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SPATIAL INEQUALITY IN SUB-SAHARAN AFRICA

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Spatial Inequality in sub-Saharan Africa

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Abstract
This paper provides within-country spatial and national inequality estimates in SSA using comparable data from the DHS. Two indicators are used to measure household welfare. First, detailed information on living standards indicators is used to calculate asset indices using data from 24 SSA countries with comparable data in recent years. The inequality estimates based on the asset indices are used to provide contemporary asset inequality estimates in SSA. Results reveal high levels of within-country spatial and national asset inequalities in SSA, with large variations across countries. The second indicator of household welfare is based on data on access to basic services. Access to basic services is measured by deriving an index calculated using indicators such as access to water, sanitation, electricity, a telephone, and education. We compare changes in inequalities in access to basic services using data from 27 SSA countries that have comparable data for at least two periods between 1995 and 2018. The findings suggest that, apart from a few countries, within-country spatial and national inequalities in access to basic services have declined over time. Nevertheless, the level of inequality and the magnitude of the changes in inequality over time varies greatly across countries, and disparities in access to basic services remain quite large in some SSA countries. Our findings, using both indices, show that within-country regional inequality is a significant component of national inequality in the majority of SSA nations, with significant policy implications.

Keywords
Spatial inequality, asset inequality, basic services, Africa

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Introduction

In most Sub-Saharan African (SSA) countries, the spatial dimension of inequality (i.e. within-country regional inequality) is one of the key components of national inequality (Kanbur, Venables & Wan 2005; McKay & Perge, 215; Beegle et al., 2016). In addition, within-country regional disparities in SSA are often largely associated with pre-existing social divisions such as religion and ethnicity leading to an increase in ethnic conflicts (Stewart, 2008; Kanbur et al., 2005; McKay & Perge, 2015).[1] Despite the potential role of spatial inequality in reducing overall inequality and improving social cohesion, and political stability, there is limited work which analyses the spatial dimension of inequality in SSA countries. This is because of the lack of comparable data to measure income/consumption and prices at sub-regional levels.

Household surveys that are the bases of income poverty and inequality estimates are not regularly available and plagued with non-response and comparability issues (see Deaton, 2005; Chen & Ravallion, 2013; Beegle et al., 2016). This is especially true in measuring inequality where the expenditure and consumption data that are the bedrock of poverty analysis are often less well suited than income or wealth data in measuring and analysing inequality (Zizzamia et al., 2021). But data on income or wealth are much less readily available and reliable (Robilliard,2020). Given this, some studies have used indirect methods to assess income poverty and inequality trends in Africa. Young (2012), for example, predicted trends in real consumption growth in 29 African countries using data on household assets and other indicators of living standards from the Demographic and Health Survey (DHS). Young's (2012) findings imply higher average consumption growth rates and significant poverty reduction in SSA since the 1990s than other studies that used consumption data from household surveys (Chen & Ravallion, 2010; McKay, 2013). Similarly, in order to measure and explain spatial inequality, recent studies have used satellite night-time

[1] Some empirical works have found a relationship between societal divides such as ethnicity and religion and access to publicly provided goods and services in SSA (see e.g. Brockerhoff & Hewett, 2000; Kimenyi, 2006; Jackson, 2013). See, for example, Østby, Nordås, and Rød (2009) and Fjelde and Østby (2012) on the relationship between spatial inequality and ethnic conflict.

light data as a proxy indicator (or predictor) of income or economic activity (Alesina, Michalopoulos & Papaioannou, 2016; Lessmann & Seidel, 2017; Mveyange, 2018).

Although these studies have significantly contributed to our understanding of the extent of poverty and inequality in developing countries, the use of night-time light data or household assets to predict consumption or income has several limitations, particularly in estimating trends over time (see Howe et al.,2009; Vollmer et al.,2013). Vollmer et al. (2013), for example, demonstrate that there is no significant relationship between asset index growth and consumption growth in Africa or elsewhere.[2] This is not to say that assets are not useful tools for analyzing poverty and inequality. Assets, when measured correctly, can be used to measure non-income dimensions of household well-being in a variety of settings without the need to predict consumption levels based on asset holdings (Vollmer et al.,2013). However, only a few studies used non-income dimensions of household well-being to estimate national and within-country spatial inequalities in SSA (Sahn & Stifel, 2003; Shimeles & Nabassaga, 2018).

In this paper, we examine trends and patterns of within-country spatial and national (interpersonal) inequalities in SSA using comparable data from the DHS. Two indicators are used to measure household welfare. First, we calculate household asset indices using detailed information on various living standards indicators from 24 SSA countries with comparable data in recent years. Within each country, asset indices are created as measures of household welfare or standard of living. Inequality estimates are then created from these asset/wealth indices as the basis for our estimation of contemporary inequality in SSA.

We use data on access to basic services as a second, narrower measure of household welfare to assess how inequalities have been evolving over time. To this end, we use data from 27 countries that have comparable data between 1995 and 2018 for at least two periods. Access to

[2] Vollmer et al. (2013) give four reasons why assts aren't a good proxy for estimating household consumption: Changes in relative prices can lead to a demand shift favoring some assets at the expense of other household expenditures, assets are stocks while consumption is a flow, preferences for certain assets (e.g. televisions and telephones) may increase over time, and states heavily subsidize access to certain assets (e.g., electricity and water) (Vollmer 2013: p41). Furthermore, in the absence of data on asset age and depreciation, asset values and predicted consumption may be overestimated.

basic services is measured on the basis of an index calculated using indicators such as access to water, sanitation, electricity, telephone, and education. Inequality in access to basic services is a measure of inequality of opportunity, as access to these services largely depends on public investments, such as electrification, mobile phone coverage, and school construction. Moreover, inequalities in access to basic services are associated with inequalities in the prevalence and severity of the COVID-19 pandemic and capacity to deal with the pandemic (e.g. Bambra et al., 2020; Brown, et al., 2020; Shifa et al,2021). As a result, there is considerable policy relevance in examining the distribution of access to basic services and education as important elements of overall inequality.

The paper is structured as follows: a description of the data set used for the analysis is provided in Section 2. Sections 3 and 4 discuss the methodology used to estimate regional welfare measures and inequalities. Section 5 presents the results of our inequality estimates. A summary and a discussion of our key findings are provided in Section 6.

Data and measurement

We use the DHS data, which collects information on health, population, and HIV in more than 90 countries around the world including 43 countries in SSA. We use the personal data file, which provides comparable and rich data on each household member's basic demographic characteristics (i.e. age, gender, place of residence, education levels) as well as household variables such as asset ownership and access to basic services.

One of the key limitations of the DHS in the analysis of poverty and inequality is that it does not collect information on income or consumption. However, detailed information on asset ownership and access to various basic services is useful in calculating asset indices that are often used as a measure of household economic status. Asset indices are considered better indicators of long-term economic status compared to income or consumption (Filmer & Pritchett, 2001; McKenzie, 2005). However, there is no standard approach to selecting variables to measure the economic status of an individual. Various variable combinations are used to calculate asset indices in the literature for the purpose of measuring poverty and inequality (Sahn & Stifel, 2000; Filmer & Pritchett, 2001; McKenzie, 2005; Booysen et al., 2008; Filmer & Scott, 2012; Young,2012; Sahn & Younger, 2017; Smits & Steendijk, 2015). Moreover, there is every reason to expect that these choices need to be made in a way that is sensitive to country specificities (Wittenberg & Leibbrandt, 2017). Data availability is often one of the determining factors in the selection of the number and type of indicators that can be included in asset/wealth index calculations.

Based on the literature and subject to availability of data, this study considers 18 living standards indicators to calculate our measure of asset/wealth indices for 24 SSA countries. Annexure A provides the list of variables used to estimate the asset/wealth index and how each variable is measured. The living standards indicators include ownership of durable assets (television, radio, refrigerator, car/truck, bicycle/motorcycle and telephone), basic services (access to water, sanitation and electricity) and dwelling conditions (number of rooms per capita , type of floor material, type of fuel used for cooking), education (maximum years of schooling in a household), and land and livestock ownership measures (own land usable for agriculture and own livestock such as cattle/cows/bulls, goats, sheep, chickens). The indicators used to calculate asset/wealth indices in most previous studies that examine poverty and inequality have an urban bias because rural assets such as land and livestock have not been included, which may exaggerate regional disparities in household asset holdings (Rutstein, 2008; Wittenberg & Leibbrandt, 2017). The set of indicators used to construct household asset/wealth indices in this paper reduces such biases. However, comparable data on all of these living standard indicators used to construct household asset/wealth indices are available only in recent DHS surveys. Thus, we use these asset/wealth indices to provide contemporary inequality estimates in SSA.

We use data on access to basic services as a second, narrower measure of household welfare to assess inequality trends over time. Fairly comparable data on education and access to basic services such as water, electricity, sanitation, and telephone, have been available in 36 SSA countries. Of the 36 countries, 27 had more than one survey between 1995 and 2018. Table 2 in Annexure A provides the list of countries and the number of surveys available for each country. To measure access to basic services we calculate an index for each household using the information on access to basic services (water, sanitation, electricity, telephone, and education). However, indicators of access to water and sanitation have not been consistently labelled over time and across countries. The problem is that in the case of earlier surveys it is not clear whether or not water from other sources, such as walls or springs, was protected. This prevents us from categorizing water access as "improved" and "unimproved" in the same way that we did in Table 1. There is a similar problem regarding sanitation. For these reasons, water access is measured based on whether or not a household has access to piped water (private or public), and sanitation access is measured based on whether or not a household has access to a toilet (either a flush toilet or a pit latrine toilet). The education variable is measured in the same way as Table 1 (maximum years of schooling in a household).

Calculating asset indices

In this section, we discuss the methodology used to estimate our asset/wealth indices. Once we determine which living standards indicators to include in measuring household economic status, the next step is to decide on the approaches to be used to combine these living standard indicators into a single number, which is often called an "asset index". If we have *k* variables measuring living standards, $(x_1, \ x_2 \ldots, x_k)$, one way to combine these indicators into a single index for each household is to use the following equation:

$$Asset\ Index = w_1 x_1 + w_2 x_2 + \cdots + w_k x_k \text{--------------}[1]$$

Where w_i indicates weights associated with each living standard indicator. There are various approaches suggested to generate the weights, w_i. These include assigning equal weights (i.e. counting), using prices or using data-driven procedures (statistical approaches) such as principal component analysis (PCA), multiple correspondence analysis (MCA), or factor analysis (FA). The statistical approaches are the standard approaches used in the literature to generate weights in calculating asset indices.[3] For instance, in the case of the PCA approach, we can write each living standard indicator, x, as a linear combination of k factors or components as follows (see Filmer & Scott, 2012; Wittenberg & Leibbrandt, 2017):

$$\begin{aligned}
\tilde{x}_1 &= v_{11}A_1 + v_{12}A_2 + \cdots + v_{1k}A_k \\
\tilde{x}_2 &= v_{21}A_1 + v_{22}A_2 + \cdots + v_{2k}A_k \\
&\ldots \\
\tilde{x}_k &= v_{k1}A_1 + v_{k2}A_2 + \cdots + v_{kk}A_k
\end{aligned}$$

Where $\tilde{x}_1, \ \tilde{x}_2, \ldots, \tilde{x}_k$ are living standards indicators normalized by their means and standard deviations; $A_1, \ A_2, \ldots, \ A_k$ are unobserved principal components that are uncorrelated with each other; and v_{ij} indicates the weights that relate the ownership of the assets to the principal components. The weights used to calculate asset indices are obtained from the first "principal component", A_1, which is a linear

[3] Price data is hardly available, and it is difficult to justify the use of equal weights.

combination that accounts for the highest variance in the asset distribution. We can write the solution for the first principal component as follows:

$$A_1 = v_{11}\tilde{x}_1 + v_{12}\tilde{x}_2 + \cdots + v_{1k}\tilde{x}_k$$

The first principal component is the factor that explains what is common to the living standards indicators, which is assumed to be household economic status, “wealth”. Thus, a higher asset index corresponds to a higher measure of household “wealth”. This is used to measure household and individual welfare.

A number of limitations have been identified in the use of standard statistical approaches to generate weights (see McKenzie, 2005; Wittenberg & Leibbrandt, 2017). First, the asset indices constructed using these approaches include negative and positive values, therefore have zero mean values by construction. This is problematic if we use conventional inequality measures such as the Gini coefficient. Some linear transformation is used in the literature to solve this problem. However, with conventional inequality measures such as the Gini coefficient, this is not appropriate since such inequality measures are not translation invariant (Wittenberg, 2013; Wittenberg & Leibbrandt, 2017). Thus, inequality is mismeasured when this is done.

Second, given that the PCA procedure works by isolating what is common to included assets, non-common assets could be considered as “bad” and assigned negative weights (Wittenberg & Leibbrandt, 2017). For example, most of the living standards indicators in the DHS data are common in urban areas and therefore rural assets such as livestock could be assigned negative weights. We could thus end up ranking rural households with livestock lower than households with no assets at all (Wittenberg & Leibbrandt, 2017). In order to solve this problem, Wittenberg and Leibbrandt (2017) suggested the use of the uncentered PCA (UCPCA) approach in the calculation of asset indices, a method originally proposed by Banerjee (2010). The key adjustment in the calculation of the UCPCA is that the standard variables of the assets are not demeaned. Instead, each x_i is divided by its average value. One of the problems with the use of the UCPCA is that, due to the standardization procedure, assets with small mean values are likely to have higher weights, which will be problematic if the ownership of such assets does not reflect higher wealth. In such cases, it is suggested that such assets should be removed from the analysis (Wittenberg & Leibbrandt, 2017).

Following Wittenberg and Leibbrandt (2017), we use the UCPCA procedure to calculate household asset/wealth indices and indices of access to basic services. The living standards indicator variables in the DHS or other household surveys are measured at a household level. Thus, we calculate asset indices at a household level. Since there is no standard way to calculate per-capita asset index values (Rutstein & Kiersten, 2004), everyone in a household will be assigned the same asset index values calculated at a household level.

Weights are generated after pooling the surveys from the 24 countries for computing household asset/wealth indices. Similarly, in order to compare inequality estimates across time within countries, we compute basic services indices for each country based on asset weights derived by pooling datasets over time within each country. Table 3 in Annexure A provides the weights generated using the UPCA procedure and descriptive statistics for the variables used in calculating household asset/wealth indices. Using clean fuel for cooking, having a car/truck and a refrigerator all have relatively higher weights whereas having a rural asset (such as livestock) and owning a bicycle/motorcycle have lower weights.

We also create the basic services indices based on asset weights generated by pooling datasets from all countries and survey years in order to make cross-country comparisons. The basic services indices estimated using the two methodologies, however, are highly correlated (correlation coefficient of 0.95 (p=000)). As a result, we only provide estimates of inequality based on asset weights obtained after pooling records from all countries and survey years. We use sampling weights in all of our estimates to account for the differential probabilities of selection used in each country when selecting samples.

Spatial inequality estimation

In this section, we discuss the approach used to measure spatial inequality within a given country (within-country regional disparities). In measuring regional disparities, geographical locations/regions may indicate administrative units such as provinces, regional states, districts, and municipalities. In our case, we use the first administrative units (i.e. provinces, districts, or regions) in each country as our spatial unit. Inequality indices such as the population-weighted coefficient of variation, Theil index, and Gini coefficient are the common methods used to measure spatial inequality in the literature (Williamson, 1965; Lessmann, 2014; Ezcurra & Rodríguez-Pose, 2017; Lessmann & Seidel, 2017). Some argue that the population-weighted coefficient of variation (COV_w) is the preferred approach to estimating spatial inequality (Portnov & Felsenstein, 2005; Lessmann, 2014). For example, Lessmann (2014) argues that unlike the other indices, the COV_w is independent of the number and the sizes of spatial units included, it is mean-independent, it is not sensitive to single extreme values, and satisfies the transfer principle. However, Gluschenko (2018: p. 40) shows that the population-weighted inequality indices are only proxy measures for interpersonal inequality in the entire population of a country rather than regional inequality. For this reason, Gluschenko (2018) suggested using population unweighted inequality indices to analyse spatial inequality.

In this paper, the population unweighted coefficient of variation (COV) and the Gini index are used to calculate spatial inequality. Both the population unweighted Gini index and COV satisfy the four main inequality axioms (anonymity, normalization, scale invariance, and the transfer principle). For analysing within-country regional inequalities, we estimate average household asset/wealth index values for each region within each country. The formulas for the calculation of the unweighted COV and Gini coefficient are given as follows:

$$COV = \frac{\sqrt{\sum_i^k (Y_i - \bar{Y})^2/k}}{\bar{Y}}$$

$$G=\sum_{i=1}^k \sum_{j=1}^k \frac{|y_i - y_j|}{2k^2\bar{Y}}$$

Where, k is the number of regions in each country, Y_i is the average asset/wealth index value across households in region i in a given country, $\bar{Y}$ is the mean of the regional average asset/wealth index value ($\bar{Y} = Y_1 + Y_2 +, \dots, +Y_k)/k$) for a given country.

The number of regions varies from three in Comoros to 30 in Tanzania. Given that the value of the COV ranges from zero to infinity and it depends on the number of regions, comparison across countries is difficult. To reduce this problem, Gluschenko (2018) suggests dividing the COV values by its upper bound, which is given as the square root of the number of regions minus one ($\sqrt{k-1}$). Similarly, we normalize the values of the Gini coefficient by (k-1)/k. Both the raw and standardized COV and Gini coefficient estimates are provided.

We also provide estimates of interpersonal (i.e. national) inequalities based on the Gini coefficient. To do this, we use individual level asset/wealth index values (i.e. household level asset/wealth indices assigned to each individuals within as household). Moreover, using the Theil T index, we decompose overall (national) inequality estimates in each country to between and within region components. Such decomposition analysis helps to highlight the contribution of interregional inequality to overall national inequality in each country. The formula for estimating the Theil T index is as follows:

$$T_T = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{y_i}{\bar{Y}}\right) ln\left(\frac{y_i}{\bar{Y}}\right)$$

Where Y_i is individual level asset index values, N is the number of observations in a country, and $\bar{Y}$ is mean asset value of a country.

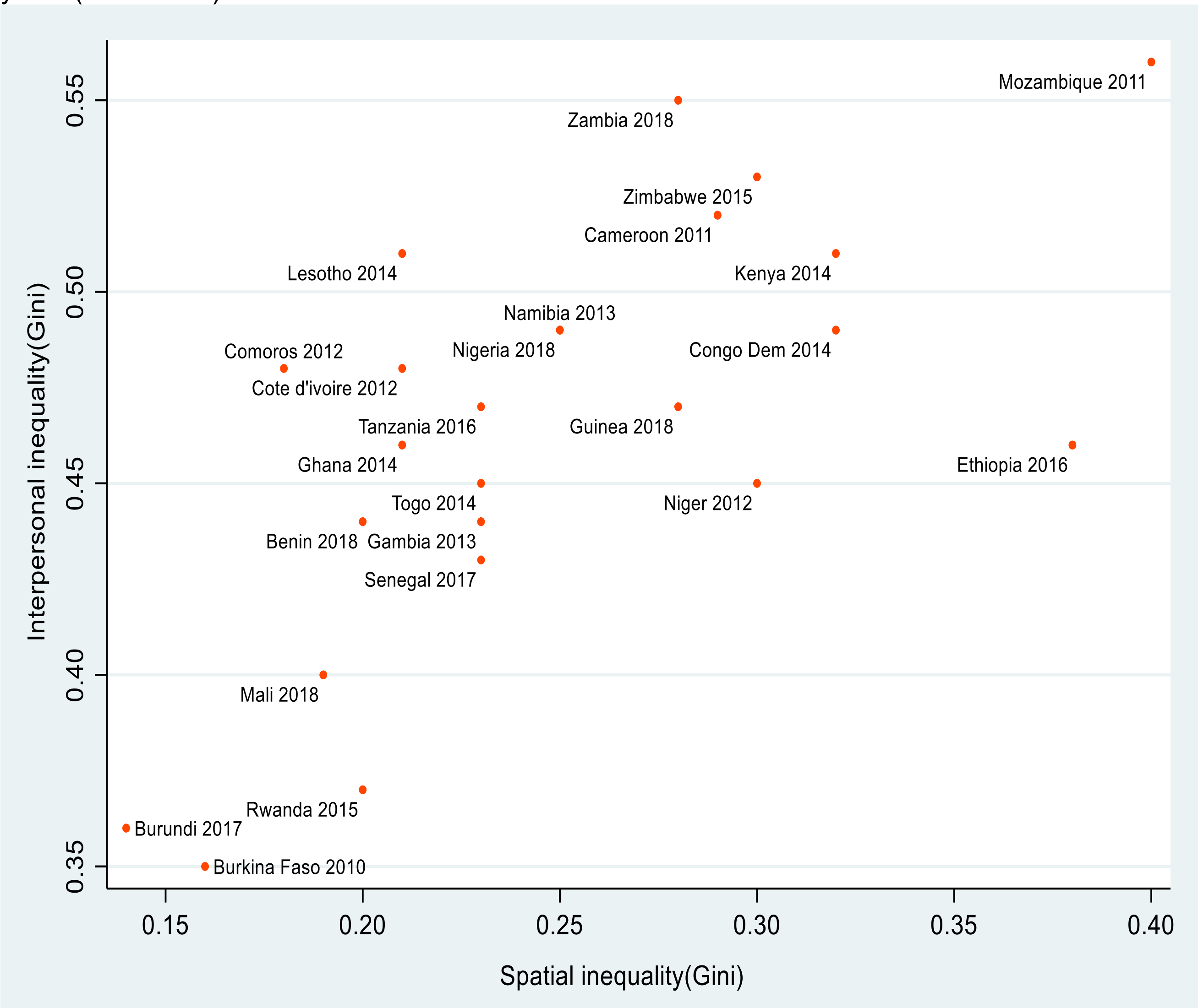
Results and discussions

In this section, we present inequality estimates based on household asset/wealth indices and access to basic service indices. In both cases, we provide estimates of national (interpersonal) and spatial (interregional) inequalities.

Inequalities in household asset/wealth

The inequality estimates based on household asset/wealth indices are used to provide contemporary asset inequality estimates in SSA. Interpersonal and spatial asset inequality estimates for the 24 countries with recent comparable data are presented in Figure 1 and Table 4 (Annexure B). The findings reveal high levels of spatial and interpersonal asset inequalities in SSA in recent years. However, there is significant variation across countries. In terms of regional disparities, the Gini coefficient was relatively higher in Mozambique (0.40), followed by Ethiopia (0.38), Kenya (0.32) and the Democratic Republic of the Congo (0.32), while the figure was relatively lower in Burundi (0.14), Burkina Faso (0.16) and Comoros (0.18). Interpersonal asset inequality was the highest in Mozambique (0.56), followed by Zambia (0.55) and Zimbabwe (0.53), while the figure was relatively low in Burkina Faso (0.35) and Burundi (0.36).

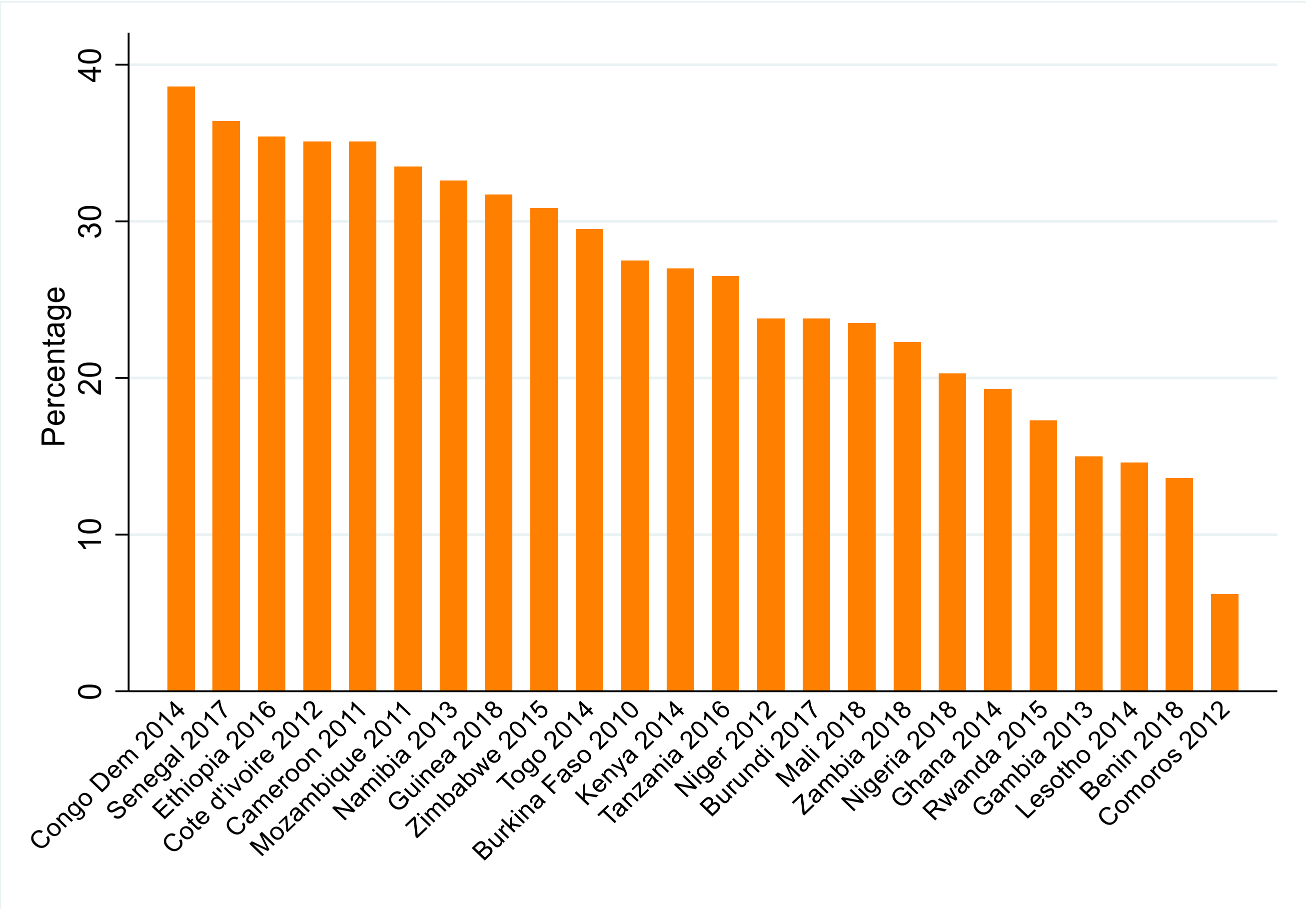
Figure 1: The relationship between Interpersonal and spatial asset inequalities, most recent years (2010-2018)



Source: Own estimates using data from DHS.

Figure 1 reveals that countries with comparatively higher regional inequalities have higher national inequalities with a correlation coefficient of 0.67 (p=000) between the two inequality measures. The positive and significant correlation between national and regional inequality estimates suggest that spatial inequality accounts for a large proportion of national inequality in SSA. Decomposing national inequality estimates into between and within region components indicates that the between component accounts for a large proportion of national inequality. The figure ranges between 35 percent and 40 percent in 9 of the 24 countries considered in this analysis (Figure 2). These findings suggest that reducing spatial inequality can make a significant contribution to the reduction of national (interpersonal) inequality in most SSA countries.

Figure 2: Between-region inequality contributions to national inequalities (asset inequality), most recent years (2010-2018)



Source: Own estimates using data from DHS.

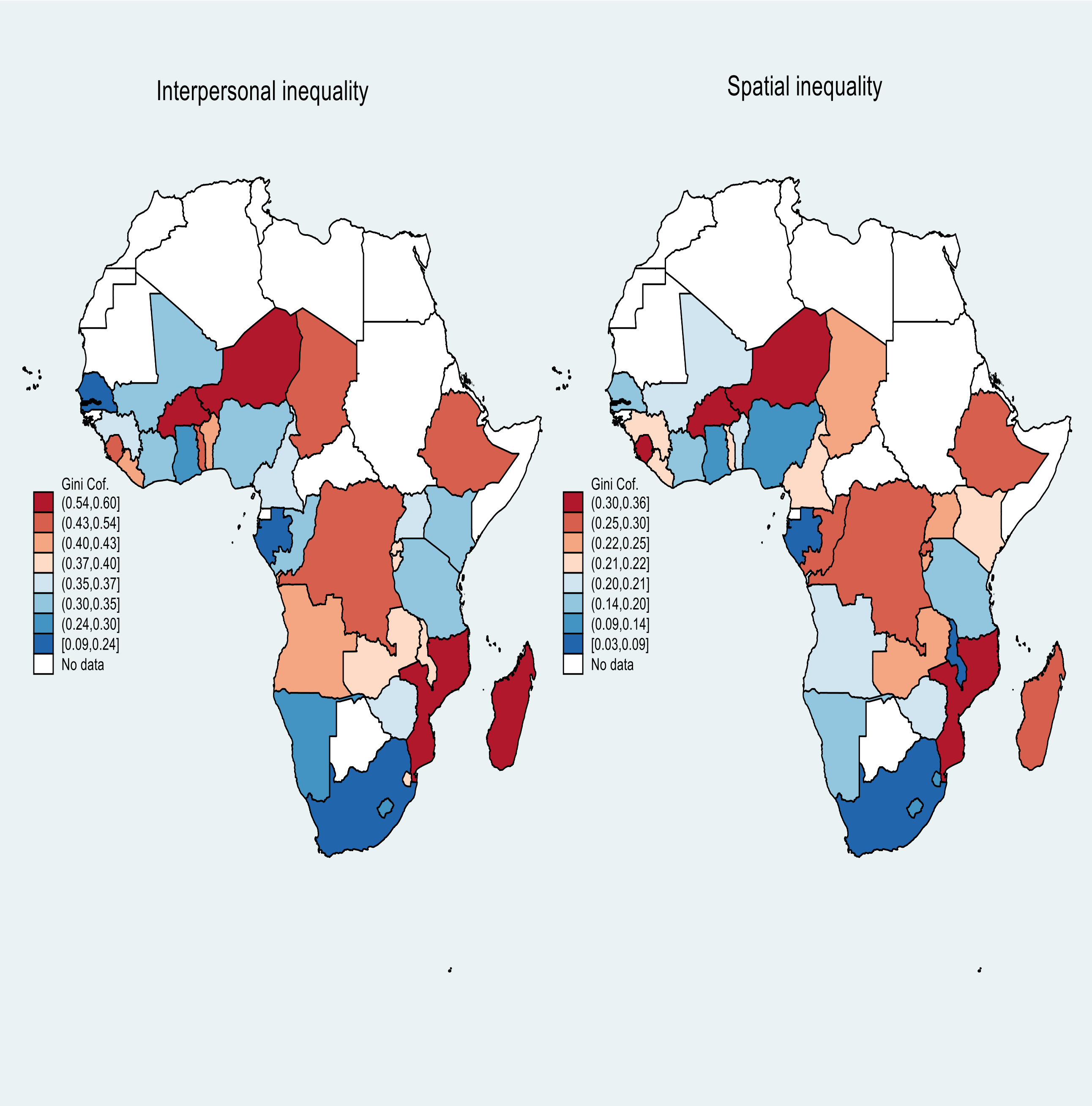
Overall, our analysis in this section shows that inequalities in SSA countries have remained very high in recent years. The Gini coefficient for interpersonal asset inequality estimates ranges from 0.4 to 0.5 in 13 of the 24 countries included in the analysis. For six of the countries (Kenya, Cameron, Zimbabwe, Zambia, Lesotho, and Mozambique), the Gini coefficient for interpersonal asset/wealth inequality is over 0.5. Apart from Lesotho, these countries also have relatively higher spatial inequalities.

Inequalities in access to basic services

In this sub-section, we present inequality estimates based on access to basic service indices. Table 5 (Annexure B) provides both interpersonal and spatial inequality estimates of access to basic services for each country and survey year. The map below (Figure 3) shows inequality estimates based on access to basic service indices for 36 SSA countries with comparable data in recent years. Except for Swaziland (2007), São Tome (2009) and Madagascar (2009), the latest data available for all the countries was collected after 2010.

Results indicate that interpersonal inequality in access to basic services in recent years was relatively higher in Niger (0.57), Mozambique (0.56), Chad (0.53) and Ethiopia (0.49) while the figure was relatively lower in countries such as South Africa (0.09), Gabon (0.11), Comoros (0.21), Senegal (0.23) and Ghana (0.24). In terms of spatial inequality, the Gini coefficient was relatively higher in Sierra Leone (0.36), Mozambique (0.35) and Niger (0.33), while the figure was relatively lower in Gabon, Malawi, Comoros and South Africa, with Gini estimates being less than 0.1.

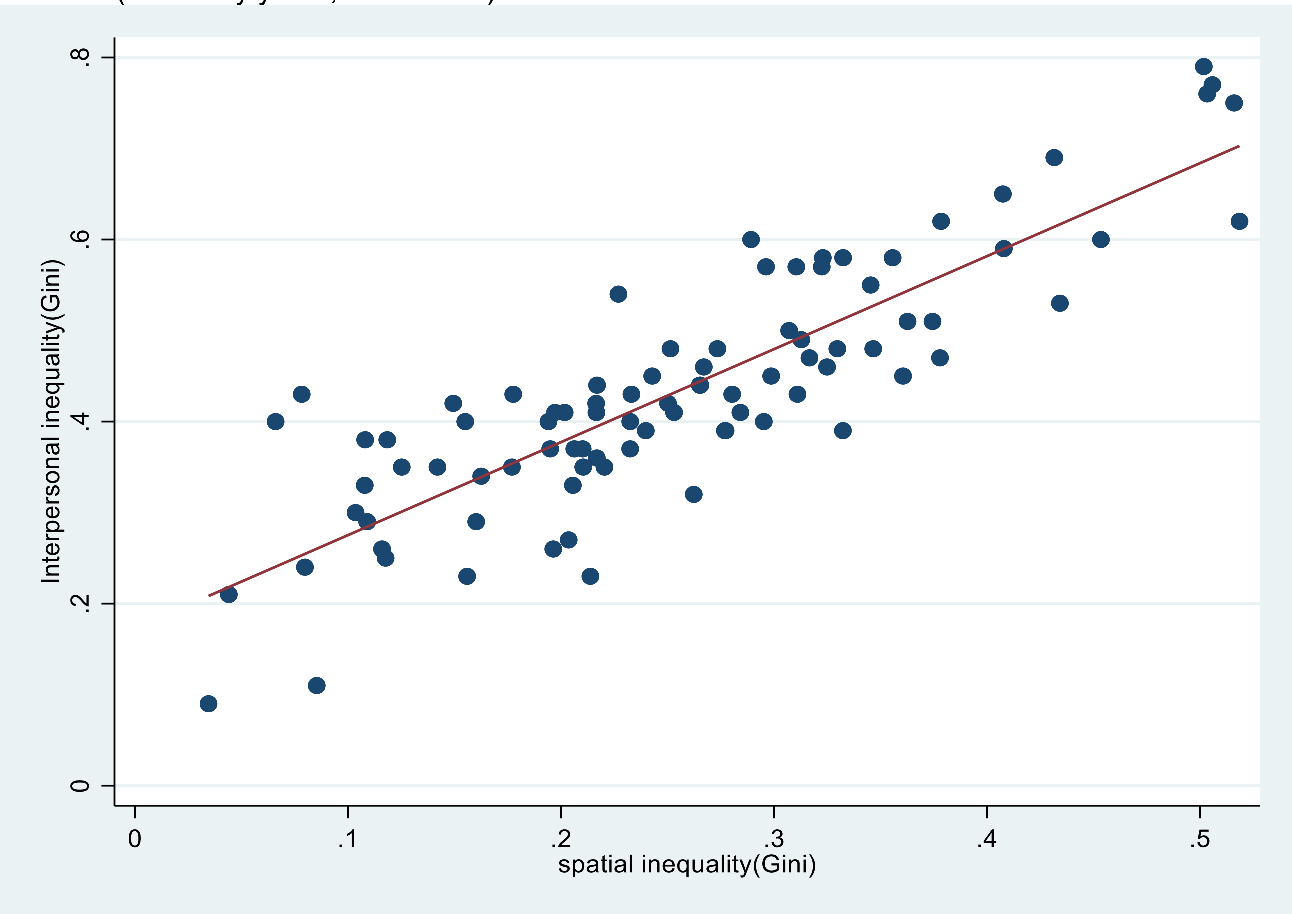
Figure 3: Spatial and interpersonal inequalities in access to basic services, most recent years (2007-2018)



Source: Own estimates using data from DHS.

Figure 4 also presents a scattered plot of spatial and interpersonal inequality estimates based on the Gini coefficient, using data from all countries and survey years (1995-2018). The result shows a positive and significant relationship between the measures of interpersonal and spatial inequalities, with a correlation coefficient of 0.84(p=000) between the two inequality measures. This indicates that spatial inequality accounts for a large proportion of national inequality in access to basic services in most SSA countries.

Figure 4: The relationship between spatial and interpersonal inequality in access to basic services (all survey years, 1996-2018)

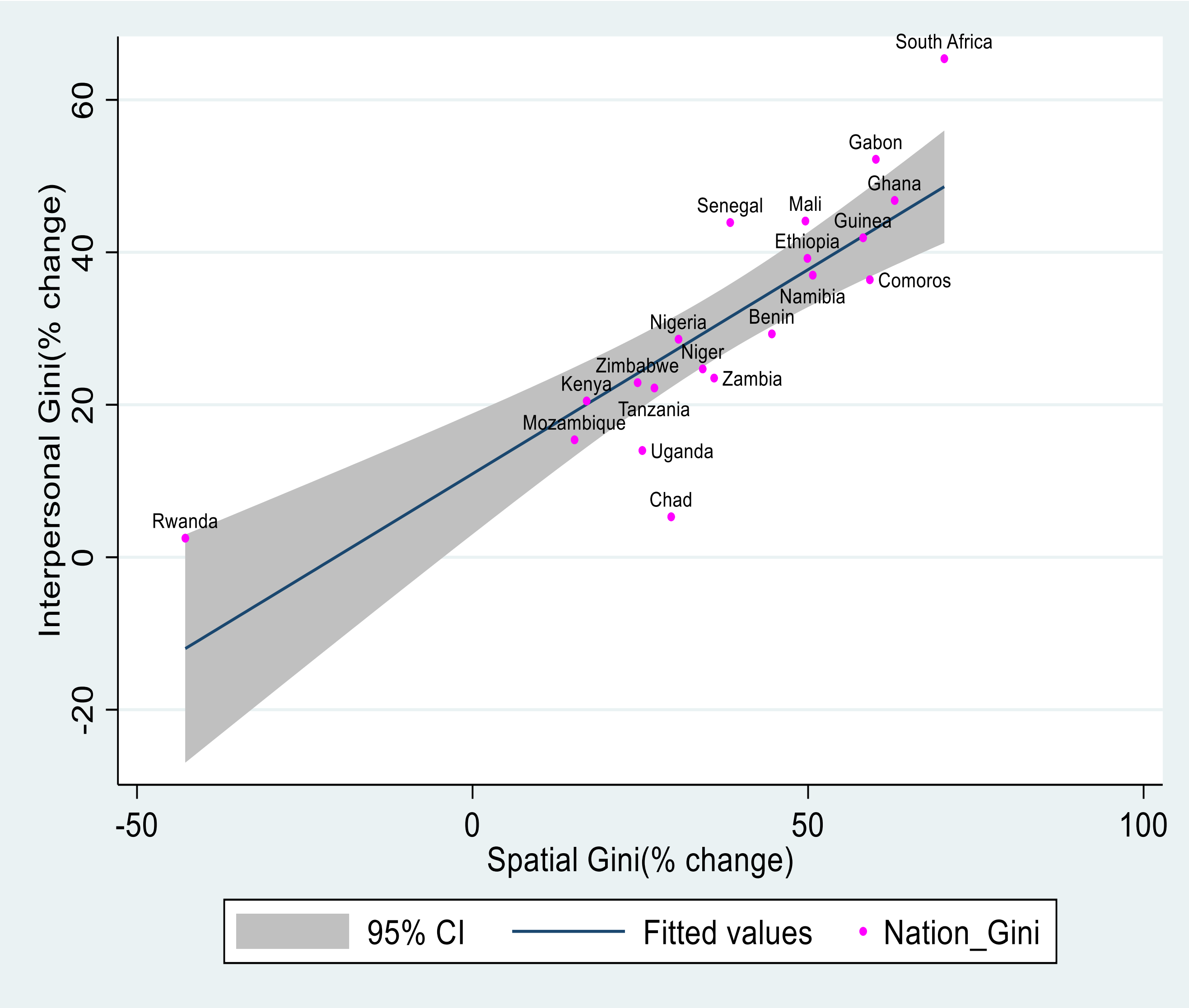


Source: Own estimates using data from DHS.

Inequality trends in access to basic services

Next, we examine inequality trends in access to basic services. However, it is difficult to compare changes in inequality measures across countries, given that the timing and frequency of surveys vary by country. For this reason, we discuss here changes in inequality over time based on inequality estimates from 20 countries that conducted at least one survey after 2010 and one survey before, with at least 10 years of a gap (Figure 5). Table 6 (Annexure B) provides percentage changes in inequality estimates for all 27 countries with more than one survey. In Figure 5, we multiplied the percentage change values by a negative one for simplicity of interpretation, with positive percentage changes indicating a fall in inequality over time and negative percentage changes indicating an increase in inequality.

Figure 5: Changes in spatial and interpersonal inequality estimates (in access to basic services)



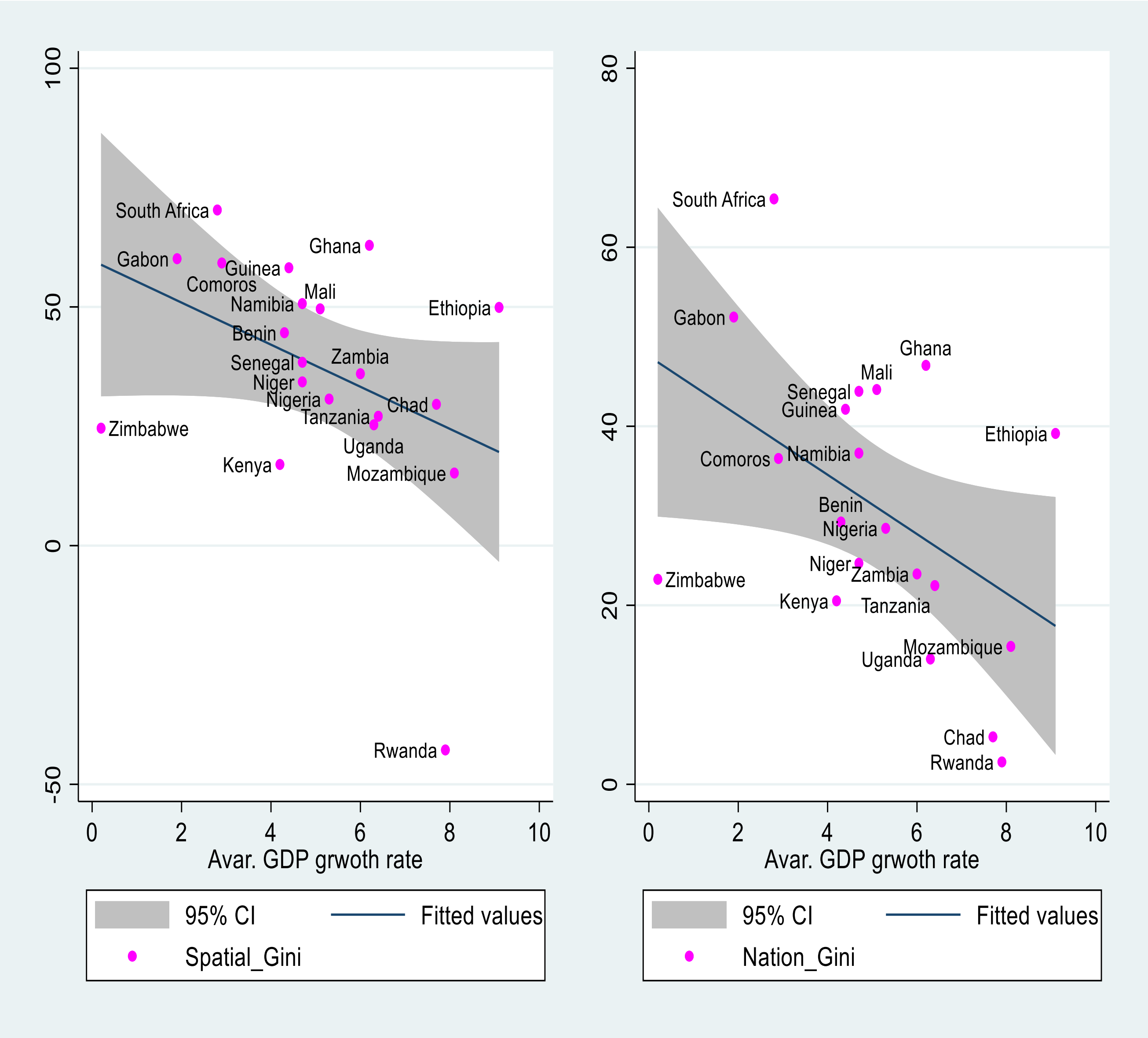
Source: Own estimates using data from DHS.

The spatial Gini coefficient fell by more than 50 percent in Guinea, Comoros, Gabon, Ghana, Namibia and South Africa; while it decreased by less than 20 percent in Mozambique and Kenya and increased by 42 percent in Rwanda. Similarly, in countries such as South Africa, Gabon, Mali and Senegal, the extent of reduction in national (interpersonal) inequality was more significant, while in Rwanda, Chad, Uganda and Mozambique, the figure was relatively small. These results suggest that countries, where regional disparities have reduced fast, are also those where national (interpersonal) inequalities have decreased the most substantially. The findings show that, with the exception of a few countries, spatial and interpersonal inequalities in access to basic services have decreased substatilaly over time. However, the level of inequality and the extent of the changes in inequality over time vary considerably across countries. Countries also differ significantly in terms of initial level inequalities. Countries such as Ethiopia, Niger, Guinea, Mali, Benin, and Burkina Faso had extremely high levels of initial inequalities. On the other hand, South Africa, Gabon, and Comoros were among the countries with relatively low initial level inequalities.

Understanding the drivers of changes in inequality across countries in SSA requires a careful examination of the context of each country, which is beyond the scope of this paper. Countries differ in terms of historical factors, economic and governance structures, and strategies they have adopted to reduce inequalities. Rwanda and Ethiopia, for example, are both landlocked and less resource-dependent (oil and minerals) countries that have experienced significant economic growth in recent decades, after the end of devastating civil wars in both countries in the early 1990s. However, the initial level inequities and the extent to which inequalities in access to basic services have been reduced differs significantly between the two countries. In Ethiopia, the Gini coefficient for national inequality was 0.79 in 2000 and 0.48 in 2016; while the spatial Gini coefficient was 0.52 and 0.25, respectively. In contrast in Rwanda, the national Gini coefficient remained the same between 2000 and 2015 (0.4) while the spatial Gini coefficient increased from 0.19 to 0.28. Thus, Ethiopia is one of the countries that has experienced high economic growth rates and significantly reduced inequality, whereas, despite Rwanda having high average economic growth rates, inequalities in access to basic services have only marginally been reduced (Figure 6).

Figure 6 indicates that there is a negative relationship between the extent to which inequality fell and average GDP growth rates. Countries with relatively high average GDP growth rates, such as Chad, Rwanda, Mozambique, and Uganda, only slightly reduced inequality. For example, between 1997 and 2011, Mozambique's average GDP growth rate was 8.1 percent, while estimates of spatial and national inequalities fell by only 15 percent. Similarly, Chad's average GDP growth rate was 7.7 percent from 1997 to 2015, while national inequality fell by 5.3 percent and spatial inequality fell by 30 percent. In Gabon (2000-2012) and South Africa (1998-2016), however, inequality fell by more than 50 percentage points, while average GDP growth was only 1.9 percent in Gabon and 2.8 percent in South Africa during the same period. These results indicate that although rapid economic growth is required to improve access to basic services to the poor, the heterogeneities in the extent to which African countries have reduced social inequities since 1995 cannot be explained by economic growth rates. Other factors, such as initial conditions, countries' economic structures, and economic and social policies aimed at reducing inequality, can help to explain these heterogeneities.

Figure 6: Changes in inequalities in access to basic services against average GDP growth rates



Source: Own estimates using data from DHS and the World Bank. Note: The average GDP growth rate for each country is calculated between the initial and final years of inequality estimates.

There is also a weak link between estimates of income inequality and inequalities in access to basic services. A comparison of natonal (interpersonal) income inequality estimates from the World Income Inequality Database (WIID)[4]and national inequality estimates based on access to basic services produce different cross-country rankings (Figure 7). For example, countries like South Africa with a very high level of interpersonal income inequality is the least unequal in terms of inequality in access to basic services. Likewise, countries with relatively low levels of interpersonal

[4] UNU-WIDER(https://www.wider.unu.edu/data).

income inequality estimates, such as Niger and Ethiopia, are among the most unequal in terms of access to basic services. The correlation improves when we compare our interpersonal asset inequality estimates with income inequality estimates (Figure 8). A simple linear regression of income inequality on asset inequality (Income_inequality(Gini) = 0.322 + 0.553Asset_inequality(Gini), (t=2.28)) indicates a positive and significant relationship between income inequality estimates and asset inequality estimates. The result suggests that asset inequality explains a significant proportion of income inequality. However, as previously documented elsewhere, even asset indices based on a broader range of asset indicators are less likely to accurately capture income or consumption expenditures (Sahn & Stifel ,2003; Vollmer, 2013; Wittenberg & Leibbrandt, 2017).

Next, we compare our inequality estimates based on asset/wealth indices with inequality estimates based on access to basic service indices. Figure 9 contrasts estimates of interpersonal inequalities based on asset/wealth indices with estimates based on access to basic service indices. The findings indicate that there is a weak correlation between the two measures of inequalities. The limited correlation between our interpersonal inequality estimates based on asset/wealth indices and indices of access to basic services may be attributed to approaches used to generate asset weights. In addition to the difference in the number of indicators used, we use 89 surveys when calcaulting indices of access to basic services (covering the period, 1995-2018), while only 24 of the most recent surveys were used to estimate the asset/wealth indices (covering the period 2010-2018). This is evident as a comparison of our estimates of interpersonal inequality based on data on access to basic services with estimates of asset/wealth inequality from Shimeles and Nabassaga (2018) for similar survey years (Figure 10) shows a very high correlation between the two inequality measures (Spearman's roh=0.83, Prob>|t|=0.000).[5] This high level of correlation indicates that most of the additional variables used by Shimeles and Nabassaga (2018) are highly correlated with indicators of basic services used in this paper. Thus, while we only use five indicators to measure inequalities in access to basic services, our inequality estimates are highly correlated

[5] Shimeles and Nabassaga (2018) used DHS data from more than 30 African nations from 1990 to 2013. They used ten items to calculate their asset/wealth indices. They do not, however, cover rural assets, unlike our asset/wealth index.

with those obtained from other comparable previous studies that used more asset indicators in addition to the ones we use in this paper.

In terms of measuring spatial inequalities, estimates of inequality based on a broader range of assets and estimates of inequality based on access to basic services provide a better consistent country ranking (Figure 11). The correlation coefficient between the two spatial inequality measures is 0.4 and it is significant. The positive correlation between the two spatial inequality measures could be attributed to the fact that, unlike estimates of interpersonal inequality, spatial inequality estimates are based on regional averages, which reduces the extent of variation in the data. We also find a positive and significant correlation between our spatial inequality estimates based on data on access to basic services (recent years only) and spatial inequality estimates based on data on predicted GDP per capita from Lessmann and Seidel (2017) (Figure 12).The correlation coefficient between the two inequality measures is 0.33 (Prob > |t| = 0.0515). Lessmann and Seidel (2017) used night lights data to predict GDP per capita.

Overall, our analysis in this section shows that there is substantial decline in inequality of access to basic services in many SSA countries. The decile in inequality of access to basic services is due to increases in the provision of access to basic services to the poor. Improved access to basic services and education can contribute positively to individual welfare and is an important determinant of regional development (Gennaioli et al., 2012; Bajar & Rajeev, 2016; Christina et al., 2019). However, this does not always result in less income inequality. Countries with relatively low levels of inequality of access to basic services, such as South Africa, is among the most unequal in terms of income inequality. Several factors may explain why improvements in access to basic service may not necessarily translate into reduction in income inequality. One factor is that the availability and quality of basic services vary greatly depending on location and socioeconomic status (Jerome, 2011; Majgaard & Mingat, 2012; Torpey-Saboe, 2018). For instance, in many African countries, educational attainment has increased significantly without improving educational quality.

Poor education quality and lack of formal jobs are among the barriers to effective school-to-work transitions in several African countries (Fares et al.,2005; Leibbrandt et al., 2010; Laterite, 2019). In South Africa, for example, massive increases in educational attainment have had no significant impact in reducing overall income inequality. Although returns to education have improved for the majority of Blacks since the end of Apartheid, there are still significant racial and spatial disparities in educational outcomes and returns to education (Branson et al., 2012; Spaull, 2013; Salisbury, 2016; McKeever, 2017). In countries with relatively high skills premiums, such as South Africa, inequalities in educational outcomes tend to exacerbate inequalities in labour market outcomes and income (Leibbrandt et al., 2010). Thus, the impact of improved access to education and other basic services on income inequality and mobility in a given country can be influenced by the country's economic structure as well as policies implemented to address the various dimensions of inequality.

Conclusion

In this paper, we analyse spatial and national (interpersonal) inequalities based on data on access to basic services and a broader range of household assets in SSA. Our results show that inequality levels in SSA countries have remained very high in recent years. The Gini coefficient for national asset inequality ranges from 0.4 to 0.5 in 13 of the 24 countries included in the analysis. With the exception of a few countries (Rwanda, Chad, Uganda and Mozambique), inequalities in access to basic services have substantially declined over time in SSA. In most countries, however, inequalities in access to basic services remain very high. The Gini coefficient for interpersonal inequalities in access to basic services ranges from 0.54 to 0.60 in Burkina Faso, Chad, Madagascar, Mozambique and Niger, and is between 0.4 and 0.50 in eight other countries.

The high level of inequalities in access to basic services in most SSA countries is expected to pose a significant challenge in promoting inclusive growth in the continent and progress towards achieving the Sustainable Development Goals (UN, 2016). Access to education and basic services are important in providing equality of economic opportunities. Moreover, it has been shown that inequities in access to basic services in a country could increase that country's vulnerability to health-related crises such as COVID-19 (Ahmed et al., 2020; Mollalo et al., 2020; Shifa et al.,2021). It is therefore now more important than ever to invest in education and access to basic services in SSA.

We find a strong and positive relationship between the measures of national (interpersonal) and spatial inequalities. In countries where regional disparities have rapidly fell, interpersonal inequalities have also decreased significantly. Thus, policies aimed at reducing regional disparities have the potential to make a significant contribution to reducing both national and different dimensions of horizontal inequalities in SSA. This is important because ethnic groups in Africa tend to cluster in specific regions, and location plays a significant role in determining access to basic services such as water, electricity, and education. As a result, reducing spatial and other horizontal inequalities lowers the likelihood of violent conflict between different groups within a country (Stewart, 2011).

Finally, our findings show that inequality patterns differ across countries depending on the type of welfare indicator used. Given the differences in economic structure and policies implemented to reduce the various dimensions of inequality across countries, this is to be expected. The use of different indicators and methods for analysing inequality captures various aspects of inequality. As a result, multiple dimensions of welfare must be considered in order to fully describe and understand the causes and drivers of inequalities in a given country. However, due to data constraints, even measuring inequality in a single dimension such as education remains difficult, as data on education quality is not readily available in many African countries. Similarly, using a broader range of assets to estimate inequalities has limitations; the list of assets included is limited to those available in the dataset, and information on the quantity and quality of assts for most assets is either missing or poorly captured. As a result, estimates of inequality like ours can only be considered lower bound estimates of inequality.

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Annexure A: Asset variable description

Table 1 provides the list of variables used to calculate the asset/wealth indices using data from 24 SSA countries. Although most of the variables in the DHS dataset are standardized, variables indicating water sources, toilet facility types and floor types are country specific. In such cases, we have tried to standardize these variables. Based on the guidance of the UN MDGs, we coded the source of drinking water variable into "improved" and "unimproved" sources. "Improved" drinking water sources include piped water into a dwelling, piped water to a yard/lot, piped water to a neighbour’s house, public pipe, protected well, pumped borehole, protected spring, rainwater, bottled water. "Unimproved" sources include unprotected well, unprotected spring, surface water (lack/pond/river/channel/irrigation), tanker truck, small tank cart, three-well motorcycle, vendor and others.

Table 1: List of variables used to calculate asset/wealth indices.

Variable	Description
Source of water for drinking	1, improved, 0 not improved
Type of toilet facility	0, unimproved ,1, improved
Access to electricity	1, yes, 0, no
Own radio	1, yes, 0, no
Own television	1, yes, 0, no
Own refrigerator	1, yes, 0, no
Own bicycle/motorcycle	1, yes, 0, no
Own car/truck	1, yes, 0, no
Type of floor material	0, poor quality, 1 good quality
Highest Education level	years of schooling
number of rooms for sleeping	Per capita number of rooms used for sleeping
Own phone (land line or cell)	1, yes, 0, no
Type of fuel used for cooking	0 unclean 1 clean
Own land usable for agriculture	1, yes, 0, no
Own cattle /cows/bulls	1, yes, 0, no
Own goats	1, yes, 0, no
Own sheep	1, yes, 0, no
Own chickens	1, yes, 0, no

We also coded the type of toilet facility variable into two categories: “Improved” toilets, “unimproved” toilets. “Improved” toilets include indoors flush to piped public system, indoors flush to septic tank, indoors flush open pit, inside yard flush to piped public system, inside yard flush to septic tank, inside yard flush to open pit, indoors to piped public system, indoors latrine to septic tank, and inside yard latrine to piped public system. The “unimproved” toilet category of toilet includes those who reported no toilet and used bucket/pottery/other containers, pit latrine without slab, open pit, hanging toilet, and others.

The variable indicating the type of fuel used for cooking is coded into two categories: “Clean” and “non-clean”. The clean sources include electricity, LPG, natural gas, biogas, petroleum/kerosene, no food cooked. The unclean category includes coal/charcoal, wood straw/shrubs/gas, agricultural crops, animal dung cardboard/paper, others. Households who have reported that “no food is cooked” are coded as clean assuming that there is no health-related problem with the use of unclean cooking fuel. With respect to type of flooring, the variable is coded as “poor quality” and “good quality”. “Good quality” includes wood, palm/bamboo, wooden bats, ceramic, mosaics, cement, marble/granite, carpet. The “poor quality” category includes earth/sand, dung, mud/clay/stone, wet floor.

Ownership of livestock is measured using a dummy variable indicating whether the household owns each of the livestock (i.e., cattle, sheep, goats, chickens). The variable indicating the number of rooms used for sleeping is a continuous variable expressed in per capita terms. The education variable measures the highest level of education in the household (years of schooling). The rest of the variables are dummy variables that indicate the ownership of each asset. As far as telephone ownership is concerned, we combined cell phone and landline into one variable.

Table 2: List of countries with comparable data on access to basic services.

Country	Number of surveys	Latest survey year
Angola	1	2016
Benin	3	2018
Burkina Faso	2	2010
Burundi	1	2017
Cameroon	2	2011
Chad	2	2015
Comoros	2	2012
Congo Brazzaville	2	2012
Congo Dem	2	2014
Cote d 'ivoire	1	2012
Ethiopia	4	2016
Gabon	2	2012
Gambia	1	2013
Ghana	4	2014
Guinea	4	2018
Kenya	4	2014
Lesotho	3	2014
Liberia	1	2013
Madagascar	1	2009
Malawi	2	2016
Mali	4	2018
Mozambique	3	2011
Namibia	3	2013
Niger	3	2012
Nigeria	4	2018
Rwanda	4	2015
Sao Tome	1	2009
Senegal	3	2017
Sierra Leone	2	2013
South Africa	2	2016
Swaziland	1	2007
Tanzania	3	2016
Togo	1	2014
Uganda	3	2016
Zambia	4	2018
Zimbabwe	4	2015

Source: Own estimates using data from DHS.

Table 3: Descriptive statistics and asset weights.

Variable	Obs	Mean	Std. Dev.	Min	Max	UCPCA weights
Highest Education level	328,601	7.3	4.7	0	23	0.15
Access to electricity	328,601	38.1	0.5	0	1	0.23
Own radio	328,601	55.4	0.5	0	1	0.14
Own television	328,601	32.7	0.5	0	1	0.23
Own refrigerator	328,601	15.1	0.4	0	1	0.37
Own bicycle/motorcycle	328,601	32.0	0.5	0	1	0.09
Own car/truck	328,601	6.5	0.2	0	1	0.46
Own phone (land line or cell)	328,601	73.2	0.4	0	1	0.13
Source of water for drinking	328,601	70.9	0.5	0	1	0.13
Type of toilet facility	328,601	49.3	0.5	0	1	0.18
Type of floor material	328,601	55.8	0.5	0	1	0.18
Type of fuel used for cooking	328,601	17.1	0.4	0	1	0.59
number of rooms for sleeping (per capita)	328,601	0.57	0.4	0	12	0.17
Own land usable for agriculture	328,601	60.0	0.5	0	1	0.07
Own goats	328,601	25.8	0.4	0	1	0.06
Own sheep	328,601	14.6	0.4	0	1	0.06
Own chickens	328,601	39.2	0.5	0	1	0.07
Own cattle/cows/bulls	328,601	22.8	0.4	0	1	0.08

Source: Own estimates using data from DHS. Note: Except for the education and number rooms variables, all numbers are expressed as percentages.

Annexure B: Inequality estimates

Table 4: Interpersonal and spatial asset/wealth inequality estimates by country

Country_year	Interpersonal inequality		Spatial inequality				Between region contrib. (%)	Num. of regions
			COV		Gini coeff			
	Gini	Theil T	Raw	Stand.	Raw	Stand		
Benin 2018	0.44	0.37	0.45	0.13	0.19	0.20	13.6	12
Burkina Faso 2010	0.35	0.30	0.40	0.11	0.15	0.16	27.5	13
Burundi 2017	0.36	0.29	0.40	0.10	0.13	0.14	23.8	18
Cameroon 2011	0.52	0.46	0.52	0.16	0.26	0.29	35.1	12
Comoros 2012	0.48	0.39	0.24	0.17	0.12	0.18	6.2	3
Congo Dem 2014	0.49	0.49	0.73	0.23	0.29	0.32	38.6	11
Cote d'Ivoire 2012	0.48	0.40	0.49	0.15	0.19	0.21	35.1	11
Ethiopia 2016	0.46	0.47	0.74	0.23	0.34	0.38	35.4	11
Gambia 2013	0.44	0.32	0.39	0.15	0.21	0.23	15.0	8
Ghana 2014	0.46	0.34	0.35	0.12	0.19	0.21	19.3	10
Guinea 2018	0.47	0.40	0.53	0.20	0.24	0.28	31.7	8
Kenya 2014	0.51	0.46	0.57	0.22	0.28	0.32	27.0	8
Lesotho 2014	0.51	0.45	0.34	0.11	0.19	0.21	14.6	10
Mali 2018	0.40	0.29	0.37	0.13	0.17	0.19	23.5	9
Mozambique 2011	0.56	0.61	0.78	0.25	0.36	0.40	33.5	11
Namibia 2013	0.49	0.41	0.41	0.12	0.23	0.25	32.6	13
Niger 2012	0.45	0.43	0.56	0.21	0.26	0.30	23.8	8
Nigeria 2018	0.49	0.40	0.36	0.16	0.21	0.25	20.3	6
Rwanda 2015	0.37	0.27	0.37	0.18	0.16	0.20	17.3	5
Senegal 2017	0.43	0.29	0.44	0.12	0.22	0.23	36.4	14
Tanzania 2016	0.47	0.42	0.48	0.09	0.22	0.23	26.5	30
Togo 2014	0.45	0.39	0.44	0.20	0.19	0.23	29.5	6
Zambia 2018	0.55	0.54	0.50	0.17	0.25	0.28	22.3	10
Zimbabwe 2015	0.53	0.49	0.57	0.19	0.27	0.30	30.85	10

Source: Own calculations using data from DHS.

Table 5: Interpersonal and spatial inequalities in access to basic services by country

	Interpersonal inequality	Spatial inequality				Num. of regions
		COV		Gini coeff.		
Country_year	Gini coeff.	Raw	Stand	Raw	Stand	
Angola 2016	0.41	0.36	0.09	0.19	0.20	18
Benin 2001	0.58	0.55	0.24	0.30	0.36	6
Benin 2012	0.43	0.43	0.13	0.21	0.23	12
Benin 2018	0.41	0.37	0.11	0.18	0.20	12
Burkina Faso 2003	0.75	1.16	0.32	0.48	0.52	14
Burkina Faso 2010	0.58	0.66	0.19	0.30	0.32	13
Burundi 2017	0.40	0.46	0.11	0.22	0.23	18
Cameroon 2004	0.42	0.41	0.12	0.23	0.25	12
Cameroon 2011	0.37	0.34	0.10	0.19	0.21	12
Chad 1997	0.57	0.58	0.15	0.30	0.32	15
Chad 2015	0.54	0.54	0.12	0.22	0.23	21
Comoros 1996	0.33	0.13	0.09	0.07	0.11	3
Comoros 2012	0.21	0.06	0.04	0.03	0.04	3
Congo Brazzavill 2005	0.39	0.48	0.27	0.25	0.33	4
Congo Brazzavill 2012	0.32	0.47	0.14	0.24	0.26	12
Congo Dem 2007	0.48	0.65	0.20	0.30	0.33	11
Congo Dem 2014	0.45	0.60	0.19	0.27	0.30	11
Cote d 'ivoire 2012	0.34	0.30	0.10	0.15	0.16	11
Ethiopia 2000	0.79	0.94	0.30	0.46	0.50	11
Ethiopia 2005	0.69	0.81	0.26	0.39	0.43	11
Ethiopia 2011	0.57	0.55	0.17	0.27	0.30	11
Ethiopia 2016	0.48	0.45	0.14	0.23	0.25	11
Gabon 2000	0.23	0.32	0.16	0.17	0.21	5
Gabon 2012	0.11	0.15	0.05	0.08	0.09	10
Gambia 2013	0.26	0.31	0.12	0.17	0.20	8
Ghana 1999	0.47	0.52	0.17	0.28	0.32	10
Ghana 2003	0.46	0.44	0.15	0.24	0.27	10
Ghana 2008	0.37	0.32	0.11	0.18	0.19	10
Ghana 2014	0.25	0.19	0.06	0.11	0.12	10

Table 5: Interpersonal and spatial inequalities in access to basic services by country (contd.)

	Interpersonal inequality	Spatial inequality				Num. of regions
		COV		Gini coeff.		
Country_year	Gini coeff.	Raw	Stand.	Raw	Stand.	
Guinea 1999	0.62	0.93	0.47	0.41	0.52	5
Guinea 2005	0.60	0.99	0.38	0.40	0.45	8
Guinea 2012	0.48	0.68	0.26	0.30	0.35	8
Guinea 2018	0.36	0.40	0.15	0.19	0.22	8
Kenya 1998	0.44	0.48	0.19	0.23	0.27	7
Kenya 2003	0.47	0.65	0.25	0.33	0.38	8
Kenya 2009	0.41	0.49	0.19	0.25	0.28	8
Kenya 2014	0.35	0.36	0.13	0.19	0.22	8
Lesotho 2005	0.38	0.20	0.07	0.10	0.11	10
Lesotho 2010	0.35	0.20	0.07	0.11	0.13	10
Lesotho 2014	0.29	0.18	0.06	0.10	0.11	10
Liberia 2013	0.41	0.37	0.19	0.17	0.22	5
Madagascar 2009	0.60	0.53	0.12	0.28	0.29	22
Malawi 2010	0.43	0.10	0.07	0.05	0.08	3
Malawi 2016	0.40	0.09	0.06	0.04	0.07	3
Mali 1996	0.59	0.68	0.26	0.36	0.41	8
Mali 2001	0.49	0.61	0.22	0.28	0.31	9
Mali 2006	0.57	0.70	0.25	0.28	0.31	9
Mali 2018	0.33	0.37	0.13	0.18	0.21	9
Mozambique 1997	0.65	0.78	0.25	0.37	0.41	11
Mozambique 2004	0.62	0.80	0.25	0.34	0.38	11
Mozambique 2011	0.55	0.60	0.19	0.31	0.35	11
Namibia 2000	0.46	0.53	0.15	0.30	0.32	13
Namibia 2007	0.35	0.34	0.10	0.19	0.21	13
Namibia 2013	0.29	0.26	0.08	0.15	0.16	13
Niger 1998	0.77	1.04	0.47	0.42	0.51	6
Niger 2006	0.76	0.98	0.37	0.44	0.50	8
Niger 2012	0.58	0.61	0.23	0.29	0.33	8
Nigeria 2003	0.42	0.22	0.10	0.12	0.15	6
Nigeria 2008	0.43	0.27	0.12	0.15	0.18	6
Nigeria 2013	0.35	0.21	0.09	0.12	0.14	6
Nigeria 2018	0.30	0.15	0.07	0.09	0.10	6

Table 5: Interpersonal and spatial inequalities in access to basic services by country (contd.)

	Interpersonal inequality	Spatial inequality				Num. of regions
		COV		Gini coeff.		
Country_year	Gini coeff.	Raw	Stand.	Raw	Stand.	
Rwanda 2000	0.40	0.39	0.12	0.18	0.19	12
Rwanda 2005	0.40	0.35	0.10	0.14	0.15	12
Rwanda 2011	0.39	0.48	0.24	0.22	0.28	5
Rwanda 2015	0.39	0.48	0.24	0.22	0.28	5
Sao Tome 2009	0.24	0.12	0.07	0.06	0.08	4
Senegal 2005	0.41	0.44	0.14	0.23	0.25	11
Senegal 2011	0.27	0.34	0.09	0.19	0.20	14
Senegal 2017	0.23	0.26	0.07	0.14	0.16	14
Sierra Leone 2008	0.53	0.73	0.42	0.33	0.43	4
Sierra Leone 2013	0.45	0.59	0.34	0.27	0.36	4
South Africa 1998	0.26	0.18	0.06	0.10	0.12	9
South Africa 2016	0.09	0.06	0.02	0.03	0.03	9
Swaziland 2007	0.38	0.17	0.10	0.09	0.12	4
Tanzania 2005	0.45	0.44	0.09	0.23	0.24	26
Tanzania 2010	0.42	0.39	0.08	0.21	0.22	26
Tanzania 2016	0.35	0.32	0.06	0.17	0.18	30
Togo 2014	0.44	0.38	0.17	0.18	0.22	6
Uganda 2006	0.43	0.66	0.23	0.28	0.31	9
Uganda 2011	0.40	0.58	0.19	0.27	0.30	10
Uganda 2016	0.37	0.44	0.12	0.22	0.23	15
Zambia 2002	0.51	0.67	0.24	0.33	0.37	9
Zambia 2007	0.51	0.65	0.23	0.32	0.36	9
Zambia 2014	0.43	0.52	0.17	0.25	0.28	10
Zambia 2018	0.39	0.42	0.14	0.22	0.24	10
Zimbabwe 1999	0.48	0.53	0.18	0.25	0.27	10
Zimbabwe 2006	0.50	0.57	0.19	0.28	0.31	10
Zimbabwe 2011	0.44	0.49	0.16	0.24	0.27	10
Zimbabwe 2015	0.37	0.40	0.13	0.19	0.21	10

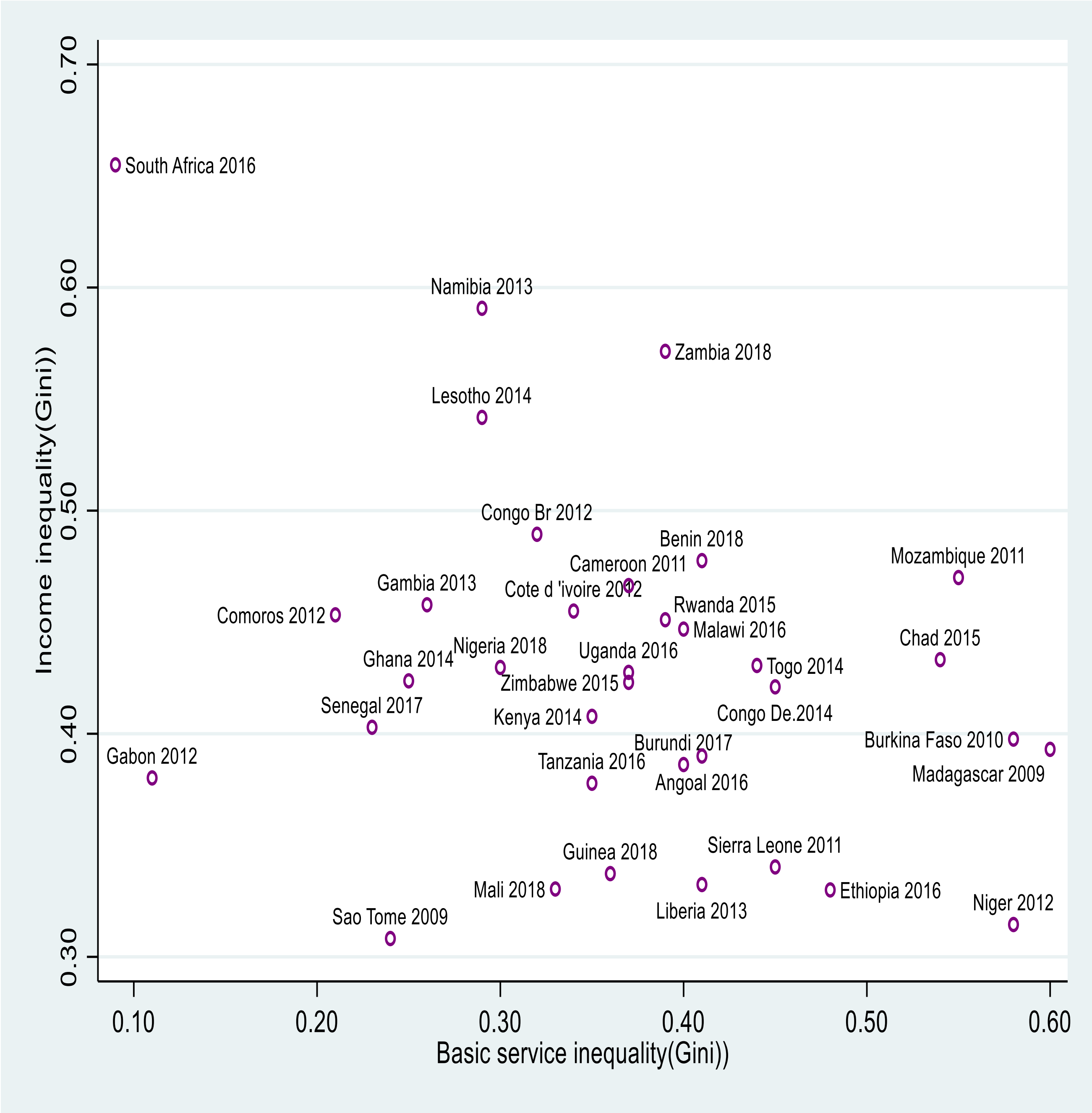
Source: Own calculations using data from DHS.

Table 6: Changes in inequality estimates (access to basic services)

Country year	Initial year	Latest year	Changes in interpersonal Gini (%)	Changes in spatial Gini (%)
Ethiopia	2000	2016	-39.2	-49.9
Ghana	1999	2014	-46.8	-62.9
Kenya	1998	2014	-20.5	-17.0
Lesotho	2005	2014	-23.7	0.9
Nigeria	2003	2018	-28.6	-30.7
Namibia	2000	2013	-37.0	-50.7
Sierra Leone	2008	2013	-15.1	-17.0
Senegal	2005	2017	-43.9	-38.4
Zambia	2002	2019	-23.5	-36.0
Zimbabwe	1999	2015	-22.9	-24.6
South Africa	1998	2016	-65.4	-70.3
Uganda	2006	2016	-14.0	-25.3
Tanzania	2005	2016	-22.2	-27.1
Chad	1997	2015	-5.3	-29.6
Rwanda	2000	2015	-2.5	42.8
Niger	1998	2012	-24.7	-34.3
Mozambique	1997	2011	-15.4	-15.2
Malawi	2010	2016	-7.0	-15.7
Mali	1996	2018	-44.1	-49.6
Comoros	1996	2012	-36.4	-59.2
Guinea	1999	2018	-41.9	-58.2
Gabon	2000	2012	-52.2	-60.1
Cameroon	2004	2011	-11.9	-16.0
Congo Brazzavill	2005	2012	-17.9	-21.1
Congo Dem	2007	2014	-6.3	-9.4
Benin	2001	2018	-29.3	-44.6
Burkina Faso	2003	2010	-22.7	-37.4

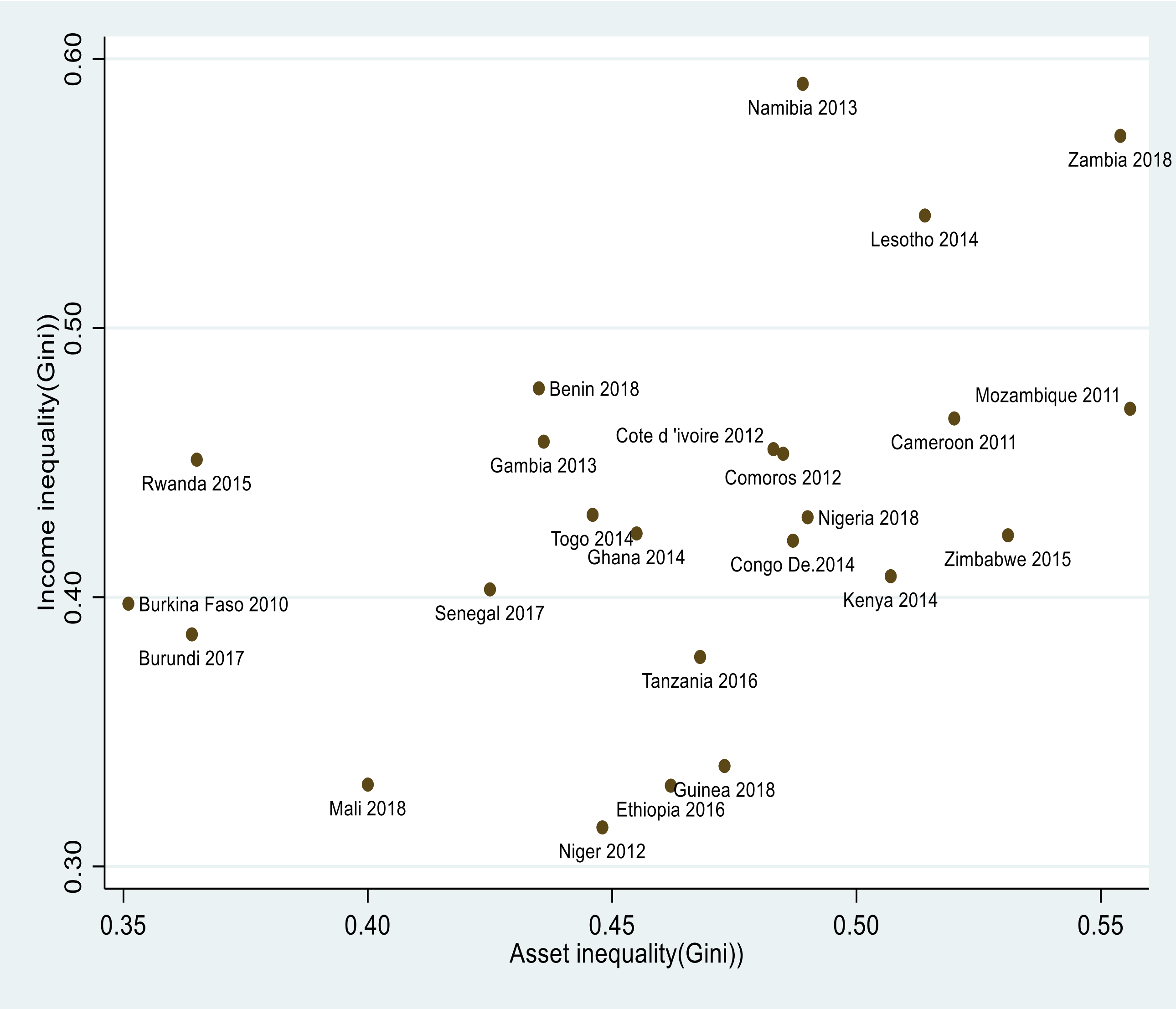
Source: Own calculations using data from DHS.

Figure 7: The relationship between interpersonal inequality in income and access to basic services



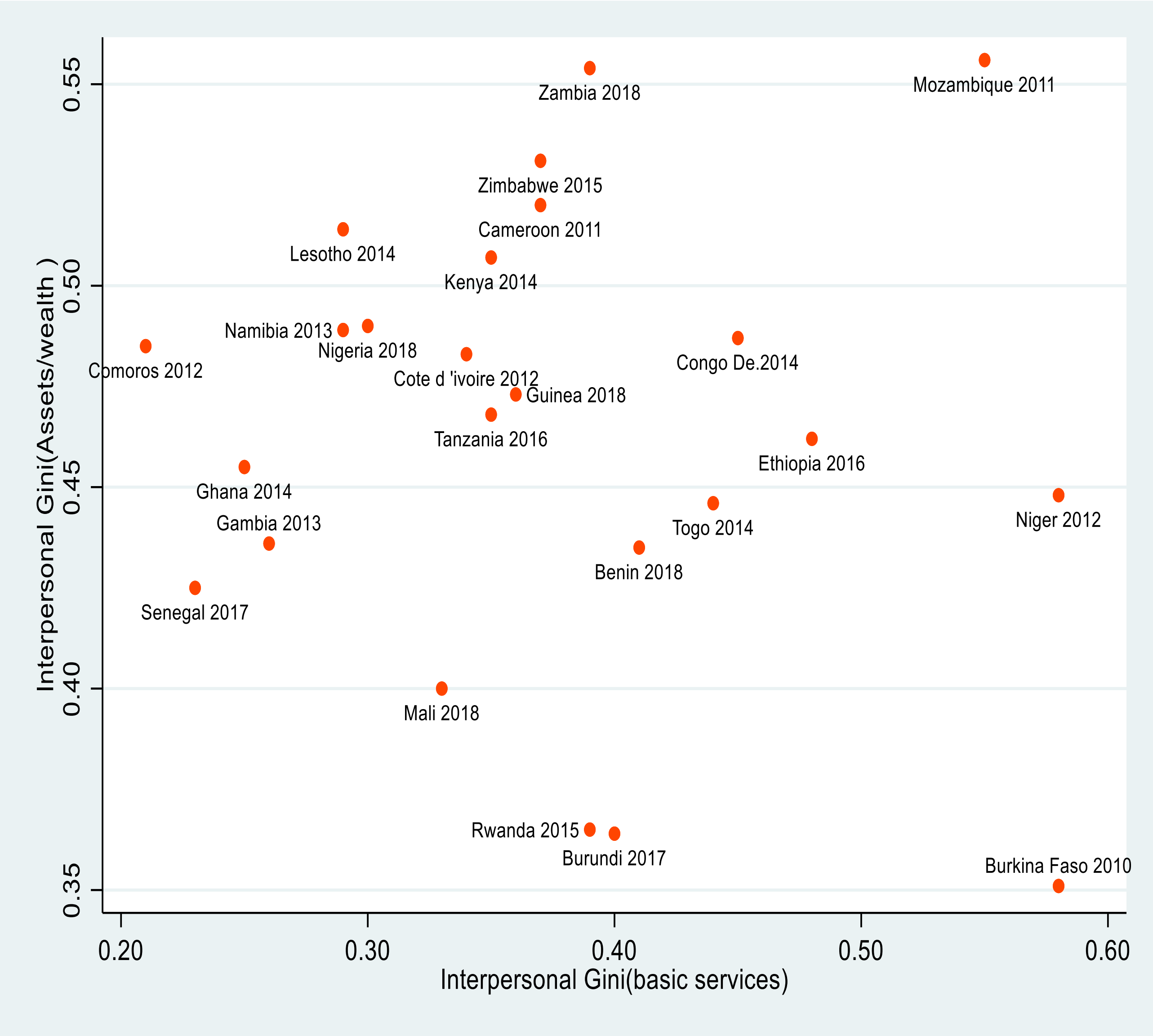
Source: Own estimates based on DHS data and the income Gini coefficient from WIID. Notes: The survey years on the graph correspond to estimates of inequality in access to basic services. We use income inequality estimates from survey years that are very close to survey years of our inequality estimates.

Figure 8: The relationship between interpersonal income and asset inequality



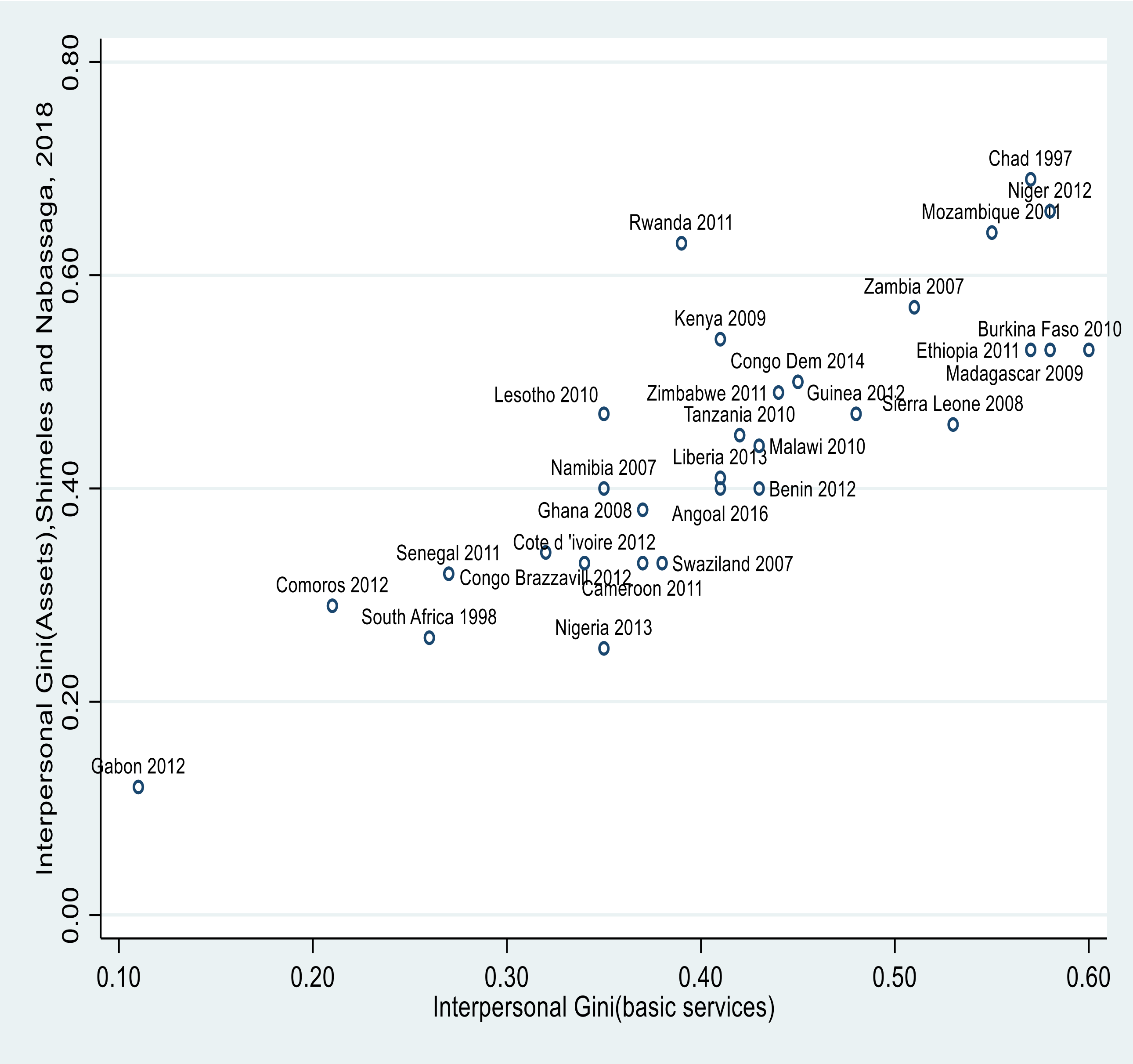
Source: Own estimates based on DHS data and the income Gini coefficient from WIID. Notes: The survey years on the graph correspond to asset inequality. We use income inequality estimates from survey years that are very close to survey years of our inequality estimates.

Figure 9: The relationship between interpersonal inequality in asset/wealth and access to basic services



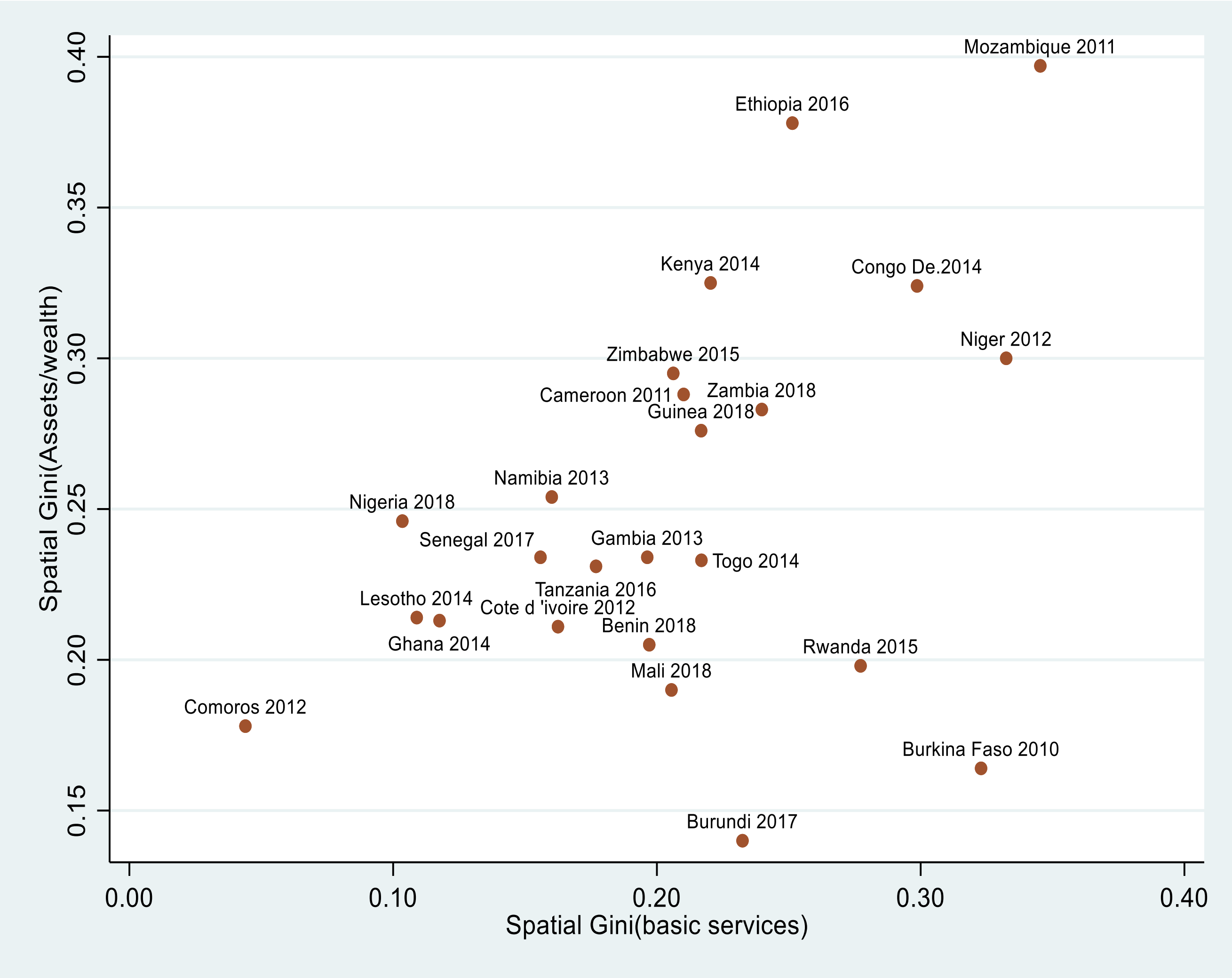
Source: Own estimates using data from DHS.

Figure 10: The relationship between interpersonal inequality in assets and access to basic services



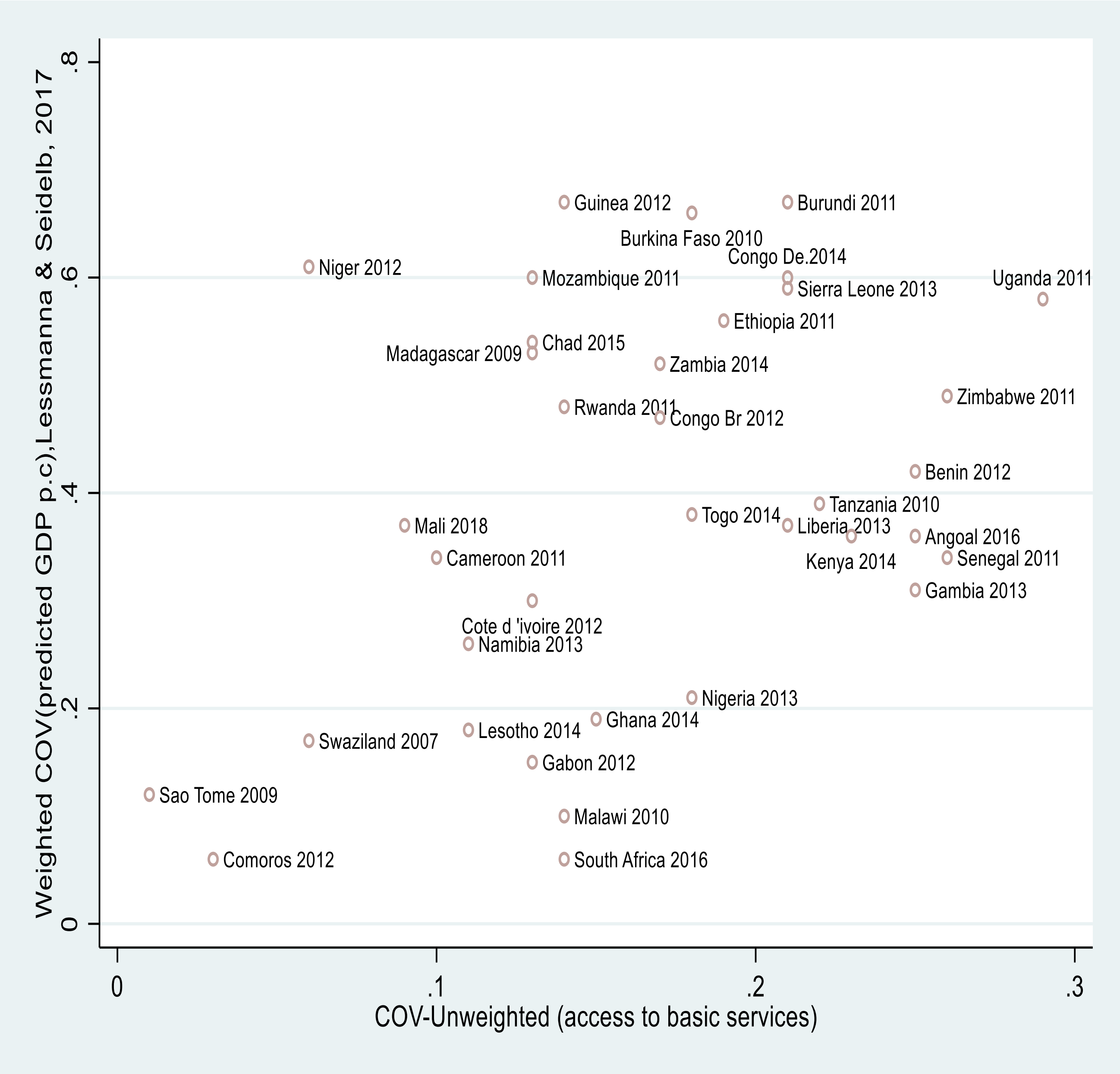
Source: Own estimates using data from DHS and asset Gini estimates from Shimeles and Nabassaga(2018).

Figure 11: The relationship between spatial inequality in asset/wealth and access to basic services



Source: Own estimates using data from DHS.

Figure 12: The relationship between spatial inequality in predicted GDP p.c. and access to basic services



Source: Own estimates using data from DHS and COV estimates from Lessmann and Seidel (2017).

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