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Marta Schoch
(World Bank)
mschoch@worldbank.org

Jonathan Lain
(World Bank)
jlain@worldbank.org

Tara Vishwanath
(World Bank)

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Jonathan Lain
Marta Schoch
Tara Vishwanath

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Abstract

Issues of data availability and incomparability in the measurement of household consumption arise frequently when measuring poverty trends over time. Yet, understanding these trends is key to guide national and international policy makers in their poverty reduction efforts. This paper aims to estimate a long-run poverty trend for Nigeria, a country whose poverty trends are crucial for regional and global estimates. In 2020, the Nigerian National Bureau of Statistics released the first official poverty estimates for Nigeria in almost a decade, calculated using the 2018/19 Nigerian Living Standards Survey. Yet the official poverty estimates from the 2018/19 Nigerian Living Standards Survey cannot technically be compared with those from the 2009/10 Harmonized Nigerian Living Standards Survey—the previous official household consumption survey—given key differences in the way household consumption was measured and concerns around data quality in the 2009/10 survey. To address this challenge, this paper uses two distinct methodologies to construct a poverty trend for Nigeria in the decade before the COVID-19 crisis. First, it uses sector-level gross domestic product growth rates combined with microdata from the 2018/19 Nigerian Living Standards Survey to "backcast" poverty rates back to 2009. Second, it uses survey-to-survey imputation methods and data collected throughout the decade through the General Household Survey panel. Despite their very different foundations, these two approaches produce very similar results, suggesting that there was a small reduction in poverty at the beginning of the decade, followed by a period of stagnation or even a slight uptick in poverty following the 2016 economic recession. The paper estimates a poverty rate of between 42.2 and 46.3 percent in 2009, translating into a reduction in the poverty headcount rate of between 3 and 7 percentage points between 2009 and 2018/19.

This paper is a product of the Poverty and Equity Global Practice. It is part of a larger effort by the World Bank to provide open access to its research and make a contribution to development policy discussions around the world. Policy Research Working Papers are also posted on the Web at http://www.worldbank.org/prwp. The authors may be contacted at jlain@worldbank.org or mschoch@worldbank.org.

Estimating a Poverty Trend for Nigeria between 2009 and 2019

Jonathan Lain, Marta Schoch, and Tara Vishwanath[1]

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[1] All authors are with the World Bank. Corresponding authors: Jonathan Lain (jlain@worldbank.org) and Marta Schoch (mschoch@worldbank.org). The authors are extremely grateful for guidance received from Dean Jolliffe, Christoph Lakner, Berk Ozler, Aibek Baibagysh Uulu, Nobuo Yoshida, Paul Corral, Roy Van der Weide, Shinya Takamatsu, and the members of the Global Poverty Working Group. The authors gratefully acknowledge financial support from the UK government through the Data and Evidence for Tackling Extreme Poverty (DEEP) Research Programme.

1. Introduction

Measuring poverty trends is a complex exercise that requires data on household welfare that can be compared over time. Limited availability of household-level data and changes, or improvements, to the methodology used to measure household consumption can affect the comparability of survey-based poverty estimates. These issues arise frequently in poverty measurement exercises (Deaton, 2005; Beegle et al. 2012) and can severely limit the availability of evidence needed to guide policies for reducing poverty.

This paper considers this issue in the context of Nigeria and seeks to understand the country's poverty dynamics for the period between 2009 and 2019. Nigeria contains the largest number of extreme poor – that is, those living below the international poverty line of US$1.90 per person per day – in Sub-Saharan Africa, the world's poorest region (World Bank, 2020). As such, understanding poverty trends in the country is crucial to inform policy at the country, regional, and global levels. Moreover, Nigeria has faced a series of compounding negative shocks to households' well-being: even prior to the COVID-19 pandemic, the country suffered frequent conflict and climate shocks, as well as a deep recession following the collapse of global oil prices 2016. These crises are likely to have affected Nigeria's progress towards poverty reduction.

Despite its high levels of poverty and its importance for regional and global poverty reduction, the household data needed to measure poverty have not been collected frequently in Nigeria over the past decade. In 2020, the Nigerian National Bureau of Statistics (NBS) released the first official poverty estimates in the country in almost a decade, calculated using data from the 2018/19 Nigerian Living Standards Survey (NLSS; see NBS 2020). The 2018/19 estimates show that 39.1 percent of Nigerians lived below the international poverty line of US$1.90 per person per day, corresponding to 78.5 million people (Castaneda et al., 2020).[2] While the 2018/19 estimates provide a crucial "snapshot" of the state of poverty just before the COVID-19 crisis, they do not provide information on poverty *trends* in Nigeria. Prior to the 2018/19 NLSS, the last official poverty estimates for Nigeria came from the 2009/10 Harmonized Nigerian Living Standards Survey (HNLSS), but given crucial differences in the methodology used to collect

[2] Poverty measured at the US$1.90 poverty line using World Development Indicators for population data (available at https://data.worldbank.org/indicator/SP.POP.TOTL?locations=NG). This estimate differs from the population estimate used by the Nigerian NBS (see Data section and Table 16 for a comparison). Poverty headcount rates are expressed at the international poverty line of US$1.90 per person per day unless otherwise stated.

consumption data in the two surveys and concerns around data quality in the 2009/10 survey, it is not possible to simply compare them to construct a trend and understand the country's poverty dynamics.[3]

This paper aims to address this issue by estimating a poverty trend in Nigeria for the period 2009-2019 through two separate approaches, which leverage different data sources. First, the paper presents the results of a "backcasting" exercise that uses the latest survey estimates of household consumption from the 2018/19 NLSS and sectoral GDP growth rates for the previous decade. Second, the paper uses survey-to-survey imputation methods: a simple model linking monetary and non-monetary variables is estimated with the 2018/19 NLSS and is used to impute into another household survey – the General Household Survey (GHS) – available in 2010/11, 2012/13, 2015/16, and 2018/19. One key contribution of the paper is that the results from these two alternative and very distinct approaches are robust and similar in magnitude. While both approaches carry certain caveats (see section 7.2 for an extensive discussion), the survey-to-survey imputation methods can offset some of the limitations of the backcasting exercise and vice versa.

The backcasting exercise maps macroeconomic data on sectoral real GDP growth rates to micro-data from the 2018/19 NLSS – via the household head's sector of employment – then constructs estimates of the full consumption distribution for each year in the decade prior to 2018/19. This household consumption vector can then be used to calculate the share of the population living in poverty, defined using different poverty lines, for all years between 2009 and 2019. Using this backcasting approach, we estimate a poverty rate of between 42.2 and 46.3 percent in 2009, depending on the assumptions made about the pass-through rate from national accounts growth data to household consumption. The backcasted series suggests a small decrease in the poverty rate at the beginning of the decade and then stagnation, or even reversal, in poverty reduction following the 2016 recession. Qualitatively, these results remain unchanged even after running sensitivity analysis to test different assumptions about the pass-through rate and about the mapping between micro- and macro-data.

The survey-to-survey imputation approach constructs a consumption model using a set of comparable non-monetary variables, which are available in both the 2018/19 NLSS and the GHS, to impute consumption into the 2010/11, 2012/13, 2015/16, and 2018/19 waves of the GHS. This approach follows a wide literature on survey-to-survey imputation techniques (Christiaensen et al. 2012; Dang et al. 2017; Douidich et al. 2016; Newhouse et al. 2014; Stifel and Christiaensen 2007; Yoshida et al. 2015; Yoshida et

[3] For a discussion on data quality concerns around the 2009/10 HNLSS surveys, see Nigeria Poverty Assessment 2016.

al. 2020). The Nigerian data landscape presents two key advantages for survey-to-survey imputation techniques. First, while the GHS and NLSS differ in their data collection schedules, a wide range of non-monetary variables were collected in exactly the same way in both surveys. Second, it is possible to check the comparability of the two surveys using data from the 2018/19 wave of the GHS, the timing of which partly overlaps with the data collection for the 2018/19 NLSS. The results of this analysis produce a poverty rate of about 44 percent for 2010/11, very close to the backcasted estimates of 42.8 (2010) and 41.8 (2011) percent. The imputed estimates for 2012/13 and 2015/16 suggest that poverty declined slightly until the 2016 recession, after which poverty stagnated or even increased: this is also entirely in line with the backcasted results. Changing the variables included in the consumption model does not substantially change this story, confirming the robustness of the results.

The finding that poverty decreased slightly in the first part of the 2010s, but subsequently stagnated is in stark contrast with the 17-percentage point drop in poverty suggested by simply comparing the estimates from the 2009/10 HNLSS and 2018/19 NLSS. The evidence presented in this paper should therefore encourage caution when using incomparable survey-based measures of household consumption for poverty measurement purposes. In the case of Nigeria, drawing a trend between the 2009/10 HNLSS and 2018/19 NLSS would impact not only the policy discussion on poverty reduction at the national level, but also any analysis of poverty trends in West Africa, Sub-Saharan Africa as a whole, and – as poverty becomes more concentrated in Sub-Saharan Africa and in conflict-affected situations – potentially the entire world (World Bank, 2020).

The paper is organized as follows. Section 2 provides general information on the country context and on Nigeria's data landscape. Section 3 explains the data used in the analysis. Section 4 outlines the two methodologies used to estimate poverty trends for Nigeria. Section 5 presents the main results. Section 6 describes a series of robustness checks. Section 7 discusses the implications of these findings and possible caveats of this analysis. Section 8 concludes.

2. Context

Nigeria is Africa's most populous country, with over 200 million people, and Africa's largest economy, with a nominal gross domestic product (GDP) of around US$450 billion (in 2019). At the same time, with around 4 in 10 Nigerans living poverty, Nigeria has the largest population of extreme poor people – those living on less than US$1.90 per person per day – in Sub-Saharan Africa and the second largest population of extreme poor people in the world. Therefore, Nigeria's importance for regional and global poverty reduction efforts cannot be overstated.

Nigeria suffered from slow growth and a series of shocks, even before the arrival of the COVID-19 crisis. Nigeria has consistently been affected by climate shocks, especially for farmers relying on rain-fed agriculture and livestock herders, as well as conflict, especially for communities in the north of the country, for several decades. In 2016, the collapse of global oil prices pushed Nigeria into recession, with real GDP dropping by 1.6 percent, given Nigeria's continued dependence on oil: fuel has made up more than 80 percent of exports since the 1970s. Growth remained subdued during the 2017-2019 period, below the growth rate of peer economies and the rate of population growth, resulting in a steady decline in per capita incomes. The onset of the COVID-19 pandemic and the corresponding drop in global oil prices has only weakened Nigeria's macroeconomy further, with real GDP dropping 1.8 percent in 2020.

Despite Nigeria's size and its importance for regional and global poverty reduction, the infrequent availability of survey data on household welfare makes it difficult to track how poverty evolved in the country in the decade before the COVID-19 crisis. The two most recent official household surveys used for poverty measurement, the 2009/10 HNLSS and the 2018/19 NLSS, capture household consumption very differently and therefore produce incomparable poverty estimates. In particular, the module used to collect information on food consumption was changed from a daily diary, handed to enumerators during four visits over the course of one month, in the 2009/10 HNLSS, to a seven-day recall, in the 2018/19 NLSS. Additionally, the approaches for measuring meals outside the home and own-produced food were changed between the two surveys. Key non-monetary variables were also collected differently in the 2009/10 HNLSS. Evidence suggests that changes to the survey questions used to capture consumption can alter poverty estimates considerably (Deaton 2005, Beegle at al. 2012). The poverty headcount rate estimated using the 2009/10 HNLSS is 56.4 percent. Given these differences, it would be erroneous to compare this estimate with the latest poverty headcount rate of 39.1 percent estimated using data from the 2018/19 NLSS.[4,5] This paper explores other analytic solutions to fill this gap and finds alternative methods to estimate a long-run poverty trend in Nigeria.

[4] Beyond changes in the consumption module, the data collection for the 2018/19 NLSS has substantially improved compared to previous years (detailed survey documentation can be found in the World Bank Microdata Library available here: https://microdata.worldbank.org/index.php/catalog/3827/related-materials). Among other improvements, the 2018/19 NLSS switched to CAPI allowing for better real-time monitoring of data collection.

[5] The regional and global poverty estimates currently published by the World Bank are based on an interpolated poverty trend between these two estimates for Nigeria. In effect, this trend erroneously compares the two estimates and results in estimating a drop of around 17 percentage points in Nigeria over the decade between 2009 and 2019. The evidence presented in this paper unveils a much lower reduction in poverty and stresses the importance of collecting frequent and comparable data when measuring poverty over time.

We exploit other data sources that are available in Nigeria to estimate a long-run poverty trend for the country. First, *sectoral* real GDP data are available from NBS: this allows the backcasts to be done with more granularity than if only *total* real GDP growth estimates were available.[6,7] Second, household survey data from the GHS panel are available for four waves: 2010/11, 2012/13, 2015/16 and 2018/19 (see Section 3 for more detail on the GHS data). These data lend themselves to survey-to-survey imputations as they collect household-level information on non-monetary indicators in the same way as in the 2018/19 NLSS. The two surveys not only had identical questionnaires for these non-monetary indicators, but they were also collected by the same team and followed the same methodology as part of an ongoing NBS-World Bank collaboration, therefore minimizing discrepancies driven by survey methodology and implementation. Moreover, the timing of data collection for the 2018/19 NLSS and 2018/19 GHS overlapped, so it is possible to test whether the imputed consumption and poverty estimates are well aligned with *actual* consumption and poverty estimates from a similar period.

While the GHS also collects data on household consumption, these data are subject to a series of limitations that do not allow them to be used directly for poverty measurement purposes.[8] In particular, the early rounds of the GHS imposed standard units (such as grams on kilograms) on quantities in the food consumption module when non-standard units may have been more appropriate: this was addressed in later rounds of the GHS. However, this issue does not affect the non-monetary indicators in the GHS, on which survey-to-survey imputation techniques rely.

3. Data

The analysis uses four data sources. Household-level data on consumption and non-monetary indicators come from the 2018/19 Nigerian Living Standards Survey (NLSS) and the General Household Survey (GHS) available over four waves in 2010/11, 2012/13, 2015/16, and 2018/19. National accounts and other macroeconomic data are taken from the World Bank MFM-MOD tool, which incorporates data from NBS, and from the World Development Indicators (WDIs).

[6] The World Bank's macroeconomic and fiscal model (MFMod) consists of individual country models for 181 countries. The models are used by country economists within the World Bank's Macroeconomics, Trade and Investment Global Practice to (i) generate country forecasts and (ii) simulate various policies.
[7] Backcasting poverty rates beyond 2009 proves challenging for two main reasons. First, the backcasting exercise relies on strong assumptions that are likely not to hold for a period longer than a decade. Second, sectoral GDP data for the early 2000s shows some inconsistencies and large year-on-year volatility, which could bias the backcasted poverty estimates.
[8] Moreover, the GHS survey is not representative at the state level, which makes it unsuitable to be used for official poverty measurement purposes.

The 2018/19 NLSS was conducted between September 2018 and October 2019 and was designed to provide estimates for a wide range of socioeconomic indicators – including consumption and poverty – for Nigeria's 36 states and the Federal Capital Territory (FCT), Abuja. The sample of around 22,000 households is representative at the national, zone, and state levels, aside from Borno state (which accounts for around 2.5 percent of the Nigerian population).[9] Although the sample is not explicitly stratified by urban and rural areas, it is possible to obtain urban and rural estimates from the NLSS data at the national level. The household questionnaire provides information on demographics, education, employment, food and non-food consumption, food security, shocks, safety nets, housing conditions, assets, information and communication technology, agriculture and land tenure, and other sources of household income. Overall estimates of household consumption were constructed using the modules on food and non-food consumption and spatially and temporally deflated using a price index constructed from unit prices in the food consumption module: this provides a consistent measure of welfare for the whole of Nigeria. From this, poverty estimates at the international poverty line of US$1.90 2011 PPP per person per day can be constructed by deflating over time using CPI data and converting to dollars using Purchasing Power Parities (PPP) (Atamanov et al. 2018, Lakner et al. 2018).

The backcasting exercise uses two sources of national accounts data. First, we use yearly data on sectoral (agriculture, industry, and services) GDP growth rates (available from the MFMod tool of the World Bank, see Burns et al. 2019) to backcast the 2018/19 consumption vector to 2009. Real GDP *levels* are expressed in constant local currency units – meaning that they have already been deflated by the GDP deflator – and are shown in Table *3*. Second, we use GDP and GNI data from the WDIs to estimate different pass-through rates between growth in the national accounts and in household consumption. These data on GDP and GNI growth rates are matched to survey-year estimates of average per-capita household monthly consumption available in PovcalNet (http://iresearch.worldbank.org/PovcalNet/home.aspx). The population data used in the main analysis, and for the purposes of global poverty monitoring, are also taken from the WDIs (available at https://data.worldbank.org/indicator/SP.POP.TOTL?locations=NG). However, we also provide estimates of the absolute number of poor people using NBS' population estimates.[10]

[9] Parts of Borno state became inaccessible over the course of the survey. This meant only 530 households were reached, so only 15 Local Government Areas (LGAs) were reached of 27 LGAs that were originally sampled.

[10] NBS' population estimates were used to construct the survey weights for the 2018/19 NLSS. Table 16 Table 16 shows how poverty estimates from this analysis differ when using WDI and NBS population data.

Lastly, the survey-to-survey imputation exercise uses household-level data on a range of non-monetary indicators from the GHS panel for Nigeria for 2010/11, 2012/13, 2015/16, and 2018/19. Each wave contains around 5,000 households, and is representative at the national, zone, and urban-rural level. Within each wave, data are collected in two distinct visits to the same set of households: the first "post planting" visit takes place sometime between August and October (of 2010 for the 2010/11 survey, for example) and the second "post-harvest" visit takes places sometime between January and April of the following year.[11] For the purpose of the survey-to-survey imputations, we use information on household demographic characteristics (dependency ratio), dwelling characteristics (main floors material, main source of cooking fuel, availability of toilet facility in the household), household head's demographics (age, gender) and employment indicators (employment in non-farm activities and in wage-employment), household assets ownership (TV set, air conditioner, generator, microwave, computer, cars and other vehicles, microwave, washing machine), and *frequency* of consumption – that is dummy variables for whether or not an item was consumed – for some food and non-food items (imported rice, beef, fresh fish, and recharge cards).

4. Methodology

This analysis uses two approaches to estimate a poverty trend for Nigeria for the period 2009-2019: backcasts and survey-to-survey imputations. This section describes these approaches in detail. One key contribution of the paper is that while the two methods described in this section are very different, they yield very similar results, as we show in section 5.

4.1. Backcasting

For the backcasting exercise, we start with the full consumption vector in the 2018/19 NLSS then construct the consumption vector in each previous year by "rolling back" consumption for each household using sectoral real GDP growth rates and population growth rates. The sectoral GDP data are already in real terms, having been adjusted using the GDP deflator: we therefore do not conduct any additional price adjustments to deflate the consumption vector in each year. Real sectoral GDP growth rates are converted to per capita terms by applying population growth "flat" to each sector: our approach does not, therefore, allow for sectoral switching. However, given the slow pace of structural transformation in Nigeria, this may be a tenable assumption over the period of interest.[12] We use the household head's employment

[11] Detailed documentation on the GHS survey can be found in the World Bank Microdata Library, see https://microdata.worldbank.org/index.php/catalog/1002.
[12] See Jenq, Lain, and Vishwanath (2021) https://pubdocs.worldbank.org/en/511161631652256763/pdf/Good-Jobs-for-a-New-Generation-Delivering-Quality-Jobs-for-Young-Nigerians-After-COVID-19.pdf.

sector to match the 2018/19 NLSS to real GDP growth rates in each sector. Those household heads whose sector could not be distinguished because the household contained multiple enterprises or those who were not working at all were assigned a weighted average of the per capita real GDP growth from agriculture, industry, and services.

The backcasted series starts by assuming that the 2018/19 NLSS effectively corresponds to 2019, for the purposes of mapping it to the macroeconomic data. This seems like a reasonable assumption since the data were collected between September 2018 and October 2019, covering two-thirds of 2019. We apply the growth rate between 2018 and 2019 to the survey estimate to backcast an estimate for 2018, then for 2017, and so on for all the other years until 2009.

The main formula for the backcasts can be written:

$$C_{t-1}^{s} = C_{t}^{s} \times (1 + g_{t-1}^{cons,s})$$

where $g_{t-1}^{cons,s} = pass \times g_{t-1}^{s} - p_{t-1}$

C^{s} is household consumption for households whose head is employed in sector s. $pass$ is the assumed pass-through rate value between growth in national accounts and in household consumption. g^{s} is real sectoral GDP growth in sector s. p is population growth.

The pass-through rate is initially assumed to be the same across sectors and across richer and poorer Nigerians.[13] The main results assume a pass-through rate of one, that is, they assume that growth in national accounts (in real, per capita terms) is fully passed onto household consumption. Nevertheless, sensitivity analysis, which applies different pass-through rates to check the robustness of the results, is presented in Section 6. The backcasted consumption vector is converted to US$ 2011 PPP terms to estimate poverty rates at the international poverty line.[14]

4.2. Survey-to-survey imputation

Survey-to-survey imputations use non-monetary indicators and household consumption data from a “baseline” or “training” survey to impute consumption into some “target” survey that contains the same non-monetary indicators. The survey-to-survey exercise is conducted in three main steps.

[13] This assumption is relaxed in Section 6, using “growth incidence curves” estimated using the survey-to-survey imputations.

[14] The CPI value is 2.34 (for 2018/19) and the 2011 PPP conversion factor is 83.58. For more details on the PPP and CPI data used for global poverty measurement, see Atamanov et al. (2018) and Lakner et al. (2018).

In the first step, we select a set of comparable non-monetary indicators that are available in both the NLSS and GHS (Table *2*). The advantage of using the NLSS and GHS is that the questionnaires on household characteristics, assets ownership, consumption frequency and demographics is the same and asked using the same recall periods (see Table *4*). Moreover, we can ensure comparability between the different indicators using data for from the 2018/19 NLSS and 2018/19 GHS. While the two surveys differ in their data collection schedule – with the 2018/19 GHS being collected in two visits in July-September 2018 and January-February 2019 and the 2018/19 NLSS being collected over 12 months – they provide information for part of the same year making it possible to check if the assumptions behind the survey-to-survey imputations are plausible. Column 3 in Table *2* shows the difference in means for each variable used in the survey-to-survey exercise and available in the 2018/19 NLSS and 2018/19 GHS. Zone population adjustments are applied to the 2018/19 GHS data to ensure that the zone-level population estimates match those from the 2018/19 NLSS. The indicators are overall highly comparable, with only a few variables – such as household head's employment variables and consumption frequency of food-items – showing larger differences possibly due to seasonal variation. In Section 6, we test the robustness of the results to different specifications of the consumption model that do not include this set of variables. Variables to be included in the consumption model are selected using stepwise selection with an optimal p-value of 0.01.

In the second step, we develop a consumption model using the selected variables and consumption data from 2018/19 NLSS. Variables used in the consumption model include regional dummies, demographics of the household (dependency ratio), household head characteristics (gender, employment category), living conditions (main source of cooking fuel, toilet availability), consumption frequency dummies (food and non-food items), asset ownership (air conditioning, washing machine, cars and other vehicles, generator, microwave, TV set, computer). The model therefore includes variables that capture short-run variation – such as employment and a set of dummy variables for whether certain food and non-food items were being consumed – as well as more stable household characteristics – such as location, demographics, housing amenities, and ownership of assets.[15] The model relies on the assumption that these indicators are highly correlated with poverty and explain a relatively large share of variation in poverty: the R-squared in all of the consumption models presented in this paper is at least 0.50.

[15] The analysis adopts a "SWIFT Plus" (Survey of Wellbeing via Instant and Frequent Tracking) approach to conduct the survey-to-survey imputation. This approach was developed to overcome possible limitations arising in case a large shock or crisis, as the 2015/16 oil price plunge in Nigeria, occurred between the baseline and target surveys. It consists of including variables that reflect households' current welfare status, such as employment, in the consumption model used in the imputations.

Specifically, we estimate the following regression:

$$y_{h,t} = \alpha X_{i,h,t} + \beta HH_{h,t} + \gamma Zone_t + \varepsilon_{h,t}$$

where $y_{h,t}$ is the natural logarithm of annual spatially adjusted household consumption expressed in local currency units for household h in time t. $X_{i,h,t}$is a vector of household head's characteristics, $Zone_t$ are geographical zone-areas dummy variables. The error term is drawn from a normal distribution. The results of this estimation are available in Table *5*.

In the third step, using the parameters estimated from this consumption model, we can impute consumption into the target survey and calculate the relevant poverty rates. The imputed consumption vector is estimated using 100 imputations. Table *6* shows the distribution of the imputed consumption vector and compares it to the distribution of the NLSS-based consumption aggregate.[16] The imputed consumption vector is then converted to US$ 2011 PPP to estimate poverty rates at different international poverty lines. We conduct the same exercise separately using data on the same non-monetary indicators from each wave of the GHS to impute consumption in 2010/11, 2012/13, 2015/16, and 2018/19.

5. Main results

The results of the backcasting and survey-to-survey imputation yield very similar results. Both show a decline in poverty in the first half of the decade followed by a period of stagnation – and even a slight increase – between the 2016 economic recession and 2019. The backcasted poverty series shows a decrease of at most 7 percentage points between 2009 and 2018/19, when using a pass-through rate of one. The survey-to-survey imputations show that poverty fell by around 3 percentage points between 2010/11 and 2015/16, but that progress towards poverty reduction has halted since then.

5.1. Backcasting

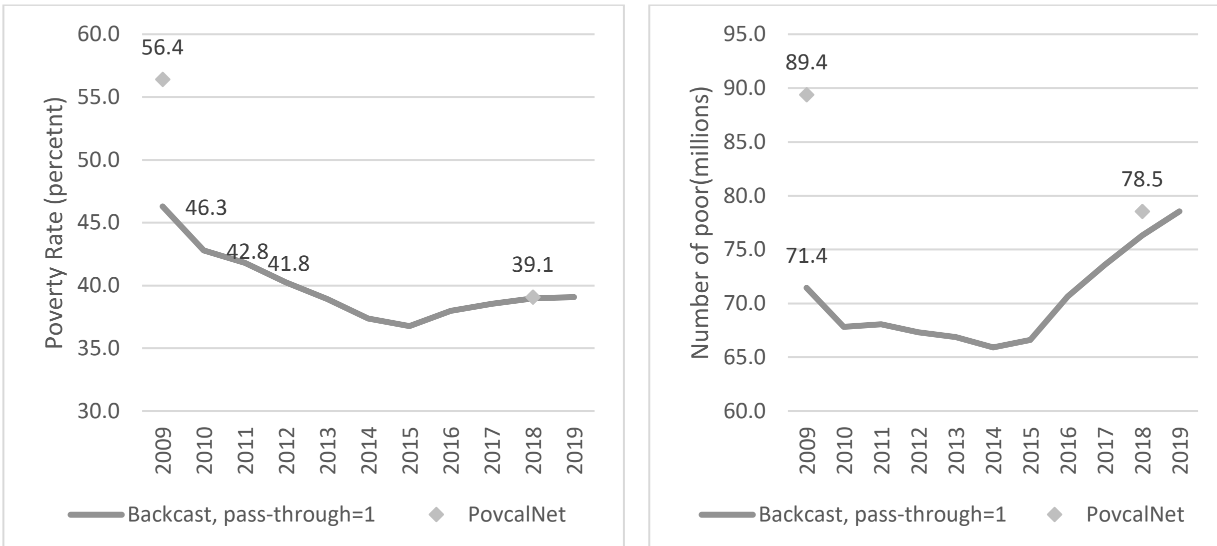
Figure 1 shows the backcasted trend in poverty headcount rates (Panel a) and number of poor (Panel b) at the US$1.90 poverty line for the period 2009-2019, assuming a pass-through rate of one, that is, the growth rate in sectoral GDP is assumed to be the same as the growth rate in household consumption. The backcasts suggest that poverty rates were considerably lower in 2009, 2010, and 2011 than the estimates obtained using the 2009/10 HNLSS directly. Specifically, the backcasted trend estimates a poverty rate of 46.3 percent in 2009, 42.8 percent in 2010, and 41.8 percent in 2011, corresponding to 71.4, 67.8 and 68.1 million poor respectively (see Table *7* in the Appendix, for the full backcasted series). The 2009/10

[16] This confirms that all values of the consumption vector are positive.

HNLSS, by contrast, suggested a poverty rate for 2009/10 of 56.4 percent (more than 10 percentage points higher) corresponding to 89.4 million people.

Figure 1 Backcasted trend in poverty rates and number of poor at the US$1.90 poverty line, pass-through of 1

a) Poverty rate, % (US$1.90) b) Number of poor, millions (US$1.90)

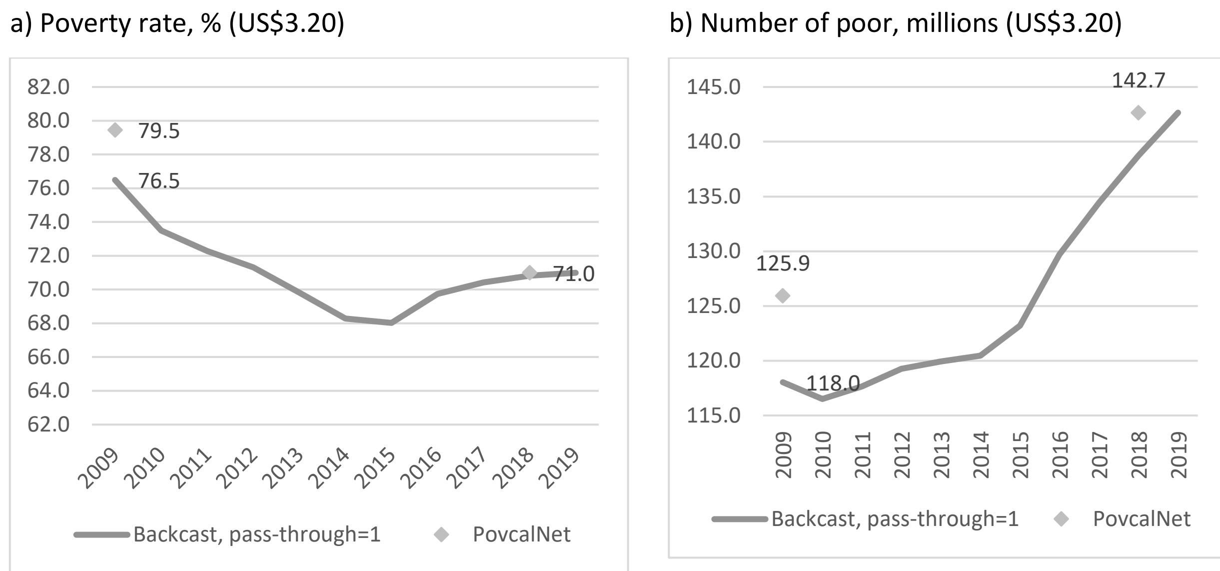


Note: the figure shows the backcasted poverty rates series at the US$1.90 poverty line (panel a). Using household consumption data from the 2018/19 NLSS and sectoral GDP growth rates from the World Bank-MFM-Tool, we backcast household consumption over the previous decade by applying the same growth rate to household consumption and mapping the sectoral information to the household's head sector of employment. Number of poor (panel b) is estimated using WDI population data.

Using the same methodology and data we can also estimate poverty at the US$3.20 poverty line. This is a relevant poverty measure for Nigeria as it reflects the typical standards of living in lower-middle-income countries (see Jolliffe and Prydz 2016, World Bank 2018, 2020).[17] Using this higher line, the backcasted series is much closer to the 2009/19 HNLSS poverty estimates. Figure 2 shows that the backcasted poverty rate for 2009 at the US$3.20 poverty line is estimated to be 76.5 percent assuming a pass-through rate equal to one between sectoral GDP consumption and household welfare. This estimate is just 3 percentage points lower than poverty rate estimated directly from the 2009/10 HNLSS (see Table *7* for full backcasted series).

[17] This follows the World Bank income group classification of economies based on a country's GNI per capita. The latest thresholds and classification can be found at https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups. Nigeria is classified as a lower-middle-income economy since 2009.

Figure 2 Backcasted trend in poverty rates and number of poor at the US$3.20 poverty line, pass-through of 1



Note: the figure shows the backcasted poverty rates series at the US$3.20 poverty line (panel a). Using household consumption data from the 2018/19 NLSS and sectoral GDP growth rates from the World Bank-MFM-Tool, we backcast household consumption over the previous decade by applying the same growth rate to household consumption and mapping the sectoral information to the household's head sector of employment. Number of poor is estimated using WDI population data (panel b).

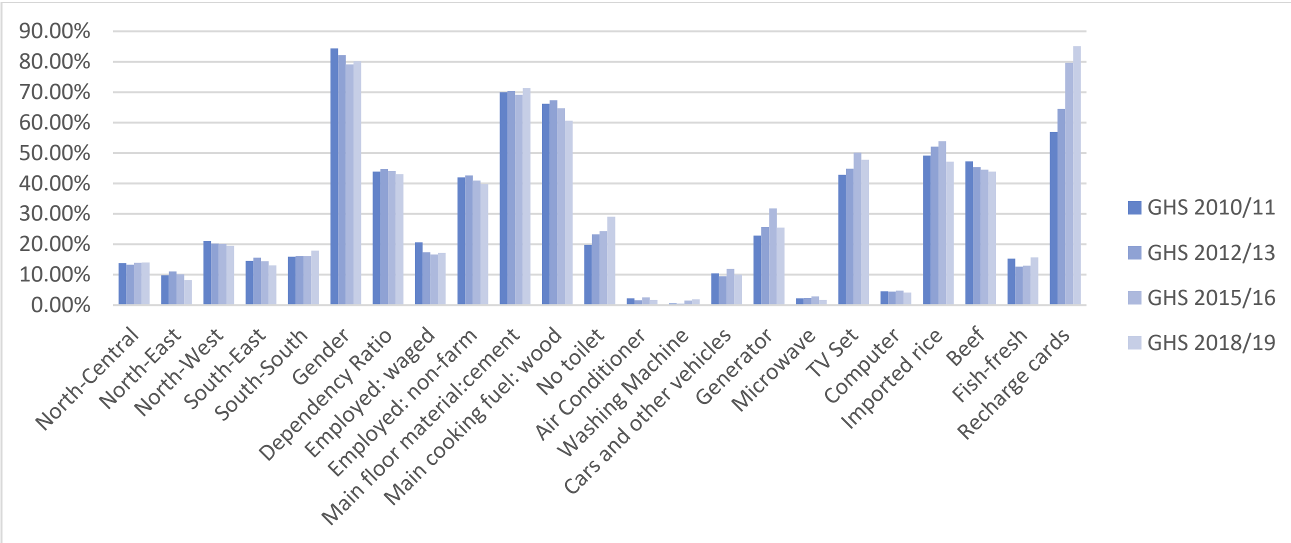
5.2. Survey-to-survey imputation

This section presents the results of the survey-to-survey imputation into the 2010/11, 2012/13, 2015/16 and 2018/19 GHS. As detailed in Section 4.2, we impute consumption using information on 23 non-monetary indicators available in the 2018/19 NLSS and all GHS rounds.

Before moving to the results, Figure *3* shows the average value of each of these indicators over the four rounds of data used in the analysis (see also Table *8*Table *8*). Several of these indicators show an improvement in household welfare over the first three periods, but then worsen after 2015/16, suggesting a reaction to Nigeria's 2016 oil-price-induced recession. For example, ownership of assets (TV set, generator, cars and other vehicles) was increasing up until 2015/16 and but then registered a decrease in the last wave suggesting that households might be selling their assets to offset a negative shock to their welfare. A similar trend can be seen in the consumption of imported rice. This trend in itself is consistent with a decrease in poverty rates in the first half of the decade and a worsening in more recent years.[18]

[18] In section 7, we provide additional evidence using data from the DHS that supports these trends in non-monetary indicators.

Figure 3 Summary Statistics of indicators used to predict consumption in survey-to-survey imputations, by GHS wave



Note: the figure shows the average value of each indicator in each wave of the GHS. These non-monetary indicators are used to develop the consumption model used in the survey-to-survey imputations for each wave.

First, we present the results of the imputation into the 2018/19 GHS. We do this to verify that the NLSS and GHS surveys are indeed comparable and to check whether, using GHS data, we can replicate – or at least get close to – the official NLSS-based poverty headcount rate for 2018/19 of 39.1 percent.[19] The results show an imputed poverty headcount rate of 41.9 percent. The imputed headcount rate at the US$3.20 poverty line shows a similar difference of 2 percentage points (72.3 percent in the imputed results vs. the official estimate of 71.0 percent), while the imputed Gini coefficient is very similar to the official NLSS estimate (34.9 vs. 35.1). The small gap between the imputed GHS-based and actual NLSS-based poverty estimates can be explained by differences in some of the non-monetary variables used in the consumption model (reported in Table 2), which are likely driven by the two surveys having different data collection schedules. Yet, we argue that the difference is small enough and, in a context of limited data availability, this result lays reasonable pre-conditions to impute back into previous GHS rounds.

[19] The imputation in the 2018/19 GHS should be considered as a check to the validity of the imputations in previous rounds. The official poverty estimate for 2018/19 should be calculated using NLSS data.

Table 1 Poverty and inequality estimates using survey-to-survey imputations compared to 2018/19 NLSS

	Poverty rate US$1.90 (percent)	Poverty rate US$3.20 (percent)	Gini coefficient	Mean Annual Consumption (US$2011PPP)	Median Annual consumption (US$2011PPP)
2010/11 GHS	43.54	72.88	35.65	81.49	64.25
2012/13 GHS	42.49	72.12	35.51	82.67	65.41
2015/16 GHS	40.75	70.44	35.88	85.62	67.44
2018/19 GHS	41.88	72.28	34.94	82.39	65.86
2018/19 NLSS	39.09	70.98	35.13	85.13	68.77

Note: the table shows the results of the survey-to-survey imputation in each round of the GHS. We develop a consumption model using data on 23 non-monetary indicators and household consumption available in the 2018/19 NLSS. Using the estimated parameters, we then impute in each round of the GHS using the same non-monetary indicators and 100 imputations. The imputed consumption vector is then converted to 2011 PPP and poverty estimates are reported at the US$1.90 and US$3.20 poverty lines. Gini coefficients are calculated as the average of 100 estimates resulting from each imputation.

Table *1* (and Table *9* in the Appendix) shows the results of the survey-to-survey imputations in each round of the GHS. The imputed poverty headcount rate at the US$1.90 poverty line is 43.5 percent in 2010/11, decreasing to 41.5 percent in 2012/13 and to 40.5 percent in 2015/16. The imputed consumption vector can also be used to estimate the poverty rate at the higher poverty line of US$3.20 per person per day and to produce measures of inequality (Table *1*). The latter show that inequality has barely changed between 2010/11 and 2018/19, which reinforces the assumption of distribution-neutral pass-through rates adopted in the backcasting exercise.

Overall, therefore, we find that the results are robust to using two completely different methodologies. While the imputed poverty headcounts rates are on average 2 percentage points higher than their backcasted counterparts, they show a poverty trend that runs parallel to the backcasted series (see Figure *6* in section 7). The next section presents additional sensitivity checks that confirm these findings.

6. Robustness and sensitivity analysis

6.1. Backcasting

While it is not possible to relax all the assumptions behind the backcasting exercise, we can test the sensitivity of the results to different assumptions about how much of the growth in national accounts is passed onto growth in household consumption. Extensive literature shows that growth in national accounts (GDP, GNI, or Household Final Consumption Expenditure (HFCE)) differs from growth in average household consumption measured in household surveys (Ravallion, 2003; Deaton, 2005; Pinkovskiy & Sala-i-Martin, 2016, Lakner et a. 2021). To account for the difference between growth rates in per capita household consumption expenditures in national accounts and the per capita household consumption expenditures recorded in surveys, we construct different estimates for the pass-through using global data.

Specifically, we estimate different values of the pass-through rate using survey data on monthly household consumption available in PovcalNet (http://iresearch.worldbank.org/PovcalNet/home.aspx) matched to national accounts data from the WDIs to estimate the difference in growth rates between the two. To do this, we first pool all of the available data on household welfare (measured as either income or consumption) and national accounts for country-years in PovcalNet, obtaining a data set of 1,751 country-year spells when using GDP data and 1,521 spells when using GNI data (Table *10* in the Appendix).[20] Then, we construct separate samples and run separate regressions using data for: all countries except high-income economies (column 2, Table *10*); all lower-middle-income countries (column 3, Table *10*); all countries with survey-estimates based on consumption as a measure of household welfare (column 4, Table *10*); and for countries in Sub-Saharan Africa (column 5, Table *10*). Each regression estimates a different value of the pass-through rate using the growth rate of either GDP per capita or GNI per capita as a predictor. The bottom panel of Table *10* shows the results when running the regressions on the same groups of countries but using only "comparable surveys" as defined in PovcalNet's comparability data set.[21]

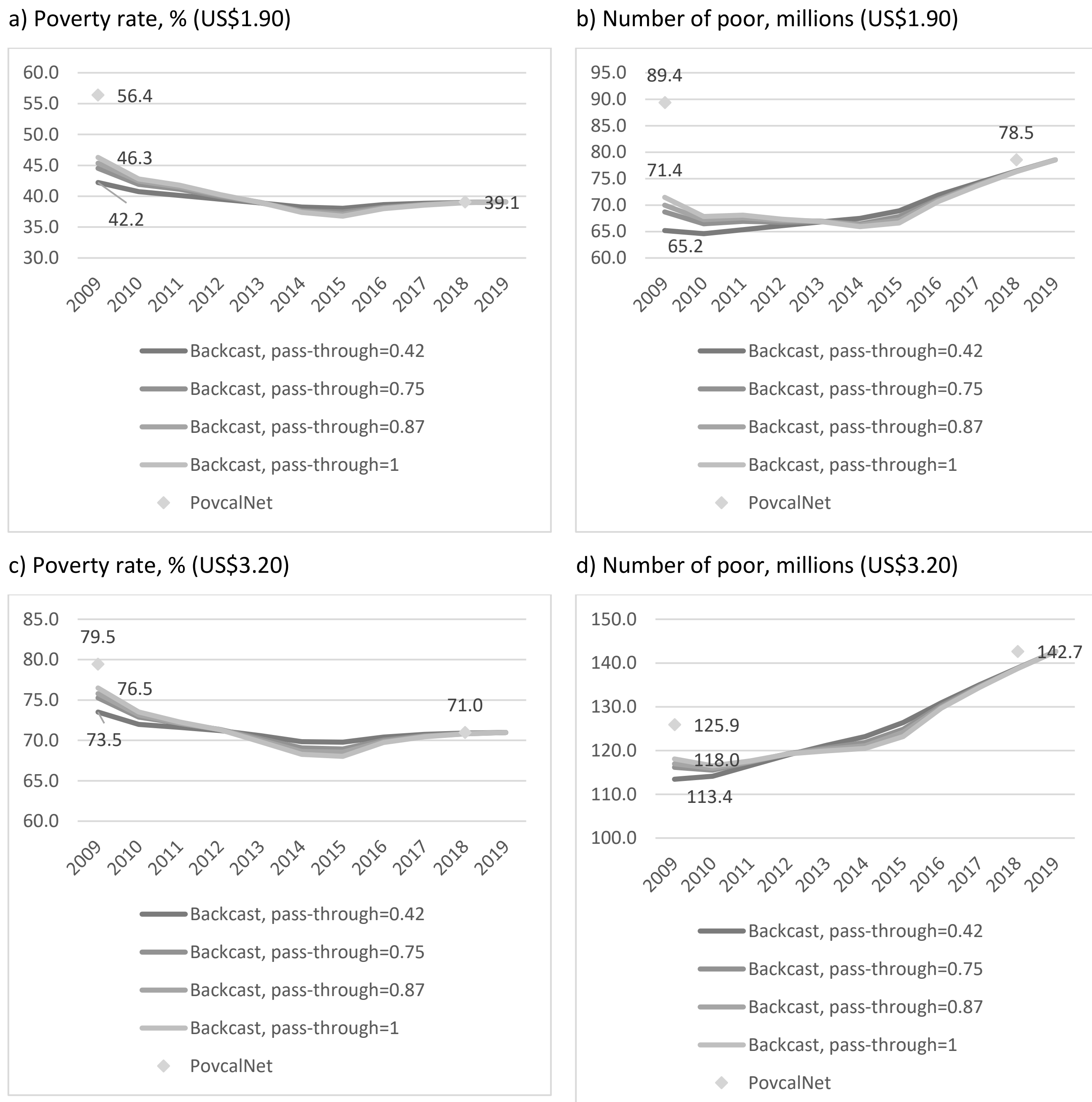
Results are reported in Figure 4 for pass-through rates between 0.42 (pass-through estimate for countries in fragile-conflict affected situations, see Corral et al. 2020) and 0.87. Poverty estimates for 2009 at the US$1.90 poverty line range between 42.2 (assuming a pass-through of 0.42) and 45.3 percent (assuming a pass-through of 0.87), and between 73.5 and 75.8 percent at the US$3.20 poverty line (assuming a pass-through of 0.42 and 0.87 respectively). These result show that changing the assumption about the pass-through rates has little effect on the backcasted series. Indeed, if anything, using lower pass-through rates

[20] We focus on GDP and GNI pass-through rates as HFCE is not currently used in PovcalNet's lining-up exercise to extrapolate household consumption estimates from surveys collected in Sub-Saharan African countries (see Prydz et al. 2019). Pass-through rates estimates using HFCE remain within the range reported in this note, for comparable consumption-based surveys we estimate a pass-through of 0.66 in line with what reported in World Bank (2020, box 2).

[21] https://development-data-hub-s3-public.s3.amazonaws.com/ddhfiles/506801/povcalnet_comparability.csv

implies even slower poverty reduction, indicating a larger gap with the 2009/10 HNLSS poverty estimate. Full information on the backcasted series using different pass-through rates can be found in Table *11*.[22]

Figure 4 Testing sensitivity of backcasted series to different pass-through rates



Note: the figure shows backcasted series using different values of the pass-through rate used to account for the difference between growth in national accounts and in household consumption as measured in household surveys. Household consumption data from the 2018/19 NLSS is matched to sectoral GDP growth rates (MFM-Tool World Bank) based on

[22] It should be noted that the purpose of this exercise is to check whether different assumptions of the pass-through rate can help explain the difference between the backcasted estimate and the 2009/10 HNLSS estimate, rather than trying to estimate a specific value of the pass-through rate for Nigeria.

household head's sector of employment. Panel a and c show the backcasted poverty rates at the US$1.90 and US$3.20 poverty lines, panel b and d show the backcasted series of number of people living below these two lines. Population estimates are from the WDI. Different values of the pass-through rate are calculated using household survey data from PovcalNet and National Accounts data from the WDI.

We also test the robustness of the results to relaxing the assumption that growth in the national accounts is passed through to growth in household consumption at the same rate across the entire consumption distribution.[23] To do this, we construct three separate "growth incidence curves" (GICs) using imputed consumption data from the survey-to-survey imputation exercise: the time periods considered are 2010/11 to 2018/19, 2010/11 to 2015/16, and 2015/16 to 2018/19 (see Table 12 in the Appendix for these GICs). Over the entire 2010/11 to 2018/19 period, Nigeria's GIC was sloped *slightly* downwards, implying that poorer Nigerians benefited slightly more from growth than richer Nigerians: this corresponds to a small drop in the Gini coefficient of just 0.6 points over this period.[24] However, this picture is somewhat distorted by the effects of the 2016 oil recession. The GICs based on imputed data indicate that richer households lost out significantly more than poorer households when the economic shock hit. [25] However, during the first part of the decade – when Nigeria was growing more strongly – richer Nigerians disproportionately enjoyed the gains. Put differently, the consumption of richer Nigerians was more sensitive to Nigeria's overall growth performance than the consumption of poorer Nigerians. Thus, it is important to separate out the periods before and after the 2016 recession when constructing the GICs and testing the robustness of the backcasts. Once they have been constructed, the GICs are then used to adjust the pass-through rate applied to each decile of the consumption distribution, holding the overall *average* pass-through fixed at 1.[26]

Relaxing the assumption of distribution-neutral pass-through alters the backcasted trend, but even under the assumption that more growth was passed through to poorer Nigerians during the decade to 2018/19, poverty reduction over that period remains in single digits. Figure 5 shows that using the 2010/11-2018/19 GIC – which was slightly pro-poor – in the backcasting exercise results in a larger reduction in poverty over the decade, such that the estimated poverty headcount rate is 47.9 percent in 2009 (1.6 percentage points higher than our main backcasted result). Conversely, using the 2015/16-2018/19 GIC results in a more

[23] In 2018/19, *overall* inequality in Nigeria was moderate: the Gini coefficient was 35.1. However, spatial inequality – especially along the north-south divide – was far more pronounced (Lain and Vishwanath, 2021; Blumenstock et al., 2021).

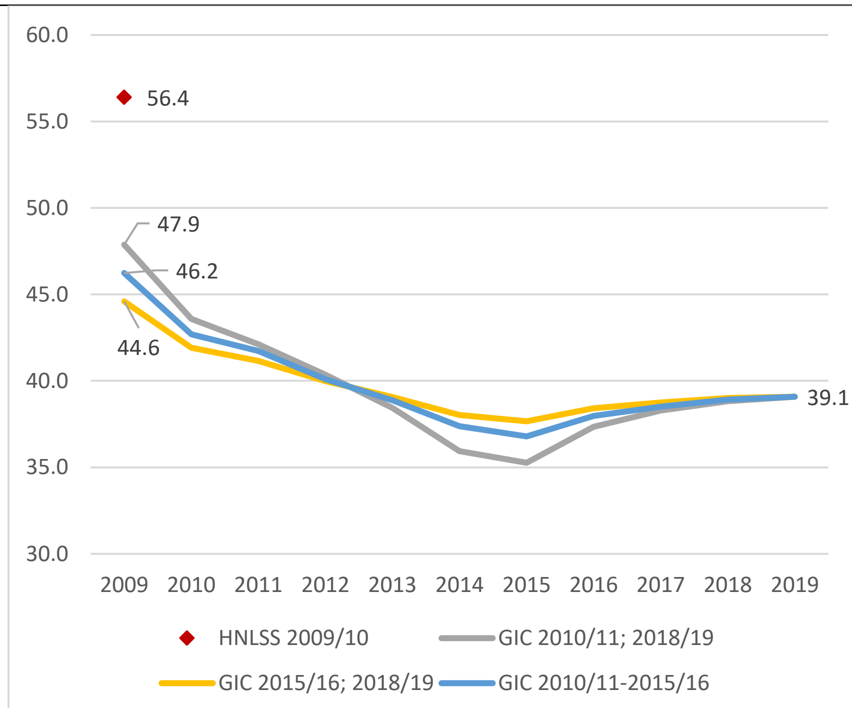
[24] Data on spatial inequality of non-monetary indicators also suggest that inequality did not significantly drop in the decade prior to the COVID-19 crisis. According to the DHS, the north-south gap in terms of education and basic infrastructure did not close substantially over this period (Lain and Vishwanath, 2021).

[25] Labor market indicators from the same period show similar patterns (see Jenq, Lain, and Vishwanath (2021)).

[26] This means that the average growth in consumption is the same as in the main results in Figure 1.

stagnant backcasted trend over the decade and in an estimated poverty headcount rate of 44.6 percent in 2009; the 2015/16-2018/19 GIC accurately captures the fact that richer Nigerians' consumption is more sensitive to Nigeria's growth. Overall, therefore, it appears that relaxing the assumption of a flat pass-through rate across the distribution shifts the backcasted estimate for 2009, but not enough to reproduce anything like the 17.3-percentage point drop implied by using 2009/10 HNLSS poverty estimate directly.

Figure 5 Backcasting poverty rates assuming different pass-through rates across the distribution of household consumption



Note: the figure shows backcasted series using different values of the pass-through rate at different deciles of the consumption distribution. Household consumption data from the 2018/19 NLSS is matched to sectoral GDP growth rates (MFM-Tool World Bank) based on household head's sector of employment. The backcasted poverty rates are calculated at the US$1.90 poverty lines. Different values of the decile-level pass-through rate are calculated using imputed household consumption data from three waves of GHS data (2010/11,2015/16, and 2018/19).

Lastly, we test the robustness of the results to using different methods to map the growth rates in sectoral GDP to the 2018/19 NLSS. In the main results, the mapping of households to sectors is based only on information about the household head's employment sector. To check whether the results are sensitive to this particular micro-macro mapping approach, we use the sector of employment of (1) the oldest working household member or (2) the household member closest to 40 in age as alternative variables to map the household data to the sectoral GDP series. This has virtually no impact on the results (see Figure 7 in the Appendix).

6.2. Survey-to-survey imputation

We test the sensitivity of the survey-to-survey imputations to different specifications of the regression model used to impute consumption into the different rounds of the GHS. These additional checks aim to address possible issues with seasonality in the non-monetary indicators used in the consumption model, such as (1) the share of household heads employed in non-farm activities and in wage-employment and (2) consumption dummies for imported rice, beef, and fresh fish. Employment and consumption of specific items might vary significantly during the year. Since the GHS is only collected during the post-planting and post-harvest seasons, the value of these indicators might be different from the average value of the same indicators collected over a 12-month period (as in the 2018/19 NLSS). For example, if a shock on imports were to hit the country during months not covered by the GHS, this could impact the comparability of indicators measuring consumption of imported rice.

One way to check if this is the case is to compare the summary statistics of the non-monetary indicators in the post-planting and post-harvesting visit of the GHS for the same survey year. Table *13* shows the average value of each indicator for each visit of the 2018/19 GHS. We find that, while many of the variables included in the regression model show little seasonal difference, others show significant differences between the two periods. The largest differences are registered for variables measuring household head's type of employment – such as employment in non-farming activities decreases between the post-planting and post-harvesting visit – and the consumption frequency dummies.

Fully testing the sensitivity of the survey-to-survey imputation approach therefore relies on excluding these potentially-seasonal variables from the estimation of the consumption model and seeing how the results change. The alternative models exclude wage-employment (Model 1); wage-employment and a dummy variable for there being no toilet facility in the household (Model 2); wage-employment, no toilet facility, and the imported rice consumption dummy (Model 3); non-farm employment (Model 4); and all employment and food consumption dummy variables (Model 5). The estimates change very little when applying these different models. Table *14* shows the results for each wave of the GHS. The imputed estimates for each wave remain stable when removing different sets of variables and estimates remain within 2 percentage points of the main results.

Lastly, we test the robustness of our results to different distributional assumptions for the household consumption vector. The survey-to-survey imputations presented so far assume that household consumption is lognormally distributed. To test whether this is a valid assumption, we apply zero-skewedness and Box-Cox transformations to the original 2018/19 NLSS consumption vector and to the imputations into the 2018/19 GHS. To test whether this improves the imputations – that is, if the imputed distribution of consumption is closer to the 2018/19 NLSS distribution – we only apply this transformation to the 2018/19 GHS to exploit information for an overlapping year.

We find that assuming a lognormal distribution is a reasonable approximation for our data, in line with other literature on survey-to-survey imputations (Tamakatsu et al., 2021). Specifically, we compare the distribution of the imputed consumption vector resulting from our main model to the one obtained after applying zero-skewedness transformations and compare whether different moments of the distribution estimated with the latter are closer to the *true* distribution from the 2018/19 NLSS. We find that the poverty headcount rate at the US$1.90 poverty line is 42.4 percent when using a zero-skewedness transformation and 42.6 percent when using a Box-Cox transformation. Both estimates confirm the robustness of the imputation exercise for 2018/19. However, the difference with the 2018/19 NLSS official poverty headcount rate (39.1 percent) is slightly higher than what we obtain with our preferred specification (41.9 percent), suggesting that assuming a lognormal distribution in the imputations is a good fit for our data. Looking at different moments of the distribution confirms this finding.

7. Discussion

The main strength of this analysis is that two very different approaches yield very similar estimates of a poverty trend for Nigeria in the period between 2009 and 2019. In this section, we discuss the implications of the main findings and discuss possible caveats of this analysis.

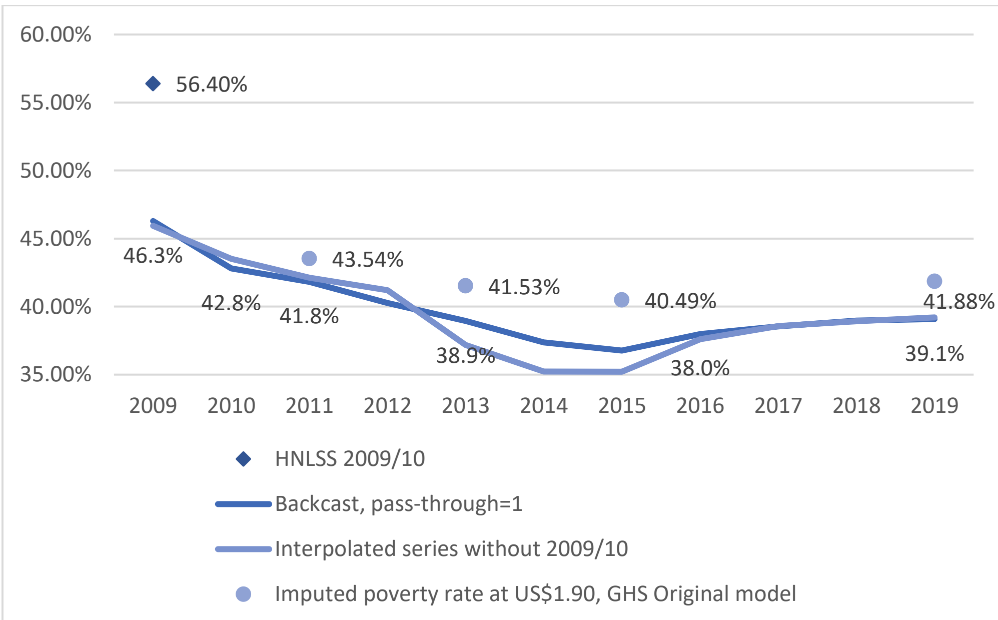
7.1. Implications for Nigeria's poverty trend

Figure *6* combines the main results of the backcasting exercise and of the survey-to-survey imputations using all waves of GHS data. As noted in Section 5.2, the survey-to-survey imputations seem to overestimate poverty by around 2 percentage points when compared to the backcasted estimates and to the 2018/19 NLSS official poverty rate. Notwithstanding this difference in levels, the two methodologies yield a very similar poverty trend showing a decline in poverty in the first half of the decade and a stagnation and even reversal in poverty reduction during the economic recession following the 2016 oil price crisis.

To illustrate this point further, Figure *6* also compares the main results of this analysis with an alternative poverty trend which interpolates between the 2003/4 NLSS and 2018/19 NLSS household consumption vector, that is, excluding 2009/10 HNLSS, using growth rates in total real GDP per capita and the World

Bank PovcalNet's interpolation methodology.[27] This alternative interpolated trend closely resembles the backcasted series described in Section 5 and further reinforces the findings of this analysis. In turn, this casts further doubt over the 17-percentage point drop implied by simply comparing the HNLSS 2009/10 and the 2018/19 NLSS: progress towards poverty reduction appears to have been much slower.

Figure 6 Comparison of imputed, backcasted and interpolated poverty rates for the period 2009-2019



Note: the figure compares the different results of this analysis over the decade 2009/2019 and compares them to the HNLSS 2009/10-based poverty headcount rate estimate. The backcasted series uses sectoral GDP growth rates to backcast household consumption from the 2018/19 NLSS using household's head sector of employment to map macro and micro-data. The interpolated trend applies PovcalNet's methodology and interpolates between the 2018/19 NLSS and 2003/04 NLSS using growth rates in GDP per capita, excluding the HNLSS 2009/10 estimate. Imputed series use survey-to-survey imputations, data from 2018/19 NLSS household consumption and GHS non-monetary indicators to impute consumption in each of the GHS survey years. All estimates are available in Table 15 (see the Appendix).

7.2. Caveats

Notwithstanding the robustness of the results to different checks, some standard caveats remain to this analysis.

[27] The interpolated trend uses PovcalNet's methodology to interpolate between two survey-based estimates using GDP per capita growth rates (Prydz et al. 2019). In this exercise, we drop available information from the HNLSS 2009/10 survey (currently available in PovcalNet) and interpolate between the 2003/04 NLSS data and the 2018/19 NLSS. In a nutshell, the interpolation applies the same growth rate as GDP per capita to the household consumption vector and allows to calculate poverty rates in each reference year. The estimate of poverty from these two distributions is the weighted average poverty rate from both distributions where whereby each poverty estimate is weighted by the inverse of the relative distance between the survey year and the reference year (Prydz et al. 2019).

The backcasting exercise relies on two particularly strong assumptions.

First, the analysis assumes that inflation is fully captured by the GDP deflator and does not account for differential effects of inflation on the poor. Accelerating inflation in Nigeria in recent years has been driven disproportionately by food prices, and even poor households – many of whom are concentrated in subsistence agriculture – purchase food, so this could have uneven effects on consumption and hence alter the progress of poverty reduction (Joseph-Raji et al., 2021). Second, it assumes that there are no switches between sectors over time. While this is an important assumption, evidence on Nigeria's labor market shows that structural transformation was slow over this period (Jenq et al., 2021) suggesting that this may not be too big of a concern for the purposes of this analysis.

While we do not address these limitations directly in the backcasting exercise, the fact that the survey-to-survey imputations produce such similar results offsets some of these concerns. Distributional effects of macroeconomic growth are likely to be picked up – at least partly – by the non-monetary indicators collected in different waves of the GHS, which are used to impute household consumption. Similarly, some of the variables included in the imputation model – such as frequency of consumption of certain food items – would be affected by inflation and reflect the larger effect of changes to food prices among poorer households.

The main drawback of the survey-to-survey imputation exercise is the difference in data collection schedules between the GHS and NLSS. The GHS data are only available during the post-planting and post-harvest seasons, which might bias our results if the indicators used in the consumption model vary significantly throughout the year and are hence different from those collected over a 12-month period in the 2018/19 NLSS. This may explain the difference between the imputed 2018/19 GHS estimate and the 2018/19 NLSS estimate. Yet, if the GHS systematically overestimate poverty rates – as also seems to be the case when comparing estimates in other waves to the backcasted series – this would suggest an even lower "true" poverty rate in 2010/11, even lower poverty reduction in the decade to 2019, and an even larger difference with the 2009/10 HNLSS poverty estimate.

7.3. Sense-checking with other surveys

The evidence of a slowdown in improvements to household welfare emanating from the backcasts and the survey-to-survey imputations is in line with other survey data collected in Nigeria in the decade prior to the COVID-19 crisis. For example, using data from the Demographic Health Survey (DHS) data set, we look at trends in non-monetary indicators that are highly correlated with monetary welfare over the period 2003-2018. Specifically, Figure *8* in the Appendix shows the trends in access to electricity, improved water source, improved sanitation facility and secondary school attendance over four waves of DHS data.[28] The trend in the share of the population with access to improved sanitation and the share enrolled in secondary school – shown in Panel c and Panel d of Figure *8* – are particularly striking. There was a remarkable improvement in all these indicators between 2003 and 2008, but virtually no change between 2008 and 2018, in line with the evidence emerging from this paper of a slowdown in household welfare improvements and poverty reduction in more recent years.

7.4. Changes to PPP conversation factors

Changes to the PPP conversion factors used for international comparisons could alter estimates of the poverty headcount rate at international poverty lines. This paper has used PPP conversion factors based on price data collected in 2011. However, Jolliffe et al. (2022) show that using new PPP conversion factors, created using price data collected in 2017, would have a large impact on estimates of the poverty headcount rate in some countries, including Nigeria. In order to understand these implied differences in the poverty estimates, further analysis is needed to examine how and why the new 2017 PPP data affect the conversion of the welfare vector from local currency units to international US$. This is left for future work.

8. Conclusion

Since the last two official household consumption surveys in Nigeria cannot be compared, this paper estimates a poverty trend for the country using two alternative approaches. First, the paper uses sectoral GDP data to backcast household consumption and hence poverty from the 2018/19 NLSS to 2009. Second, the paper uses a survey-to-survey imputation approach, constructing a model for consumption using data from the 2018/19 NLSS and imputing into several waves of the GHS. Despite having very different foundations, these two approaches produce remarkably similar results. Far from poverty dropping by 17 percentage points – as making the invalid comparison between the 2009/10 HNLSS and 2018/19 NLSS would imply – it appears that poverty dropped by between 3 and 7 percentage points in the decade before the COVID-19 crisis. The results suggest that the 2010s were initially marked by gradual poverty reduction,

[28] Similar indicators are calculated using data from the 2018/19 NLSS to calculate the multidimensional poverty measure for Nigeria (World Bank, 2020). The multidimensional poverty measure combines data on access to education, basic infrastructure and monetary welfare to better understand the different dimensions of poverty (see World Bank 2018). These non-monetary indicators are highly correlated with monetary household consumption. In fact, in Sub-Saharan Africa 40 percent of households that are multidimensionally poor are deprived under all three dimensions (World Bank, 2020). Hence, looking at trends in these non-monetary indicators can be highly informative of overall household well-being, especially in absence of frequent data on household monetary consumption.

but this subsequently stagnated and was even reversed following the 2016 recession. Given Nigeria's large population, this has sizeable implications for regional and global poverty reduction.

This analysis provides useful evidence on how to estimate a poverty trend in contexts where official household consumption survey data are infrequent and where changes to the data collection methodology do not allow comparing survey estimates over time. Rather than proposing a new methodology, the paper shows how different data sources can be used to estimate a trend and how applying different methodologies can help improve the robustness of the results. A similar approach could be replicated in contexts where data on national accounts and/or non-monetary indicators of household welfare are available, but household consumption survey data are not. While this is not uncommon, we should stress that the data environment in Nigeria was particularly rich and this analysis could not have been conducted without these conducive data "pre-conditions". In particular, the availability of GHS data for an overlapping year with the official NLSS survey was crucial to validate our imputations, before going back throughout the 2010s.

This analysis also shows the importance of regularly collecting *comparable* data on household consumption. While this work shows that alternative data sources can be useful for estimating long-run poverty trends, it also highlights how many additional assumptions and checks are needed to produce robust evidence. Having direct estimates of monetary household welfare – with trends as well as snapshots – would provide more precise and timely information on poverty. This is particularly relevant in times of economic crises, such as the current COVID-19 pandemic, when rapidly rolling out countervailing policies to help support households is critical.

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10. Appendix

Table 2 Summary statistics for comparable variables used in model to impute consumption, by survey

	(1) 2018/19 NLSS	(2) 2018/19 GHS	(3) Difference 2018/19
North-Central	14.07%	14.07%	
North-East	8.28%	8.28%	
North-West	19.51%	19.51%	
South-East	13.13%	13.13%	
South-South	17.90%	17.90%	
Gender	81.17%	80.17%	-1.00
Dependency Ratio	42.44%	43.09%	0.66
Employed: waged	19.76%	17.21%	-2.55
Employed: non-farm	37.18%	39.74%	2.57
Main floor material:cement	70.30%	71.39%	1.09
Main cooking fuel: wood	59.06%	60.57%	1.51
No toilet	25.07%	29.03%	3.96
Imported rice	43.85%	47.13%	3.28
Beef	45.35%	43.91%	-1.44
Fish-fresh	18.14%	15.71%	-2.43
Recharge cards	85.13%	85.07%	-0.06
Air Conditioner	2.57%	1.68%	-0.89
Washing Machine	2.16%	1.96%	-0.20
Cars and other vehicles	8.47%	9.99%	1.52
Generator	24.96%	25.49%	0.52
Microwave	2.47%	1.74%	-0.73
TV Set	48.03%	47.73%	-0.29
Computer	4.71%	4.17%	-0.55

Note: the table shows the average value of non-monetary indicators used in the consumption model for the purpose of survey-to-survey imputations. Data are from the 2018/19 NLSS and2018/19 GHS. For GHS data the average reflects the average value between two visits (post-planting and post-harvesting). For 2018/19 GHS zone weights are adjusted to match 2018/19 official NLSS zone population shares and ensure comparability.

Table 3 Sectoral GDP growth rates 2009-2019

	GDP, trillions (Constant LCU)	Sectoral GDP, trillions (Constant LCU)			Sectoral GDP growth rates		
	Total	Agriculture	Industry	Services	Agriculture	Industry	Services
2009	54.6	13.0	13.8	27.7	5.9	2.5	12.4
2010	57.5	13.4	15.0	29.1	5.8	5.2	12.9
2011	59.9	14.3	15.4	30.2	2.9	8.4	4.9
2012	63.2	14.8	15.7	32.8	6.7	2.4	4.0
2013	67.2	15.4	16.7	35.0	2.9	2.2	8.4
2014	69.0	16.0	16.4	36.7	4.3	6.8	6.8
2015	67.9	16.6	14.9	36.4	3.7	-2.2	4.8
2016	68.5	17.2	15.2	36.1	4.1	-8.9	-0.8
2017	69.8	17.5	15.5	36.7	3.4	2.1	-0.9
2018	71.4	18.0	15.9	37.5	2.1	1.9	1.8
2019	70.0	18.3	15.0	36.7	2.4	2.3	2.2

Note: the table shows sectoral GDP data. Data in the last three columns on sectoral GDP growth rates are used in the backcasting exercise. Source: World Bank MFM-Tool.

Table 4 Comparison between GHS and NLSS questionnaires for comparable indicators used in stepwise selection

GHS	2018/19 NLSS
What is the gender of [NAME]?	What is the gender of [NAME]?
What is [NAME]'s relationship to the head of household?	What is [NAME]'s relationship to the head of household?
How old is [NAME]? ENTER BOTH YEARS AND MONTHS IF 5 YEARS AND YOUNGER. IF OLDER THAN 5 YEARS ENTER YEARS ONLY	How old is [NAME]? ENTER BOTH YEARS AND MONTHS IF 5 YEARS AND YOUNGER. IF OLDER THAN 5 YEARS ENTER YEARS ONLY
What is [NAME]'s present marital status?	What is [NAME]'s present marital status?
During the past 7 days, has [NAME] worked for someone who is not a member of your household, for example, an enterprise, company, the government or any other individual for payment in cash or in-kind?	During the past 7 days, has [NAME] worked for someone who is not a member of this household, for example, an enterprise, company, the government or any other individual?
During the past 7 days, has [NAME] worked on a farm owned or rented by [NAME] or another member of your household, either in cultivating crops or in other farming tasks, or has [NAME] cared for livestock belonging to [NAME] or another member of your household?	During the past 7 days, has [NAME] worked on a farm owned or rented by a member of this household, either in cultivating crops or in other farming tasks, or has [NAME] cared for livestock belonging to [NAME] or a member of this household or has [NAME] gone fishing or worked in fish farming owned by the household?
During the past 7 days, have you worked on your own account or in a business enterprise belonging to you or someone in your household, for example, as a trader, shop-keeper, barber, dressmaker, carpenter or taxi driver?	During the past 7 days, has [NAME] worked on his/her own account or in a business enterprise belonging to [NAME] or someone in this household, for example, as a trader, shop-keeper, barber, dressmaker, carpenter or taxi driver?
The floor of the main dwelling is predominantly made of what material?	Main construction material of the flooring of the dwellingobserve, do not read out
What is your main source of cooking fuel?	What type of cookstove is your household's primary cookstove?
What kind of toilet facility does your household use?	What kind of toilet facility do members of your household usually use?
Within the past 7 days, did the members of this household eat/drink any of this [ITEM] within the household? PLEASE ONLY LIST ITEMS CONSUMED WITHIN THE HOUSEHOLD AND EXCLUDE FOOD CONSUMED OUTSIDE ASK THIS QUESTION FOR ALL ITEMS, BEFORE MOVING ON TO THE NEXT QUESTIONS FOR ITEMS WITH YES	Within the past 7 days, did any members of your household eat/drink any of this [ITEM] within the household? PLEASE ONLY LIST ITEMS CONSUMED WITHIN THE HOUSEHOLD AND EXCLUDE FOOD CONSUMED OUTSIDE THE HOUSEHOLD.ASK THIS QUESTION FOR ALL ITEMS, BEFORE MOVING TO Q2.
Over the past 30 days, did the household purchase or pay for any [...]?	Over the past 30 days, did your household purchase or pay for any [ITEM]?
List all the items in question 1 and the owner of the asset in question 2. If more than one item, write a description of the item below, otherwise write only the code of the item.	Does your household own any [item]? Only count items that are in working condition

Note: the table reports the original questionnaire for the non-monetary indicators used in the survey-to-survey imputation exercise. To ensure comparability between the GHS and NLSS survey, data on the non-monetary indicators needed for survey-to-survey imputations need to be collected in a comparable way and following the same methodology.

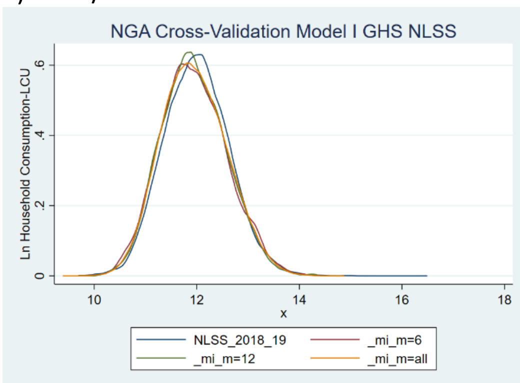
Table 5 Regression models to impute consumption into 2010/11 using variables from 2018/19 NLSS

VARIABLES	LABEL	(1) Original Model	(2) Model 1	(3) Model 2	(4) Model 3	(5) Model 4	(6) Model 5
zone_1	North Central	-0.184***	-0.184***	-0.187***	-0.263***	-0.188***	-0.242***
		(0.0140)	(0.0139)	(0.0140)	(0.0134)	(0.0139)	(0.0135)
zone_2	North East	-0.415***	-0.411***	-0.392***	-0.473***	-0.412***	-0.474***
		(0.0171)	(0.0170)	(0.0166)	(0.0158)	(0.0170)	(0.0166)
zone_3	North West	-0.325***	-0.322***	-0.298***	-0.362***	-0.319***	-0.376***
		(0.0152)	(0.0151)	(0.0143)	(0.0141)	(0.0150)	(0.0152)
zone_4	South East	-0.285***	-0.283***	-0.276***	-0.335***	-0.283***	-0.331***
		(0.0141)	(0.0140)	(0.0139)	(0.0135)	(0.0140)	(0.0139)
zone_5	South South	-0.109***	-0.110***	-0.0995***	-0.129***	-0.114***	-0.0954***
		(0.0140)	(0.0140)	(0.0138)	(0.0136)	(0.0140)	(0.0139)
sex	HH Male	-0.115***	-0.113***	-0.113***	-0.122***	-0.121***	-0.122***
		(0.0119)	(0.0119)	(0.0119)	(0.0119)	(0.0118)	(0.0123)
dep_ratio	Dependency Ratio	-0.603***	-0.603***	-0.606***	-0.608***	-0.599***	-0.591***
		(0.0172)	(0.0172)	(0.0172)	(0.0172)	(0.0171)	(0.0175)
emp_wage	HH Waged Empoyment	0.0611***				0.0342***	
		(0.0109)				(0.00991)	
emp_nonfarm	HH Non-Farm Employment	0.0569***	0.0377***	0.0409***	0.0452***		
		(0.00899)	(0.00820)	(0.00819)	(0.00827)		
floor_cement	Main floor: cement	0.0258***	0.0286***	0.0349***	0.0410***	0.0304***	0.0464***
		(0.00895)	(0.00892)	(0.00884)	(0.00897)	(0.00891)	(0.00924)
cook_fuel_wood	Main cook fuel: wood	-0.184***	-0.189***	-0.201***	-0.226***	-0.189***	-0.226***
		(0.0106)	(0.0105)	(0.0103)	(0.0104)	(0.0106)	(0.0110)
no_toilet	No toilet	-0.0558***	-0.0610***			-0.0621***	-0.0679***
		(0.00942)	(0.00944)			(0.00942)	(0.00984)
asset_314	Air Conditioner	0.120***	0.122***	0.122***	0.128***	0.121***	0.132***
		(0.0333)	(0.0333)	(0.0334)	(0.0334)	(0.0331)	(0.0338)
asset_315	Washing Machine	0.146***	0.151***	0.154***	0.158***	0.144***	0.142***
		(0.0340)	(0.0345)	(0.0346)	(0.0351)	(0.0337)	(0.0347)
asset_319	Cars and other vehicles	0.174***	0.177***	0.178***	0.185***	0.181***	0.200***
		(0.0157)	(0.0157)	(0.0157)	(0.0161)	(0.0157)	(0.0166)
asset_320	Generator	0.135***	0.134***	0.136***	0.144***	0.136***	0.159***
		(0.0105)	(0.0105)	(0.0105)	(0.0106)	(0.0105)	(0.0109)
asset_325	Microwave	0.140***	0.138***	0.142***	0.154***	0.135***	0.153***
		(0.0333)	(0.0337)	(0.0338)	(0.0339)	(0.0333)	(0.0335)
asset_327	TV set	0.106***	0.112***	0.121***	0.135***	0.110***	0.150***
		(0.0102)	(0.0102)	(0.0101)	(0.0102)	(0.0102)	(0.0105)
asset_328	Computer	0.133***	0.140***	0.141***	0.150***	0.130***	0.157***
		(0.0209)	(0.0210)	(0.0210)	(0.0212)	(0.0209)	(0.0217)
food_14	Imported rice	0.146***	0.150***	0.151***		0.150***	
		(0.00965)	(0.00960)	(0.00960)		(0.00958)	
food_90	Beef	0.149***	0.149***	0.151***	0.163***	0.150***	
		(0.00785)	(0.00786)	(0.00784)	(0.00799)	(0.00786)	
food_100	Fresh fish	0.140***	0.140***	0.136***	0.136***	0.139***	
		(0.0103)	(0.0103)	(0.0102)	(0.0103)	(0.0102)	
nonfood2_319	Recharge cards	0.131***	0.135***	0.138***	0.145***	0.136***	0.165***
		(0.0113)	(0.0113)	(0.0113)	(0.0114)	(0.0114)	(0.0116)
Constant		1.115***	1.139***	1.104***	1.205***	1.156***	1.306***
		(0.0265)	(0.0263)	(0.0255)	(0.0251)	(0.0260)	(0.0260)
Observations		21,580	21,580	21,580	21,580	21,580	21,580
R-squared		0.535	0.534	0.532	0.524	0.533	0.502

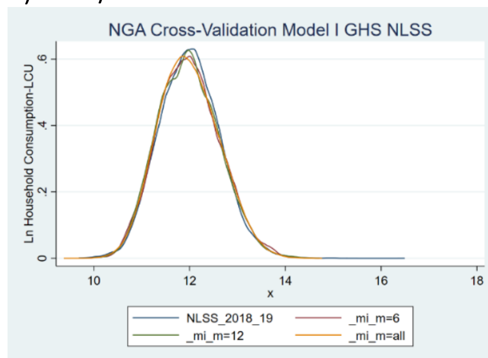
Note: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. The table shows the results of the consumption model used for survey-to-survey imputation purposes. Data are from the 2018/19 NLSS and comprise a series of non-monetary indicators that are comparable between the baseline (NLSS) and target survey (GHS). Household consumption is spatially and temporally deflated and expressed in 2011PPP.

Table 6 Distribution of imputed consumption vector across GHS waves.

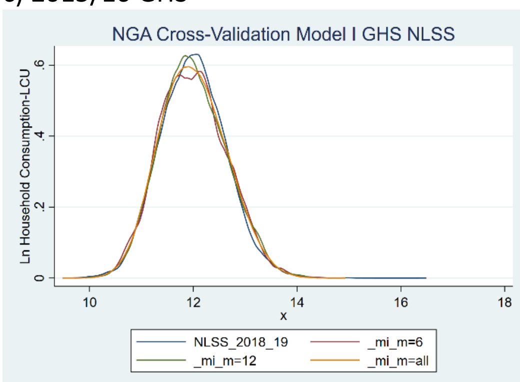
a) 2010/11 GHS



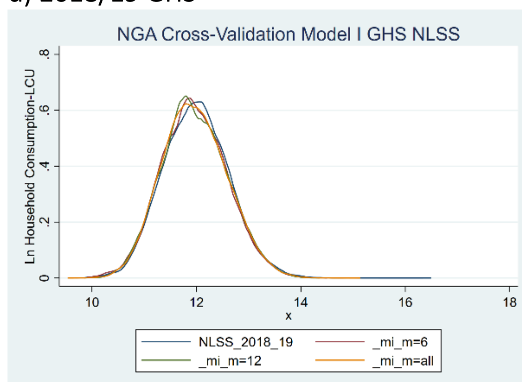
b) 2012/13 GHS



c) 2015/16 GHS



d) 2018/19 GHS



Note: Each figure shows the imputed consumption vector using separate waves of the GHS panel. Each figure compares the distribution of the imputed household consumption vector for specific imputation rounds and for all 100 imputations, to the original 2018/19 NLSS consumption data used in the consumption model. Annual household consumption is expressed in natural logarithms and spatially- deflated local currency units.

Table 7 Results of backcasting consumption from 2018/19 NLSS using sectoral GDP growth rates mapped to household head's employment sector

	Poverty rates at the US$1.90 poverty line (%)		Number of poor at the US$1.90 poverty line (millions)		Poverty rates at the US$3.20 poverty line (%)		Number of poor at the US$3.20 poverty line (millions)	
	Backcast, pass-through=1	HNLSS/NLSS	Backcast, pass-through=1	HNLSS/NLSS	Backcast, pass-through=1	HNLSS/NLSS	Backcast, pass-through=1	HNLSS/NLSS
2009	46.3	56.4	71.4	89.4	76.5	79.5	118.0	125.9
2010	42.8		67.8		73.5		116.5	
2011	41.8		68.1		72.3		117.7	
2012	40.3		67.3		71.3		119.3	
2013	38.9		66.9		69.8		119.9	
2014	37.4		65.9		68.3		120.5	
2015	36.8		66.6		68.0		123.2	
2016	38.0		70.6		69.7		129.7	
2017	38.5		73.6		70.4		134.4	
2018	39.0	39.1	76.3	78.5	70.8	71.0	138.7	142.7
2019	39.1		78.5		71.0		142.7	

Note: the table reports the results of the backcasting exercise using a pass-through of 1. The backcasting exercise uses sectoral GDP data from the World Bank MFM-Tool to backcast household consumption from the 2018/19 NLSS survey using information on household head's sector of employment to map macro- and micro-data. Estimates are reported at the US$1.90 and US$3.20 poverty line and show the poverty headcount rate and the equivalent number of people living below each poverty line. Population data are from the WDI.

Table 8 Summary statistics of non-monetary indicators used in consumption model, by GHS wave

	2010/11 GHS	2012/13 GHS	2015/16 GHS	2018/19 GHS
North-Central	13.78%	13.27%	13.93%	14.07%
North-East	9.80%	11.12%	10.18%	8.28%
North-West	21.03%	20.21%	20.16%	19.51%
South-East	14.53%	15.60%	14.41%	13.13%
South-South	15.95%	16.11%	16.11%	17.90%
Gender	84.34%	82.21%	79.14%	80.17%
Dependency Ratio	43.9%	44.75%	44.05%	43.09%
Employed: waged	20.70%	17.42%	16.63%	17.21%
Employed: non-farm	41.97%	42.65%	40.99%	39.74%
Main floor material: cement	69.96%	70.39%	69.09%	71.39%
Main cooking fuel: wood	66.14%	67.33%	64.71%	60.57%
No toilet	19.85%	23.28%	24.31%	29.03%
Air Conditioner	2.29%	1.66%	2.62%	1.68%
Washing Machine	0.57%	0.44%	1.52%	1.96%
Cars and other vehicles	10.43%	9.48%	11.90%	9.99%
Generator	22.82%	25.74%	31.76%	25.49%
Microwave	2.23%	2.33%	2.94%	1.74%
TV Set	42.86%	44.89%	50.15%	47.73%
Computer	4.61%	4.48%	4.78%	4.17%
Imported rice	49.11%	52.12%	53.87%	47.13%
Beef	47.27%	45.36%	44.55%	43.91%
Fish-fresh	15.32%	12.65%	12.98%	15.71%
Recharge cards	56.90%	64.54%	79.68%	85.07%

Note: the table shows the average value of non-monetary indicators used in the consumption model for survey-to-survey imputation purposes for each wave of the GHS. For the 2018/19 GHS we use a zone-weight adjustment using population weights from the official 2018/19 NLSS to ensure comparability.

Table 9 Imputed poverty headcount rates at the US$1.90 and US$3.20 poverty line, by GHS wave

	Poverty rate US$1.90	95% Confidence Interval	
2010/11 GHS	43.54%	40.97%	46.11%
2012/13 GHS	42.49%	39.77%	45.20%
2015/16 GHS	40.75%	37.30%	44.20%
2018/19 GHS	41.88%	38.31%	45.44%
	Poverty rate US$3.20	**95% Confidence Interval**	
2010/11 GHS	72.88%	70.45%	75.32%
2012/13 GHS	72.12%	69.58%	74.67%
2015/16 GHS	70.44%	67.00%	73.89%
2018/19 GHS	72.28%	69.22%	75.34%

Note: the table shows imputed poverty estimates for each wave of the GHS. We develop a consumption model using data on 23 non-monetary indicators and household consumption available in the 2018/19 NLSS. Using the estimated parameters, we then impute in each round of the GHS using the same non-monetary indicators and 100 imputations. The imputed consumption vector is then converted to 2011PPP and poverty estimates are reported at the US$1.90 and US$3.20 poverty lines. Poverty estimates are reported with the respective 95 percent CI.

Table 10 Estimation of different pass-through rates using growth rate in national accounts measures and growth rates in household survey estimates available in PovcalNet

	Pooled				
	(1)	(2)	(3)	(4)	(5)
VARIABLES	All	No High Income	Lower Middle Income	Consumption	Sub-Saharan Africa
GDP (growth rate)	0.869***	0.894***	0.693***	0.754***	0.715***
	(0.0392)	(0.0503)	(0.0775)	(0.0579)	(0.169)
Observations	1,751	1,184	502	696	150
R-squared	0.219	0.210	0.138	0.196	0.107

	Comparable				
	(1)	(2)	(3)	(4)	(5)
VARIABLES	Pooled	No High Income	Lower Middle Income	Consumption	Sub-Saharan Africa
GDP (growth rate)	0.876***	0.911***	0.722***	0.756***	0.718***
	(0.0384)	(0.0491)	(0.0772)	(0.0507)	(0.146)
Observations	1,403	933	391	525	150
R-squared	0.271	0.270	0.184	0.298	0.139

	Pooled				
	(1)	(2)	(3)	(4)	(5)
VARIABLES	All	No High Income	Lower Middle Income	Consumption	Sub-Saharan Africa
GNI	0.737***	0.768***	0.761***	0.791***	0.694***
	(0.0375)	(0.0485)	(0.0837)	(0.0605)	(0.122)
Observations	1,542	1,019	428	558	106
R-squared	0.200	0.198	0.162	0.235	0.235

	Comparable				
	(1)	(2)	(3)	(4)	(5)
VARIABLES	All	No High Income	Lower Middle Income	Consumption	Sub-Saharan Africa
GNI	0.836***	0.910***	0.754***	0.751***	0.684***
	(0.0385)	(0.0500)	(0.0815)	(0.0503)	(0.120)
Observations	1,266	828	339	437	106
R-squared	0.272	0.286	0.202	0.338	0.236

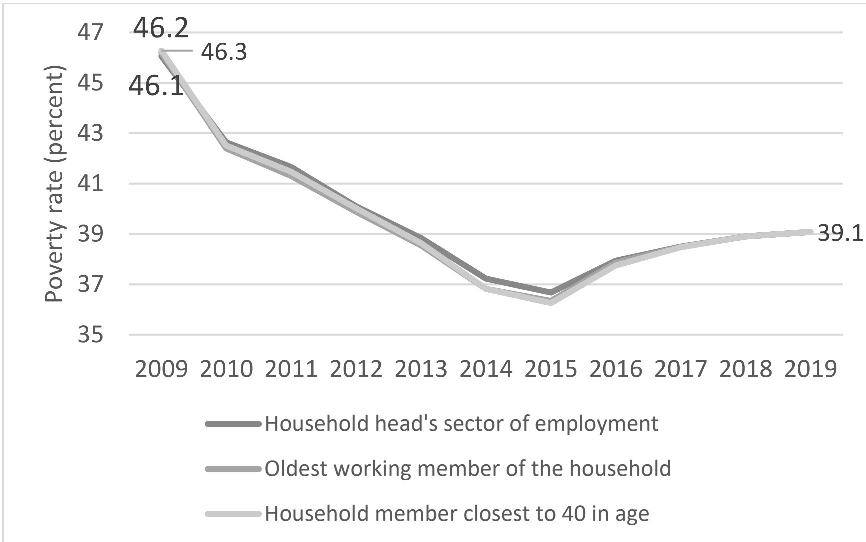
Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Each coefficient is from a different regression conducted using different samples. Each regression uses growth rates from national accounts (GDP/GNI per capita) and growth rates in average household consumption from survey-data available in PovcalNet to estimate a discount factor that accounts for the difference in growth rates between these two data sources. Different samples are used in each regression. Pooled samples use any survey-based estimate available in PovcalNet and focus on different income groups, welfare measure or region. Comparable samples use only comparable survey-based estimates available in PovcalNet (see PovcalNet's comparability dataset, available at: https://development-data-hub-s3-public.s3.amazonaws.com/ddhfiles/506801/povcalnet_comparability.csv).

Table 11 Backcasted estimates using different pass-through rates and sectoral GDP data at the US$1.90 and US$3.20 poverty lines

	Poverty rate at US$1.90 poverty line				Poverty rate at US$3.20 poverty line			
	Backcast, pass-through=0.42	Backcast, pass-through=0.75	Backcast, pass-through=0.87	Backcast, pass-through =1	Backcast, pass-through=0.42	Backcast, pass-through=0.75	Backcast, pass-through=0.87	Backcast, pass-through =1
2009	42.2	44.5	45.3	46.3	73.5	75.3	75.8	76.5
2010	40.7	41.9	42.4	42.8	72.0	72.9	73.1	73.5
2011	40.1	41.1	41.5	41.8	71.6	72.1	72.1	72.3
2012	39.5	39.9	40.1	40.3	71.2	71.3	71.3	71.3
2013	38.9	38.9	39.0	38.9	70.6	70.2	70.0	69.8
2014	38.3	37.7	37.5	37.4	69.8	69.1	68.6	68.3
2015	38.0	37.4	37.1	36.8	69.8	68.9	68.5	68.0
2016	38.6	38.2	38.1	38.0	70.4	70.1	69.9	69.7
2017	38.9	38.7	38.7	38.5	70.7	70.6	70.5	70.4
2018	39.0	39.0	39.0	39.0	70.9	70.9	70.8	70.8
2019	39.1	39.1	39.1	39.1	71.0	71.0	71.0	71.0

Note: the table shows different backcasted series for different values of the pass-through rates and different values of the poverty line. Estimates use sectoral GDP growth rates mapped to household's head sector of employment to backcast household consumption from the 2018/19 NLSS over the previous decade.

Figure 7 Backcasted poverty rates series using different variables to map sectoral GDP data to the 2018/19 NLSS



Note: the figure compares different backasted series that use different ways to map the sectoral GDP data to household consumption data from the 2018/19 NLSS. It compares the main specification that uses household head's sector of employment, to one using the sector of employment of the oldest working member of the household or the member of the household closest to 40 in age.

Table 12 Annualize change in average annual household consumption for different combinations of imputed GHS data, by decile

Deciles	Annualized Difference 2010/11 - 2018/19, percent	Annualized Difference 2010/11 - 2015/16, percent	Annualized Difference 2015/16 - 2018/19, percent
1	0.4	0.7	-0.2
2	0.4	0.8	-0.3
3	0.4	0.8	-0.4
4	0.4	0.9	-0.5
5	0.3	0.9	-0.7
6	0.3	1.0	-0.9
7	0.2	1.0	-1.1
8	0.1	1.0	-1.3
9	0.0	1.0	-1.7
10	-0.1	1.1	-2.0

Note: the table shows the annualize change in average annual consumption at the decile level between different waves of imputed GHS data. Annualized changes are calculated using the compound annual growth rate. Household consumption data for different GHS waves is imputed using the main specification presented in this paper (also referred to as “Original Model”).

Table 13 Summary statistics for selected comparable variables used to impute consumption, by visit of the 2018/19 GHS

	2018/19 GHS post-planting (%)	2018/19 GHS post-harvesting (%)	Difference (percentage points)
North-Central	14.08	14.07	-0.01
North-East	8.29	8.27	-0.02
North-West	19.50	19.53	0.03
South-East	13.20	13.07	-0.13
South-South	17.91	17.88	-0.03
Gender	80.43	79.90	-0.53
Dependency Ratio	42.88	43.30	0.42
Employed: Non-farm	42.64	36.90	-5.74
Employed: Waged	16.24	18.17	1.93
Main cooking fuel: Wood	60.52	60.62	0.10
Main flooring: Cement	71.37	71.42	0.05
Fresh Fish	15.07	16.34	1.27
Imported Rice	46.92	47.34	0.42
Beef	42.37	45.44	3.07
No Toilet	29.09	28.97	-0.12
Recharge Cards	84.24	85.88	1.64
Air Conditioner	1.69	1.66	-0.03
Washing Machine	1.98	1.95	-0.03
Cars and other vehicles	10.00	9.98	-0.02
Generator	25.50	25.48	-0.02
Microwave	1.76	1.73	-0.03
TV Set	47.71	47.76	0.05
Computer	4.19	4.15	-0.04

Note: the table shows the average value of non-monetary indicators used in the consumption model for survey-to-survey imputation purposes. Columns 1-2 show the average value for the post-planting and post-harvesting wave of the 2018/19 GHS, columns 3-4 show the summary stats for the two visits in the 2010/11 GHS. The purpose of the table is to check whether non-monetary indicators are subject to seasonal variation over the year and could bias the imputed estimates.

Table 14 Poverty rates estimated using different models to impute household consumption in 2010/11

	(1)	(2)	(3)	(4)	(5)	(6)
	Original Model	Model 1	Model 2	Model 3	Model 4	Model 5
Excluded vars	*None*	*Wage-employed*	*Wage-employed, no-toilet*	*Wage-employed, no toilet, imported rice*	*Non-farm employment*	*All food consumption, all employment*
2010/11 GHS	0.4354	0.4367	0.4409	0.4495	0.4377	0.4541
	(0.016)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
2012/13 GHS	0.4153	0.4166	0.4166	0.4285	0.4184	0.4281
	(0.016)	(0.016)	(0.016)	(0.016)	(0.017)	(0.016)
2015/16 GHS	0.4049	0.4045	0.4049	0.4130	0.4060	0.4111
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
2018/19 GHS	0.4188	0.4195	0.4175	0.4182	0.4195	0.4142
	(0.018)	(0.018)	(0.018)	(0.019)	(0.018)	(0.017)
2018/19 NLSS	0.3909	0.3909	0.3909	0.3909	0.3909	0.3909
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)

Note: SE in parentheses. The table shows different imputed poverty estimates from survey-to-survey imputation exercise. Each coefficient is from a separate imputation. Different models are used to test the robustness of the estimates to different specifications of the consumption model, which exclude different sets of covariates as reported in the table. Data are from the 2018/19 NLSS (baseline survey) and 2010/11, 2012/13, 2015/16, 2018/19 GHS.

Table 15 Comparing different estimates of the poverty headcount rate at the US$1.90 poverty line: backcasted, interpolated, imputed methods

	HNLSS 2009/10; 2018/19 NLSS	Backcast, pass-through=1	Interpolated series without 2009/10	Imputed poverty rate at US$1.90, GHS Original model
2009	56.40%	46.3%	45.9%	
2010		42.8%	43.5%	43.5%
2011		41.8%	42.1%	
2012		40.3%	41.2%	41.5%
2013		38.9%	37.2%	
2014		37.4%	35.2%	
2015		36.8%	35.2%	40.5%
2016		38.0%	37.6%	
2017		38.5%	38.6%	
2018		39.0%	38.9%	41.9%
2019	39.09%	39.1%	39.2%	

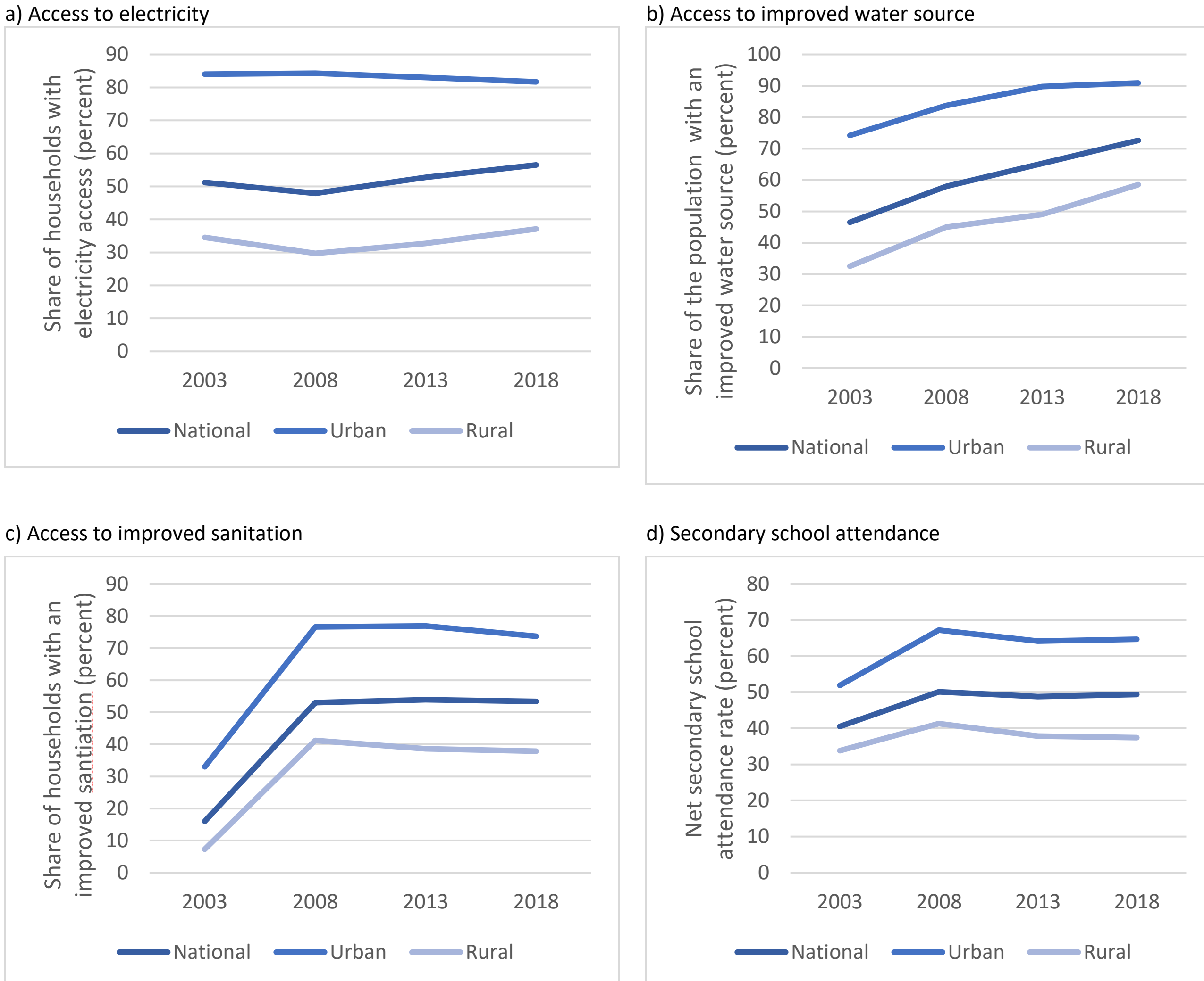
Note: the table shows a summary of the different estimates produces in this analysis. Column 1 shows the non-comparable survey-based estimates from 2009/10 HNLSS and 2018/19 NLSS. Column 2 shows the backcasted series using a pass-through of 1 and using sectoral GDP data mapped to household head's employment sector to backcast the 2018/19 consumption vector. Column 3 shows the results of interpolating between the 2003/04 NLSS and 2018/19 NLSS without using the HNLSS 2009/10 estimate and following PovcalNet's methodology (Prydz et al. 2019). Column 4 and 5 show the results of survey-to-survey imputations using GHS data from different waves and 2018/19 NLSS as a baseline survey. Column 4 shows the imputed estimates when using a full set of non-monetary indicators, column 5 shows the imputed estimates when excluding from the consumption model potentially seasonal variables such as food-consumption dummies and employment indicators.

Table 16 Main estimates using different sources of population data, WDI and NBS

	Number of poor at the US$1.90 poverty line (millions) – using NBS population estimates			Number of poor at the US$1.90 poverty line (millions) – using WDI population estimates		
	NLSS	Backcasts (pass-through 1)	S2S Imputation	NLSS / PovcalNet	Backcasts (pass-through 1)	S2S Imputation
2009/10	91.1			89.4		
2009		73.8			71.4	
2010		70.0			67.8	
2011		70.2			68.1	
2010/11			72.0			69.9
2018/19	80.8			78.5		

Note: the table shows a summary of the main estimates of number of people living below the US$1.90 poverty line using different population data. The left-hand side panel shows the number of extreme poor (in million) using the NBS population data, the right-hand side panel uses WDI population data (used throughout the rest of the paper).

Figure 8 Trends in non-monetary indicators correlated with household welfare, DHS data 2003-2018



Note: each panel shows trends in non-monetary indicators highly correlated with household welfare and monetary indicators of poverty using data from the DHS 2003, 2008, 2013, 2018. Trends are presented separately for households living in rural and urban areas as well as at the national level. Panel a shows the share of households with access to electricity, panel b shows the share of households with access to improved water source, panel c shows the share of households with access to improved sanitation and panel d shows the secondary school attendance rate.