing Power Parity (PPP). For better visualisation, the graph only shows values of the consumption distribution until the 99^{th} percentile for Nigeria and Tanzania.

As for the OLS models above, Table 10 in Appendix B shows that the coefficients on household size are negative and significant. We therefore apply a series of heterogeneity analyses around demographic and geographic characteristics of households in our sample (household size, gender of the household head and whether the household lives in a capital city or other urban area), but fail to find evidence for significant heterogeneous effects. Figure 5 plots predicted consumption growth and once again shows that consumption growth is positive until a threshold slightly above the \$3.20 poverty line, or approximately \$3.65 in Nigeria and \$4.10 in Tanzania, while initially richer households face a decrease in consumption over time. In comparison, the estimated thresholds only deviate marginally from the OLS models above (\$3.65/\$4.10 compared to \$3.35/\$4.50), which serves as a first robustness test. Further robustness checks will be based on the dynamic panel models, serving as the most consistent model with endogenous variables.

5.2 Extensions and Robustness Checks

Although our main analysis is based on households in urban areas, we test for rural-urban differences in poverty trap dynamics and replicate the analysis using only households who lived in rural areas during all three survey waves (4,771 observations per wave, 2,972 from Nigeria and 1,799 from Tanzania). The results from the system GMM model are displayed in Table 11 in Appendix B as well as Figure 9 in Appendix C, which look fairly similar to urban estimations. The coefficients on the linear term of consumption in *t-1* is negative and significant, so rural households with higher consumption in *t-1* also experience lower consumption growth. Figure

9 does suggest that the estimated threshold after which consumption growth becomes negative is lower, around \$2.20 in Nigeria, and \$1.70 in Tanzania. Hence, while initially poorer rural households are able to move up, even households living below the \$3.20 poverty line seem to face restricted upward mobility. The difference in thresholds between urban and rural households may be explained by the lower average consumption in rural areas. On top op that, the results may indicate that in fact, a large share of absolute poverty reduction around the poverty line takes place in urban, rather than rural areas.

Last but not least, we apply two sets of robustness checks. First, we correct for potential misreporting, and secondly, we re-estimate our models using food consumption only. For the former, we first trim the data by excluding the lowest and highest 1% and 5% of the consumption distribution, respectively, to avoid our results are biased by observations with extreme consumption values. Furthermore, we revert to the original data (including large outliers >5 standard deviations above the mean). We re-estimate the system GMM models based on these three adjustments, the results for which are displayed in Table 12 in Appendix B (columns (1)-(3) and (5)-(7)). Both the size and significance of coefficients are largely similar to the base specification in both countries, although the p-value for the Hansen statistic for the models using the 5% trimmed data suggest that we cannot infer the validity of instruments for all sub-estimations, which may partly be due to the reduced sample size. Lastly, we replicate the analysis using food consumption only in order to validate our results in the face of a potential rural bias in the survey modules (for instance, the consumption aggregate may underestimate rent expenditures). As Table 7 in Appendix shows, food consumption by far makes up the largest share of total expenditures, between approximately 61% in Nigeria, and 65% in Tanzania. Table 12 in Appendix B (columns (4) and (8)) shows that the results are largely in line with our base specification, and our model is robust to the exclusion of expenditures groups like rent, education and non-food consumption.

5.3 A Distribution-Sensitive Perspective

The results above suggest a lack of evidence for poverty traps among the urban population in Nigeria and Tanzania. Instead, on average (consumption) poor households move out of poverty over time given positive consumption growth, while initially richer households face a gradual decline in consumption, and eventually are vulnerable to falling back into poverty. We analyse effects across the consumption distribution, which show that consumption growth over time is particularly high amongst the very poor. However, is it really the case that all initially poor households find themselves moving out of poverty over time? To answer this question,

Table 5: Poverty transition matrices, Nigeria & Tanzania

(a) Nigeria

	Short Term			Medium Term		
	Non-Poor (%)	Poor (%)	Total	Non-Poor (%)	Poor (%)	Total
Non-Poor (%)	39.6	15.7	55.2	41.4	13.9	55.2
Poor (%)	14.6	30.1	44.8	19.5	25.2	44.8
Total	54.2	45.8	100	60.9	39.1	100

(b) Tanzania

	Short Term			Medium Term		
	Non-Poor (%)	Poor (%)	Total	Non-Poor (%)	Poor (%)	Total
Non-Poor (%)	54.4	7.8	62.2	54.3	12.3	66.6
Poor (%)	12.8	25.1	37.8	12.8	20.5	33.4
Total	67.2	32.8	100	67.2	32.8	100

Note: Poverty is estimated at the International Poverty Line ($3.20 2011 PPP), all values are reported in percent. Short term refers to the time period 2010-2012, medium term refers to time periods 2010 to 2015 for Nigeria, and 2008 to 2012 for Tanzania. Rows show baseline values, columns show follow-up values.

we perform what Carter & Barrett (2006) call a second-generation poverty analysis, or an analysis of inter-temporal poverty transitions. Table 5 displays these transitions relative to the poverty line of $3.20, both for the short as well as medium term periods. These estimates are not official poverty statistics[11], but reflect poverty headcount rates in urban areas based on our sample and the poverty line of $3.20. Generally, we see that urban poverty ranges from 33% to 46% depending on country and time period, and between 21% and 30% of households are poor in both time periods considered. Urban poverty seems to be higher in Nigeria than in Tanzania (approximately 45% compared to 33-38%), and there seems to be less movement between poor and non-poor states over time in Tanzania. While in Nigeria, 14% (19%) of households move out of poverty over time, 16% (14%) fall back depending on the time period considered. In Tanzania, 13% of households move out of poverty, while only 8% (12%) fall back. In other words, movement in both directions is considerable, which is not captured by the average consumption growth dynamics from Figures 4 and 3.

On top of that, perhaps an analysis of the transition into or out of poverty is insufficient if households are easily lifted just above (or fall just below) a defined poverty threshold. As our results show from figures 4 and 5 show, consumption growth at baseline values of $3.20 per person per day is rather close to zero, so there may be substantial movement into and out of poverty over time. However, while absolute poverty is reduced when people are lifted minimally above a set poverty line (e.g., $3.20), *a priori* this does not mean their standard of living has improved. More distribution-sensitive poverty measures are needed to analyse

[11] Official urban poverty rates based on daily per capita consumption in 2018 are 18% and 16% for Nigeria and Tanzania, respectively (World Bank, 2022a; Aikaeli et al., 2021).

Table 6: Consumption floor

	Nigeria			Tanzania		
	2010	2012	2015	2008	2010	2012
Consumption Floor (USD)	1.62	1.71	1.79	1.66	1.75	1.68
Mean Consumption (USD)	3.97	4.19	5.06	5.46	5.16	5.65
Share Floor/Mean Consumption (%)	40.87	40.87	35.33	30.37	33.88	29.73

Note: The consumption floor is measured in International Dollars at 2011 Purchasing Power Parity (PPP), based on Equation 4, and setting the poverty line z to \$3.20.

poverty dynamics at the bottom, and to confirm our finding that the poorest are moving up the distribution fastest. One innovative solution for this analysis is the concept of the consumption floor, measuring the lowest level of material living; or the floor of the income or consumption distribution (Margitic & Ravallion, 2019; Ravallion, 2016). Although poverty reduction over the last 30 years has been impressive, Ravallion (2015) argues that the world's poorest have gained disappointingly little, and the divergence in consumption between the poor and the poorest, and even more profoundly the overall mean and the poorest is large (Ravallion, 2015). As such, the consumption floor has remained remarkably stable over time, which suggests that the poorest are unable to even move up slightly. Based on Ravallion (2016) the consumption floor is measured as follows:

$$E(y^*_{\text{min}}|y) = z * (1 - \frac{SPG}{PG}) \tag{4}$$

where y^*_{min} is the expected value of the consumption floor given the consumption distribution y, PG is the poverty gap, i.e., the ratio by which the average daily per capita consumption of the poor (those living below \$3.20) falls below the poverty line, and SPG is the squared poverty gap. The poverty line z (e.g., \$3.20), is a set threshold above which the probability of a person living at the consumption floor is zero (Margitic & Ravallion, 2019). Hence, the larger the squared poverty gap (a more distribution-sensitive measure than the poverty gap or headcount) in relation to the poverty gap, the more poverty is concentrated at the lower end of the distribution, and the lower the consumption floor. The consumption floor eventually serves as a proxy for an extreme poverty trap: in case the consumption floor remains sticky and households find themselves in the vicinity of the floor repeatedly across time, they are in a poverty trap.

Table 6 shows the values of the consumption floor over the three survey waves, setting z=\$3.20. Obviously, the consumption floor as reported in Table 6 is not in fact the lowest reported level of consumption in the data. Given possible measurement errors in the tails of the distribution, the consumption floor is rather conceptualised as the expected value of the lowest consumption, and used mainly as a reference point (Ravallion, 2016). In Nigeria, the urban consumption floor rose from \$1.62 to \$1.79 between 2010 and 2015, while in Tanzania it barely changed from \$1.66 to \$1.68 between 2008 and 2012, albeit with a spike to \$1.75 in 2010. Interestingly, while mean consumption is higher in Tanzania than Nigeria, the value of the floor is very similar. At around \$1.60-\$1.70, our estimated urban consumption floor lies slightly below the international poverty line of \$1.90 per person per day.

Although our results from Section 5.1 suggest that the poor are able to move up on average, with high rates of consumption growth at very low baseline consumption levels, the consumption floor remains comparably sticky. As a consequence, some households may be stuck at the floor, or some households fall back to the floor as others depart. This is in line with Figures 2, 4 and 5, which show that confidence intervals of consumption growth at the bottom of the distribution are fairly large, and thus not all initially poor households may be able to move up. Over time, we also see a divergence of the floor with mean consumption in Nigeria, where the share of the consumption floor of mean consumption has decreased from 38% to 32%, while the share has increased and then decreased again in Tanzania. One explanation for the differences in dynamics at the floor is the difference in time periods, as our survey spans the 2008-09 global financial crisis in the case of Tanzania, which may have had a substantial impact on the poorest. However, when comparing 2010-2012 only, a slight lift in the floor for Nigeria, and a decline for Tanzania remain.

6 Discussion

Our results do not provide evidence for poverty traps as a low-level equilibrium of well-being in the countries and at the time analysed. On the contrary, we find evidence for convergence, similar to previous studies by von Fintel (2017) and McKay & Perge (2013). Based on our preferred econometric model, poorer households, those with initial per capita consumption of approximately \$3.65 per day in Nigeria, and \$4.10 in Tanzania, experience consumption growth over time. After that, there is hardly any upward mobility, but initially richer households seem to experience a relative decline in well-being and are vulnerable to falling back into poverty. Based on our initial findings, we would have to conclude that poor households in urban Nigeria and Tanzania are not trapped in poverty, but are able to move out of poverty over time. However, the confidence intervals at the bottom of the consumption distribution are fairly large, requiring caution about measurement errors as well as large variation across households. Despite high consumption growth at the lower end of the distribution, the process of convergence may be slow, as households start off with low initial consumption levels and may only experience marginal nominal improvements to their level of well-being. Furthermore, the closer poor households are to the \$3.20 poverty line, the more consumption growth approaches zero. This would imply that mobility around the poverty line may be so limited that we can barely speak of upward well-being dynamics. Despite these trends, we also find that there is considerable movement in- and out of poverty, and the consumption floor remains relatively sticky over time, particularly in Tanzania. Even though poorer households move away from the floor on average (given the high consumption growth at the bottom of the distribution), a smaller share of households may slide back, thus keeping the floor rather constant. A poverty trap at the bottom of the distribution may therefore exist, which we are unable to capture in our study due to the small sample size.

Besides that, can a daily per capita consumption between \$3.65 and \$4.10 be considered as being *out of* poverty? While these values are above the poverty line of \$3.20, it is widely acknowledged that price levels in urban areas are higher compared to rural settings. Meeting basic food and non-food needs may take up a large share of overall consumption, or require significantly higher consumption (and hence, income) levels in the first place. Even \$3.80 or \$3.90 per day may not be sufficient to afford minimum basic needs in a setting with above-average prices. For instance, Gelb & Diofasi (2016) describe a so-called Africa effect, according to which countries on the continent face disproportionately higher price levels in comparison to other low-income countries, relative to their own GDP per capita. In a paper comparing the expensiveness of African cities relative to other low- and middle-income countries, Nakamura et al. (2019) find that the price level of household consumption in urban Sub-Saharan Africa is 25% to 28% higher than in comparable countries. Therefore, concluding that urban households are moving out of poverty may be exaggerated. We might argue that the well-being dynamics we observe reduce absolute and extreme poverty as defined by international standards, but leave households vulnerable to falling back into poverty and create a (household-level) lower-middle income trap. Being stuck at a consumption level only slightly above the \$3.20 poverty line, barely sufficient to meet basic needs, could thus also be a poverty trap, albeit one with a different conceptualisation than the one our theoretical framework suggests.

All previous arguments aside, what if households in fact move out of poverty, albeit slowly, and what could be potential underlying causes? Given the recent urbanisation trends, it might be that rapidly expanding cities such as Lagos and Dar Es Salaam, and urban areas in Sub-Saharan Africa more generally, are environments where those initially worse off can grow. Despite the valid concerns about urban sprawl, the establishment of slum areas, and the intensification of poverty in cities' peripheries, our results may imply that on average, poorer households in cities are able to benefit from economic growth. Even though such growth may not generally keep pace with rapid urban expansion or high prices, those at the bottom could benefit in relative terms. As visible in Figure 2, consumption growth in urban Sub-Saharan Africa is relatively pro-poor, as consumption amongst the poor grows at a higher rate than those of the non-poor (Kraay, 2006; Ravallion, 2004). Nevertheless, our results that consumption growth is only positive until a baseline consumption between \$3.65 and \$4.10also seem to suggest that despite providing economic opportunities to the very poor, economic development processes in urban Nigeria and Tanzania fail to create the structures necessary for those just above the \$3.20 poverty line to benefit.

Last but not least, and as mentioned before, the existence of poverty traps is a foundation and rationale for policy interventions and poverty reduction measures. We know that such measures, for instance social protection schemes, are able to move households onto higher well-being trajectories (Barrett, Marenya, et al., 2006; Janzen et al., 2012; Barrett & Carter, 2013; Balboni et al., 2021). Our results and the suggestive evidence that initially poor households slowly move out of poverty over time would speak against the necessity of pushing the poor up. However, limited mobility around the poverty line, and a declining well-being over time may indeed provide a rationale for intervention, not least to prevent vulnerable households from falling back into poverty.

7 Conclusion

In this study, we have estimated consumption-based poverty trap dynamics in urban Nigeria and Tanzania. Our results do not provide evidence for multiple-equilibrium poverty traps, where the poor converge back to to a low-level equilibrium of well-being. Instead, we find evidence for convergence until an unstable equilibrium between \$3.65 and \$4.10, with relatively high consumption growth at lower levels of initial consumption, after which there is hardly any upward mobility. While there are multiple reasons and limitations behind these findings, the following stand out. Households with initially lower levels of consumption are able to catch up, which might be due to vast economic opportunities in urban areas, especially for low-income populations. Although poorer households find themselves on an upward trajectory, exiting monetary poverty over time, convergence may be slow. Households with initial consumption levels around the \$3.20 poverty line may remain vulnerable to falling back into poverty. Furthermore, high living costs in cities across Africa leave doubt whether consumption levels around \$4 per person per day are anywhere near sufficient to meet basic needs, let alone afford a decent standard of living. Lastly, while households move up on average, a rather sticky consumption floor in Tanzania, and a convergence of the floor with mean consumption leaves doubt whether we really not leaving anyone behind.

Our study is a first glimpse into the very complex poverty dynamics in urban areas in Sub-Saharan Africa, and their underlying socio-economic development processes. While these results give hope for a positive outlook in terms of (urban) extreme poverty reduction, future research would need to extend our analyses and zoom into the underlying mechanisms of the poverty dynamics we observe. The positive results in terms of upward mobility for relatively poorer household might be due to economic growth, but potentially supported by effective poverty reduction interventions. Such positive shocks could be included in the analyses to examine to what extent they escort households onto the upward trajectory of well-being or prevent a renewed descent. Lastly, we are yet to understand how these poverty trap dynamics may change in light of adverse negative shocks, such as more frequent and severe climate shocks in urban areas. This will be left to future research. Last but certainly not least, Nigeria and Tanzania serve as unique case studies for urban analyses due to the large urban sample. However, our increasingly urbanised world is not yet adequately reflected in data collection efforts and poverty measures (Lucci et al., 2018). Once again, we have to end our paper calling for better, more timely and nuanced data on urban areas, and for the inclusion of under-represented geographical areas like informal settlements. The limited spatial disaggregation and urban coverage in household surveys thus far, especially in the Global South, do not do justice to the importance of eradicating extreme poverty as stipulated by SDG 1, given growing concerns about a rising share of urban poverty. Urban data collection efforts thus need to be scaled up to allow for future research around understanding and developing effective solutions to the complexity of urban poverty.

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A Appendix

The survey rounds from the General Household Survey and National Panel Survey coincide for the GHS 2010 and 2012 (waves 1 and 2) as well as NPS 2010 and 2012 (waves 2 and 3), with one wave prior for Tanzania, and one wave afterwards for Nigeria. In Nigeria, households are surveyed twice per year, in the form of a post-planting, as well as a post-harvest visit. We only use the post-planting survey from the GHS due to the better time alignment of data collection with the NPS from Tanzania, as both surveys start between August and October (see Table 1). In our main analysis, we use the 2010 and 2012 time periods for better comparability of the data and results, but use all three survey waves for the estimations of dynamic panel models in Section 5.

In contrast to the GHS in Nigeria, the Tanzania NPS tracks split-off households. When a household member leaves its original household, they will be tracked and interviewed together with the new household in subsequent survey waves, and the household is then added into the sample. While any resulting sampling bias could be corrected by weighting the data, this process creates many duplicate observations for preceding survey rounds. Hence, we only keep these so-called parent households, which is also better aligned with the data structure of the GHS in Nigeria.

Moreover, we need to ensure that our main variable of interest, consumption, is comparable across countries and time. Although Living Standard Measurement Study (LSMS) products are not strictly standardised but allow for contextual adaptation of the surveys (Grosh & Glewwe, 1998), sampling and questionnaires are largely consistent (see Table 8 in Appendix B). The consumption modules collect comprehensive data through an extensive range of questions which are similar across countries, and are already aggregated for easier usage by the LSMS team. Generally, they consist of four different components, namely food, non-food, education (and rent, in the case of Nigeria) expenditures. To ensure maximum comparability between the consumption aggregates of Nigeria and Tanzania, we employ some additional adjustments. For instance, we add rent expenditures to the consumption aggregate from the Tanzania NPS to make it comparable to the data of Nigeria, as rent may represent a significant share of expenditures in urban areas.

Finally, we calculate per capita consumption using household size and adjust prices by converting them into 2011 Purchasing Power Parity (PPP) International Dollars. Even though there may be significant regional price differences at the national level, we do not apply any spatial adjustment of consumption, as we assume those differences to be marginal across urban areas. Lastly, we adjust remaining extreme outliers in sub-components of the consumption aggregate (i.e., food and beverages, alcohol and tobacco, utilities, health, transport, communication, recreation, education, rent and other household expenditures) by replacing values larger than five standard deviations above the mean with the median value at the state (region) level.

B Appendix

Table 7: Summary statistics

	Nigeria	Tanzania	Difference
Household size	5.06	4.62	0.44***
	(0.11)	(0.10)	(0.15)
Dependency ratio	0.89	0.78	0.10*
	(0.03)	(0.04)	(0.05)
Age of HH head	49.54	44.36	5.18***
	(0.65)	(0.86)	(1.08)
Female HH head (%)	0.18	0.29	-11.19***
	(0.02)	(0.02)	(0.02)
HH head literate (%)	0.80	0.89	-9.13***
	(0.02)	(0.01)	(0.02)
HH head ever went to school (%)	0.83	0.89	-6.03**
	(0.02)	(0.02)	(0.02)
Years education HH head	8.38	6.88	1.51***
	(0.29)	(0.17)	(0.36)
Households cultivating land (%)	23.45	34.79	-11.32**
	(0.03)	(0.04)	(0.05)
Consumption per capita and day (USD)	3.97	5.16	-1.19***
	(0.12)	(0.20)	(0.24)
Share food of tot. consumption (%)	61.67	65.12	-3.45**
	(0.01)	(0.01)	(0.01)
Share non-food of tot. consumption (%)	20.67	26.19	-5.52***
	(0.01)	(0.01)	(0.01)
Share education of tot. consumption (%)	9.41	5.47	3.94***
	(0.01)	(0.00)	(0.01)
Share rent of tot. consumption (%)	8.25	3.21	5.04***
	(0.00)	(0.00)	(0.00)

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: All values are baseline values from 2010. They are calculated using survey weights and thus representative of the urban population in the respective country. Differences refer to the difference in population means between Nigeria and Tanzania.

Table 8: Overview: key variables

Group	Variable	Nigeria	Tanzania
HH Characteristics	HH size	Definition of household: A household is a group of people who have usually slept in the same dwelling and share their meals together.	Definition of household: A household comprised all members of the immediate (nuclear) family who normally live and eat their meals together.
HH Characteristics	Dependency ratio	The dependency ratio is calculated as the number of household members aged 0-15 and 65+ divided by the number of household members aged 16-64.	The dependency ratio is calculated as the number of household members aged 0-15 and 65+ divided by the number of household members aged 16-64.
HH Characteristics	Age HH head	In what day, month and year was [NAME] born? and the answer to "What is [NAME]'s relationship to the head of household?" is "Head"[12].	In what month and year was [NAME] born? and the answer to "What is [NAME]'s relationship to the head of household?" is "Head".
HH Characteristics	Female HH head	Female head of household if the answers to "What is the sex of [NAME]?" is "Female".	Female head of household if the answers to "Sex" is "Female".
HH Characteristics	HH head literate	Can you read and write in any language? (Yes/No)	Can [NAME] read and write? (Kiswahili/English/Kiswahili & English/Any other language/No)
HH Characteristics	HH head ever went to school	Have you ever attended school? (Yes/No)	Did [NAME] ever go to school? (Yes/No)
HH Characteristics	Years education HH head	What is the highest educational level you completed? (grades based on the Nigerian school system, translated into years of education)	What is the highest grade completed by [NAME]? (grades based on the Tanzanian school system, translated into years of education)

[12] The latter applies to all categories referring to the head of household.

Table 8 continued from previous page

Group	Variable	Nigeria	Tanzania
HH Characteristics	Land cultivation	Did a member of this household cultivate any land? (Yes/No)	Does anyone in the household cultivate any plot? (Yes/No)
Consumption	Aggregate	Aggregate consumption per capita and day composed of four categories: non-food, food, (imputed) rent and education expenditures.	Aggregate consumption composed of four categories: non-food, food, rent and education expenditures.
Consumption	Food[13]	Food consumption composed of the following components (measured as expenditures or the market value of food components purchased/consumed during the past 7 days): meals away from home; grains and flours; starchy roots, tubers and plantain; pulses, nuts and seeds; oil and fats; fruits; vegetables; poultry and poultry products; meat; fish and sea-food; milk and milk products; coffee, tea, cocoa and the like beverages; sugar, sweets and confectionary; other miscellaneous foods; non-alcoholic drinks; alcoholic drinks (bottle and can).	Food consumption composed of the following components (measured as expenditures or the market value of food components purchased/consumed during the past 7 days): food consumption outside the household; cereal and cereal products; starches; sugar and sweets; pulses (dry); nuts and seed; vegetables; fruits; meat, meat products and fish; milk and milk products; oil and fats; spices and other foods; beverages.

[13]Household questionnaires provide a more detailed breakdown of food items included in this category.

Table 8 continued from previous page

Group	Variable	Nigeria	Tanzania
Consumption	Non-Food[14]	Non-food consumption composed of the following components (measured as expenditures on components during the past 7 days, past month, past 6 months or past 12 months): water; electricity; firewood; kerosene; other liquid fuels; refuse, sewage collection, disposal and other services; clothing and footwear; furnishings and routine household maintenance; maintenance and repairs of dwelling unit; domestic household services; petrol; diesel; fares; other transportation; communication (postal and telephone); recreation and culture; health; other insurance excluding education and health; expenditures on frequent non-food not mentioned elsewhere.	Non-food consumption composed of the following components (measured as expenditures on components during the past 7 days, past month, past 6 months or past 12 months): water; electricity; firewood; kerosene; other liquid fuels; refuse, sewage collection, disposal and other services; clothing and footwear; furnishings and routine household maintenance; maintenance and repairs of dwelling unit; domestic household services; petrol; diesel; fares; other transportation; communication (postal and telephone); recreation and culture; health; other insurance excluding education and health; expenditures on frequent non-food not mentioned elsewhere.
Consumption	Education	How much was spent on your education in the last 12 months by members of your household? (school fees and registration; contributions to school repairs, parents-teachers association; uniforms and sports clothes; books and school supplies, transportation to and from school; food, board and lodging at school; extra-tuition (extra classes); other expenses cash and in kind).	How much was spent on [NAME]'s education in the last 12 months by members of your household) (school fees; books and materials; uniform; transport; extra-tuition; other contributions).
Consumption	Rent	Over the past 30 days, how much did your household pay for house rent?	How much does this household pay per month to rent this dwelling?

[14]Household questionnaires provide a more detailed breakdown of non-food items included in this category.

Table 9: OLS fixed effects regression, full output

	Nigeria		Tanzania		Both	
	(1)	(2)	(3)	(4)	(5)	(6)
	Δ Cons.	Δ Cons.	Δ Cons.	Δ Cons.	Δ Cons.	Δ Cons.
Log Consumption (t-1)	-0.57***	-0.66***	-0.52***	-0.54***	-0.58***	-0.66***
	(0.06)	(0.07)	(0.17)	(0.19)	(0.06)	(0.07)
Log Consumption (t-1) Squared	0.04	0.02	0.07	0.03	0.04	0.01
	(0.06)	(0.07)	(0.11)	(0.12)	(0.05)	(0.06)
Log Consumption (t-1) Cubic	-0.00	-0.00	-0.01	-0.00	0.00	0.01
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
Household Size		-0.04***		-0.01		-0.03***
		(0.01)		(0.01)		(0.01)
Dependency Ratio		-0.12***		-0.08***		-0.12***
		(0.03)		(0.03)		(0.02)
Female HH Head		-0.01		0.03		-0.00
		(0.05)		(0.04)		(0.04)
Age HH Head		0.00*		-0.00		0.00
		(0.00)		(0.00)		(0.00)
Years Education HH Head		0.02***		0.01		0.02***
		(0.01)		(0.01)		(0.01)
HH Cultivates Land		-0.07		-0.07		-0.07
		(0.05)		(0.05)		(0.04)
Country (TZA)					0.18	0.24
					(0.18)	(0.16)
Missing Controls	No	Yes	No	No	No	Yes
Country FE	No	No	No	No	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.37	0.42	0.27	0.29	0.36	0.41
Observations	1271	1266	820	820	2091	2086

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: Time period: 2010-2012. Dependent variable: Δ Consumption ($lnC_t - lnC_{t-1}$). Control variables are defined as baseline values. Standard errors are clustered at the primary sampling unit (enumeration area) level. Consumption reflects daily per capita consumption based on household size, measured in International Dollars at 2011 Purchasing Power Parity (PPP) and transformed into natural logarithms. In pooled regressions (columns (5) and (6)) adjusted survey weights are applied according to the population size of the respective country and year using the formula $weight\_adj_{it} = weight_{it} * population_t / sum(weight_{it})$.

Table 10: Dynamic panel models, full output

	Nigeria		Tanzania	
	(1)	(2)	(3)	(4)
	Δ Cons.	Δ Cons.	Δ Cons.	Δ Cons.
Log Consumption (t-1)	-0.96***	-0.93***	-1.26***	-1.24***
	(0.10)	(0.09)	(0.27)	(0.27)
Log Consumption (t-1) Squared	0.05	0.04	0.30	0.28
	(0.09)	(0.09)	(0.19)	(0.19)
Log Consumption (t-1) Cubic	0.02	0.01	-0.05	-0.05
	(0.02)	(0.02)	(0.04)	(0.04)
Household Size		-0.13***		-0.11***
		(0.01)		(0.02)
Dependency Ratio		-0.05		-0.08*
		(0.03)		(0.04)
Female HH Head		-0.11		0.04
		(0.07)		(0.11)
Age HH Head		-0.00		0.01
		(0.00)		(0.00)
Years Education HH Head		0.03***		0.08***
		(0.00)		(0.01)
HH Cultivates Land		-0.11		-0.03
		(0.07)		(0.07)
Nr. of Instruments	8	16	8	15
Household Control Instruments	No	Yes	No	Yes
Year Instruments	Yes	Yes	Yes	Yes
Hansen J Statistic (Overidentification)	1.51	2.02	.40	.65
Prob > chi-squared	.68	.57	.94	.89
Observations	2542	2542	1640	1640

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: Dependent variable: Δ Consumption ($lnC_t - lnC_{t-1}$). Consumption reflects daily per capita consumption based on household size, measured in International Dollars at 2011 Purchasing Power Parity (PPP) and transformed into natural logarithms.

Table 11: Dynamic panel models, rural areas

	Nigeria (Rural)		Tanzania (Rural)		Nigeria (Rural-Urban)		Tanzania (Rural-Urban)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Δ Cons.	Δ Cons.	Δ Cons.	Δ Cons.	Δ Cons.	Δ Cons.	Δ Cons.	Δ Cons.
Log Consumption (t-1)	-0.89***	-0.93***	-0.93***	-0.92***	-0.92***	-0.94***	-0.93***	-0.91***
	(0.06)	(0.04)	(0.10)	(0.09)	(0.06)	(0.04)	(0.11)	(0.10)
Log Consumption (t-1) Squared	0.04	0.02	-0.07	-0.07	0.05	0.03	0.04	-0.00
	(0.04)	(0.03)	(0.13)	(0.10)	(0.04)	(0.03)	(0.12)	(0.11)
Log Consumption (t-1) Cubic	-0.00	-0.00	0.08*	0.06*	-0.00	-0.00	0.01	0.01
	(0.01)	(0.01)	(0.04)	(0.04)	(0.01)	(0.01)	(0.03)	(0.03)
Urban Sample					0.42***	0.16***	0.68***	0.49***
					(0.03)	(0.03)	(0.05)	(0.06)
Household Size		-0.13***		-0.08***		-0.13***		-0.09***
		(0.01)		(0.01)		(0.01)		(0.01)
Dependency Ratio		-0.06***		-0.11***		-0.05***		-0.10***
		(0.02)		(0.03)		(0.02)		(0.02)
Female HH Head		0.01		-0.16**		-0.05		-0.11
		(0.08)		(0.08)		(0.05)		(0.07)
Age HH Head		-0.00		-0.00		-0.00		0.00
		(0.00)		(0.00)		(0.00)		(0.00)
Years Education HH Head		0.04***		0.04***		0.04***		0.05***
		(0.00)		(0.01)		(0.00)		(0.01)
HH Cultivates Land		-0.01		0.02		-0.05		0.00
		(0.06)		(0.08)		(0.04)		(0.06)
Nr. of Instruments	8	16	8	15	9	17	9	16
Household Control Instruments	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Instruments	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hansen J Statistic (Overidentification)	8.56	5.43	8.18	6.77	16.26	10.20	9.46	8.97
Prob > chi-squared	.04	.14	.04	.08	.00	.02	.02	.03
Observations	5944	5944	3598	3598	8486	8486	5238	5238

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

Note: Dependent variable: Δ Consumption ($lnC_t - lnC_{t-1}$). Consumption reflects daily per capita consumption based on household size, measured in International Dollars at 2011 Purchasing Power Parity (PPP) and transformed into natural logarithms.

Table 12: Dynamic panel models, robustness checks

	Nigeria				Tanzania			
	(1) Trim 1%	(2) Trim 5%.	(3) With Outliers	(4) Food Cons.	(5) Trim 1%	(6) Trim 5%.	(7) With Outliers	(8) Food Cons.
Log Consumption (t-1)	-0.83***	-0.93***	-0.90***		-1.34***	-1.36***	-0.91***	
	(0.13)	(0.21)	(0.11)		(0.28)	(0.29)	(0.12)	
Log Consumption (t-1) Squared	0.03	0.08	0.07		0.41**	0.49**	0.07	
	(0.13)	(0.24)	(0.08)		(0.20)	(0.22)	(0.09)	
Log Consumption (t-1) Cubic	-0.02	-0.04	-0.01		-0.08*	-0.11**	-0.01	
	(0.04)	(0.07)	(0.02)		(0.04)	(0.05)	(0.02)	
Log Food Cons. (t-1)				-0.93***				-1.04***
				(0.06)				(0.18)
Log Food Cons. (t-1) Squared				0.04**				0.13
				(0.02)				(0.23)
Log Food Cons. (t-1) Cubic				0.01				-0.03
				(0.01)				(0.07)
Household Size	-0.12***	-0.12***	-0.13***	-0.14***	-0.11***	-0.12***	-0.13***	-0.10***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)
Dependency Ratio	-0.06**	-0.05*	-0.06*	-0.04	-0.05	-0.09**	-0.06*	-0.06
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)	(0.05)
Female HH Head	-0.14*	-0.19***	-0.04	-0.15*	0.02	-0.01	-0.05	0.07
	(0.07)	(0.06)	(0.09)	(0.08)	(0.11)	(0.13)	(0.09)	(0.13)
Age HH Head	0.00	0.00	0.00	0.00	0.01	-0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)
Years Education HH Head	0.03***	0.03***	0.03***	0.02***	0.07***	0.05***	0.03***	0.06***
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
HH Cultivates Land	-0.10	-0.09	-0.12*	-0.15**	-0.05	-0.03	-0.11*	-0.08
	(0.07)	(0.07)	(0.07)	(0.08)	(0.07)	(0.06)	(0.07)	(0.09)
Nr. of Instruments	16	16	16	16	15	15	15	15
Household Control Instruments	No	No	No	No	No	No	No	No
Year Instruments	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hansen J Statistic (Overidentification)	5.07	12.03	1.54	5.54	4.88	15.89	1.33	3.64
Prob > chi-squared	.17	.01	.67	.14	.18	.00	.72	.30
Observations	2490	2286	2542	2542	1607	1476	2542	1640

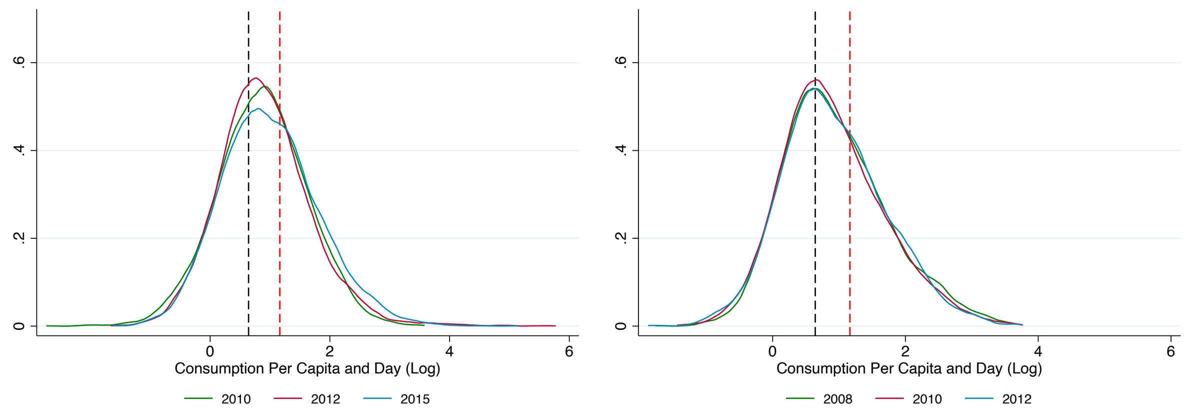
Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: Dependent variable: Δ Consumption ($lnC_t - lnC_{t-1}$). Consumption reflects daily per capita consumption based on household size, measured in International Dollars at 2011 Purchasing Power Parity (PPP) and transformed into natural logarithms.

C Appendix

Figure 6: Kernel density graphs: daily per capita consumption

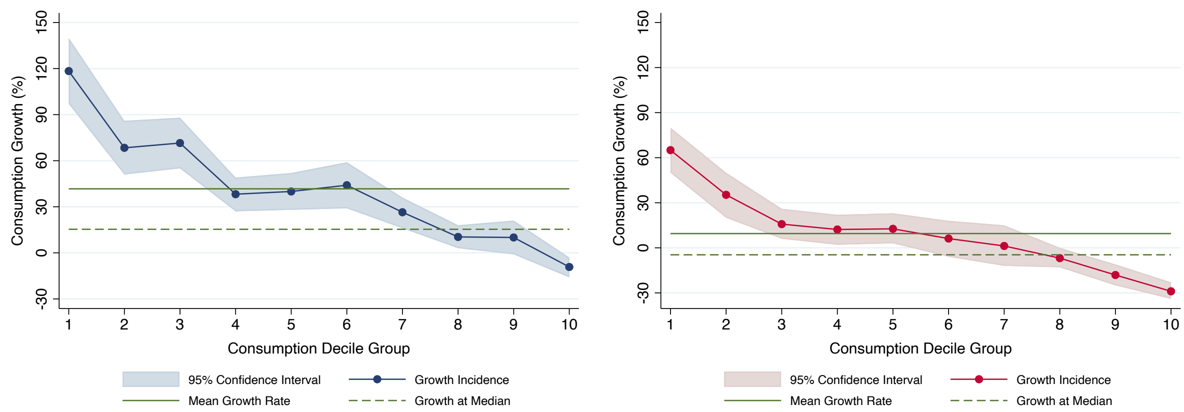
(a) Nigeria **(b)** Tanzania



Note: Consumption at 2011 Purchasing Power Parity (PPP) is expressed in natural logarithms. The black dashed line shows the \$1.90, and the red dashed line the \$3.20 International Poverty Lines, respectively.

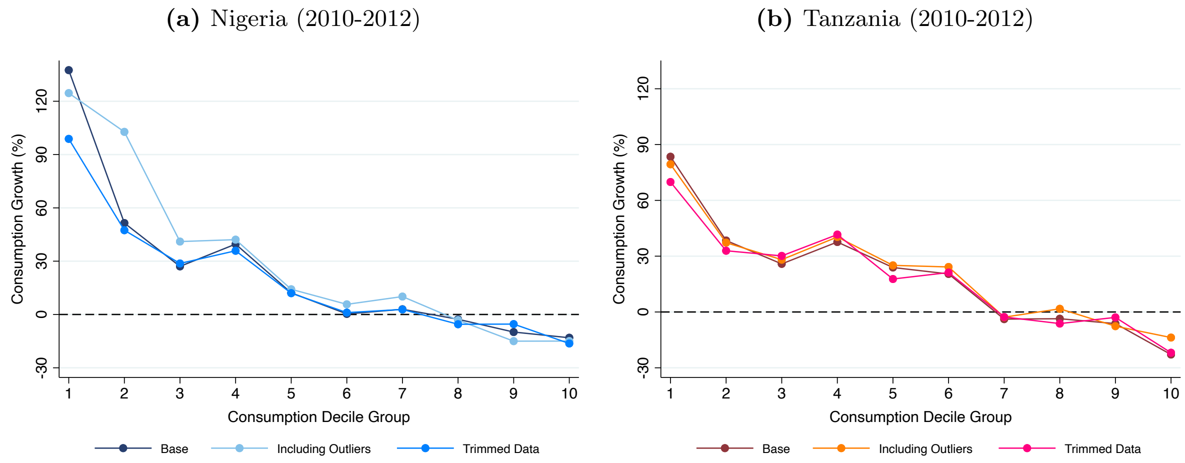
Figure 7: Growth incidence curves, extended time periods

(a) Nigeria (2012-2015) **(b)** Tanzania (2008-2010)



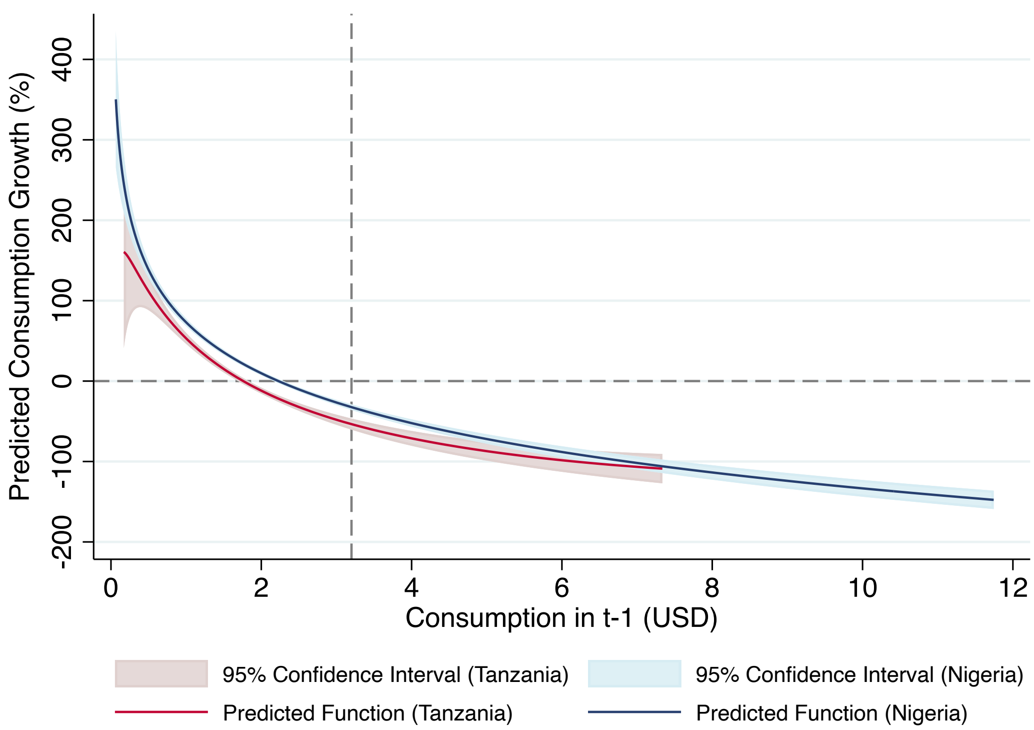
Note: Weighted mean consumption growth per consumption decile group. Consumption deciles have been calculated using observed consumption values in International Dollars at 2011 PPP and survey weights.

Figure 8: Growth incidence curves, robustness checks



Note: Weighted mean consumption growth per consumption decile group in 2010, consumption growth between 2010 and 2012. Consumption deciles have been calculated using observed consumption values in International Dollars at 2011 PPP and survey weights from 2010. The base specification excludes outliers by replacing values in sub-components of the consumption aggregate that are larger than five standard deviations above the mean with its median value at the district level. For the trimmed data, consumption values below the 1^{st} and above the 99^{th} percentile are excluded.

Figure 9: Marginal predictions of consumption growth, rural areas



Note: Consumption is measured in International Dollars at 2011 Purchasing Power Parity (PPP). For better visualisation, the graph only shows values of the consumption distribution until the 99^{th} percentile for both countries.

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