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Understanding inequality and its evolution in Kenya

The contribution of the UNU-WIDER World Income Inequality Database initiative

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Abstract: Globally, there are several initiatives being undertaken to ensure the availability of information across countries that can be used to analyse the inequality phenomenon in and among countries. The data are easily accessible for use in comparative research on inequality across regions and countries, especially those covered by the UNU-WIDER World Income Inequality Database (WIID) initiative. This initiative is among the leading data innovations in the field of inequality research. This study explores how well the WIID Companion's standardized inequality measures relate to those derived using locally based data, such as the Kenyan inequality diagnostics and the fiscal incidence studies conducted by the African Centre of Excellence for Inequality Research (ACEIR). The findings show that the WIID Companion's standardized inequality measures are much higher than those in the original WIID, the Kenyan inequality diagnostic, and the fiscal incidence studies. The study demonstrates that inequality measures based on per capita consumption are likely to be lower than those based on net per capita income, partly due to the former not capturing the savings portion of disposable income. It is difficult to authenticate how well the WIID's standardized inequality measures relate to measures of per capita income inequality in Kenya due to lack of quality data on income and taxation. This issue needs to be investigated further as better data become available.

Key words: inequality measures, data, WIID, Kenya

JEL classification: C8, D3, E2, H3, I3

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1 Introduction

Kenya is one of the countries in Africa that has moderately high levels of inequality. In East Africa, Kenya has the highest inequality compared with neighbouring nations Uganda, Tanzania, and Ethiopia, but has a relatively lower inequality compared with South Africa, Namibia, Rwanda, and Nigeria, which are among the continent's topmost unequal countries (see KNBS 2020). Some early studies that focused more on inequality in Kenya include the Bigsten (1986) study that analysed income inequality and poverty regionally and nationally using primarily administrative data. Thereafter, several inequality estimates have been undertaken by the Kenya National Bureau of Statistics (KNBS), World Bank, and individual researchers (Bigsten et al. 2014) utilizing household budget surveys conducted in the 1990s and the 2000s. Generally, the present study shows that inequality mostly increased from 1914 to 1950 and then declined in the period till 1961. It then increased until 1971 and again declined between 1971 and 2016. In the period from 1994 to 2016, inequality increased slightly from a Gini coefficient of 0.46 in 1994 to 0.47 in 2005/06 before declining to 0.404 in 2015/16 (KNBS 2020). Although estimates of income inequality using nationally representative data are below 0.50, Mwabu (2023) reports very high Atkinson and Gini measures using data from a phone-based survey conducted by the World Bank and KNBS during the COVID-19 pandemic (also see Nafula et al. 2020).

With the adoption of Sustainable Development Goals (SDGs) by many countries (including Kenya), the need to reduce and monitor inequality in response to SDG 10 has increased the focus on inequality (see United Nations 2023). The realization that inequality has many dimensions—in addition to income inequality—has led to several studies that examine various aspects of inequality in Kenya. One such study is KNBS (2020) that analyses multidimensional inequality rather than just focusing on income inequality. In particular, KNBS (2020) estimates the different types of measures and dimensions of inequality over the period 1994–2016 and shows that while inequality in Kenya declined between 2006 and 2016 it varies across rural and urban areas, across counties, and socioeconomic characteristics such as gender and education.

Inequality has generally declined at the national level, in rural and urban areas, and across social strata in the decade from 2005/06 to 2015/16 (KNBS 2020). Inequality indices declined in 2015/16 relative to 2005/06, with the Gini coefficient increasing slightly from 0.460 in 1994 to 0.470 in 2005/06 before declining to 0.404 in 2015/16. The Theil and Atkinson indices show a similar declining trend in inequality, whereas the Palma ratio remained the same at 2.8 in 1994 and 2005/06 but declined to 2.0 in 2015/16. Inequality is higher in urban areas than in the countryside, with the decline in inequality between 2005/06 and 2015/16 being much higher in urban areas than in rural areas. The Gini coefficient for urban dwellers decreased from 0.473 in 1994 to 0.447 in 2005/06, and further declined to 0.363 by 2015/16. In rural areas, inequality declined marginally from 0.386 in 1994 to 0.347 in 2015/16.

To a large extent, access to education has improved over time. Enrolment rates in pre-primary, primary, and secondary education increased over time, as did health status indictors, suggesting an increase in access to basic education and health in the country. However, at about 67 per cent in 2015/16, net enrolment rates in secondary school are still low. Access to improved water sources, electricity, internet, and mobile phones increased over the period 2009 and 2015/16, whereas access to safe human waste disposal services remained the same over the period at 65 per cent. However, disparities in access to education, health, water and sanitation, electricity, internet, and phones are more serious across regions and counties and across groups. For example, urban areas enjoy more access to the services than rural areas (KNBS 2020).

Globally, several initiatives are underway to facilitate access to inequality data to allow comparisons of inequality across countries and in research analyses involving inequality. One such initiative is the UNU-WIDER World Income Inequality Database (WIID). The current WIID original/general/full (hereafter WIID) version includes observations up to 2021 and covers 201 countries (including historical entities) with a total of more than 22,000 data points. The database contains more than 3,800 unique country-year observations. It currently provides the most comprehensive set of income inequality statistics that can be accessed freely from the UNU-WIDER website (see UNU-WIDER 2022a).

Kenya is one of the 200 countries covered by WIID. The WIID for Kenya provides 32 inequality measures (Gini coefficients) for the period 1914–2016, with multiple inequality statistics given for 1969 (four), 1976 (two), 1977 (two), 1999 (two), and 2006 (four). The inequality measures in the WIID cover most national populations and social groups; they exclude the inequality statistics for 1969 in urban areas and also for two in 2006 for urban and rural areas. The WIID Companion for Kenya provides 9 years of standardized inequality measures (Gini coefficients) for the period 1961–2016 (see UNU-WIDER 2022b). Whereas the WIID has some statistics within the country on regional inequality measures on Kenya, the WIID Companion focuses on inequality statistics that cover all regions and groups. Appendix Table A1 shows only the Gini coefficient estimates in the WIID and the WIID Companion extracted from WIID database Excel sheets.

The WIID provides inequality statistics from various sources for many years, with some of the estimates based on per capita income and others based on per capita consumption expenditure. Given that some of the inequality measures are based on per capita income and others on per capita consumption expenditure, comparing the inequality measurements over time and across countries may be problematic. In the context of the WIID, the WIID Companion attempts to provide standardized measures of inequality based on net per capita income, thus creating comparable country-level inequality indices and series for the longest periods possible in recent history. The datasets offer user-friendly, curated sets of inequality statistics, with the necessary data needed to analyse, describe, or compare levels of inequality between and within countries or over time. The WIID Companion reports annual country and global net per capita income distributions at the percentile level, including a set of measures that summarize the distribution, such as the relative and absolute inequality indices and various income share ratios. It presents trends in the income distribution within countries, between countries, and globally to improve the study of income inequalities and contribute to better monitoring of inequality trends and dynamics (volatilities around a trend).

Given the UNU-WIDER's effort to assemble evidence on inequality over time across the globe and have it standardized for purposes of comparability and the African Centre of Excellence for Inequality Research's (ACEIR) efforts and other research on inequality in Kenya, this study provides an assessment of how well the inequality measures in these works relate to each other. In carrying out the assessment, we focus on examining the WIID Companion (UNU-WIDER 2022b), which is the preferred inequality series from the WIID in relation to the estimates from the Kenyan inequality diagnostics and the fiscal incidence studies. A contextual narrative is offered in an attempt to validate the inequality estimates and their comparability over time for the period 1990–2016.

The remaining sections of this paper are organized as follows. Section 2 looks at data used in the WIID inequality measurement and the locally available datasets that could be used to analyse inequality levels and trends. Section 3 provides a comparison of inequality measurements from different Kenyan datasets with the sets contained in the WIID Companion and assesses the narrative that comes out of the Kenyan ACEIR inequality diagnostics and fiscal incidence studies versus the narrative that one gets from the WIID Companion in terms of inequality magnitudes and trends. Section 4 contains the summary and conclusions.

2 The WIID Companion and other available datasets in Kenya

Table 1 shows the data used in estimating income inequality reported in the WIID and in the WIID Companion. Nearly all the inequality measures from 1914 to 1976 are from Bigsten (1986). The 1976 estimates are based on national accounts rather than on nationally representative household sample surveys. The other datasets used are from the Welfare Monitoring Surveys (WMS) I, II, and III of 1992, 1994, and 1997, respectively. The Kenya Integrated Household Budget Surveys (KIHBS) for 2005/06 and 2015/16 are used in estimating inequality statistics for 2006 and 2016, respectively. All these datasets are based on national samples collected by KNBS (1994, 1996, 1998, 2001, 2009, 2018).

Table 1: Datasets used to estimate WIID inequality measures

Year	WIID original	WIID Companion
1961	Adelman and Morris (1972)	Adelman and Morris (1972)
1976	Based on national accounts	Based on national accounts
1977	Social Accounting Matrix (synthetic data)	Social Accounting Matrix (synthetic data)
1982	Milanovic (1994)	Milanovic (1994)
1992	Kenya Welfare Monitoring Survey (WMS) I 1992 (KNBS 1994)	Kenya Welfare Monitoring Survey (WMS) I 1992 (KNBS 1994)
1994	Kenya Welfare Monitoring Survey (WMS) II 1994 (KNBS 1996)	Kenya Welfare Monitoring Survey (WMS) II 1994 (KNBS 1996)
1997	Kenya Welfare Monitoring Survey (WMS) III 1997 (KNBS 1998)	Kenya Welfare Monitoring Survey (WMS) III 1997 (KNBS 1998)
1999	1998/99 Integrated Labour Force Survey (ILFS) (KNBS 2001)	1998/99 Integrated Labour Force Survey (ILFS) (KNBS 2001)
2006	Kenya Integrated Household Budget Survey (KIHBS 2005/06) (KNBS 2009)	Kenya Integrated Household Budget Survey (KIHBS 2005/06) (KNBS 2009)
2016	Kenya Integrated Household Budget Survey (KIHBS 2015/16) (KNBS 2018)	Kenya Integrated Household Budget Survey (KIHBS 2015/16) (KNBS 2018)

Source: authors' construction based on WIID inequality Excel data from UNU-WIDER (2022a, 2022b).

Table 2 shows the datasets that have information that can be used to analyse money metric inequality and whether they are available. As shown in the table, there is no other dataset outside this list that is good enough for the purpose of analysing inequalities in Kenya. All the available datasets shown in Table 2 have national coverage except for the rural household budget survey that excludes information on urban areas. With the exception of the rural household budget survey (1982), which is not available for our use, all the datasets in the table are available in Kenya and could also be available elsewhere (see Evenson and Mwabu 2002). The 1998/99 integrated labour force survey contains information on the labour market and can only be useful to estimate inequality in the labour market. All the survey data are cross-sectional and are unevenly distributed over time, meaning that estimates of inequality measures are also unevenly distributed over time. For instance, the WMS datasets are collected two to three years apart while the KIHBS datasets are collected about 10 years apart with about 7 years between the last WMS in 1997 and KIHBS in 2005/06. As a result, it is difficult to have a longer run series of estimates of inequality in Kenya that has gaps and so the WIID estimate for Kenya faces the same difficulty. Furthermore, only WMS II, WMS III, KIHBS 2005/06, and KIHBS 2015/16 are currently at our disposal for use. Although WMS II, WMS III, KIHBS 2005/06, and KIHBS 2015/16 may have fairly comparable data on per capita consumption expenditure, information on household income is very poor in

WMS II, WMS III, and KIHBS 2005/06 and only moderately good in KIHBS 2015/16, making it impossible to estimate inequality based on net per capita income—a fact that is also noted by the WIID Companion.

Table 2: Relevant micro datasets that can be used for inequality analysis in Kenya

Year	Micro data	Availability	Coverage
1992	Kenya Welfare Monitoring Survey (WMS) I 1992	Available	National
1994	Kenya Welfare Monitoring Survey (WMS) II 1994	Available	National
1997	Kenya Welfare Monitoring Survey (WMS) III 1997	Available	National
1999	1998/99 Integrated Labour Force Survey (ILFS)	Available	National
2006	Kenya Integrated Household Budget Survey (KIHBS 2005/06)	Available	National
2016	Kenya Integrated Household Budget Survey (KIHBS 2015/16)	Available	National

Source: authors' construction based on study data.

2.1 Comparison of WMS II 1994, KIHBS 2005/06, and KIHBS 2015/16 datasets

Table 3 compares three of the datasets (WMS 1994, KIHBS 2005/06, and KIHBS 2015/16) that are used to estimate inequality measures contained in the Kenyan inequality diagnostics study and those in the WIID and WIID Companion for the same years for their suitability for use in analysing inequality.[1] The table shows that the survey domains are national, and cover all the regions in the country, in both rural and urban areas. The 47 districts in 1994 are the entities that were turned into the 47 counties in the 2010 Constitution of Kenya. However, the 69 districts in 2005/06 are as a result of sub-dividing some of the 47 districts that existed in 1994, and it is a straightforward exercise to merge them into the 47 counties to ensure comparability at the county level.

The three datasets have similar recall periods for food consumption, non-food expenditures, and durable goods that can be used to construct inequality statistics based on per capita consumption expenditure. However, the survey design for KIHBS 2005/06 and KIHBS 2015/16 involves consecutive visits to the same household. It is said to be bounded if the recall is based on the period 'since my last visit'. Under this definition, the reference periods used in the KIHBS (last week, last month, last year) were not bounded, which can lead to serious telescoping (misdating) errors. The data on food consumption used a 7-day recall period, regular non-food expenditures used a 1-month recall period, and data on household durables used a 1-year recall period (see KNBS 2020).

The weighting of the three datasets was based on the selection probabilities in each domain. The design weights were adjusted using the survey responses to give the final weights. The weights are available in each of the datasets. The weights are necessary for correcting biases in the realized sample due to uneven non-response in the field. Additionally, some of the sampled households did not respond to the interviews, but this is a negligible issue (see KNBS 2020).

According to KNBS (2020), the results based on the datasets might be affected by the seasonal effect on household expenditure because seasonality was not controlled for while collecting the data. Also, some districts/counties, especially those from north-eastern Kenya, may be under-represented in the sample. Further, other than telescoping errors, which are common to the three datasets, household data collected in different cycles where the reference period was long (e.g.,

[1] Table 3 in the present paper is reproduced from Table 3.1 in KNBS (2020) and data in this section are based on data reported in KNBS (2020).

'last 1 year') might have different midpoints of the reference period compared with other datasets with shorter reference periods. For example, household data on durables collected in the first cycle essentially covered transactions during the year preceding the official survey period, whereas data for households in the last cycle covered the entire survey period. The time midpoint for the data on household durables, therefore, is the beginning of the survey, whereas the time midpoint for shorter reference periods is roughly halfway between the commencement and completion of the survey (see KNBS 2020).

Table 3: Comparison of WMS II 1994, KIHBS 2005/06, and KIHBS 2015/16 datasets

Comparison parameters	WMS II 1994	KIHBS 2005/06	KIHBS 2015/16
Sample designs			
Survey domains	National, 47 districts	National, 69 districts	National, 47 counties,
Sampling frame	Rural/urban National Sample Survey and Evaluation Programme III (1,377 clusters)	Rural/urban National Sample Survey and Evaluation Programme IV (1,800 clusters)	Rural/urban National Sample Survey and Evaluation Programme V (5,360 clusters)
Data collection logistics			
Cycles	Snapshot survey	17	24
Days	60	21	14
Sample size and allocation			
National	10,860 households (1,258 clusters)	13,430 households (1,343 clusters)	24,000 households (2,400 clusters)
Rural	10,480 households (1048 clusters)	8,610 households (861 clusters)	14,120 households (1,412 clusters)
Urban	2,100 households (210 clusters)	4,820 households (482 clusters)	9,880 households (988 clusters)
Data collection			
Field data collection teams	Not given	44 (100 survey personnel)	50 (323 survey personnel)
Data collection dates	June/July 1994	May 2005–April 2006	May 2005–April 2006
Consumption module recall periods (days)			
Food consumption—recall	7	7	7
Non-food expenditures—regular	30	30	30
Non-food expenditures—non-durables	90	90	90
Durables	365	365	365

Source: reproduced with permission from Table 3.1 of KNBS (2020); also see KNBS (2009, 2018) reports.

As noted earlier, the datasets have varying information on income. The data on income is not sufficiently good for use in estimating income inequality indices. For instance, when estimating income inequality one needs to use the outlined preferred set of underlying income concepts for income estimates used in WIID (see Table 4). The estimated income is then divided by the number of individuals in each household to get net per capita income that is then used to estimate the income Gini coefficients. However, in our case, data on all of the preferred sets of underlying income concepts in measuring income are not available.

As shown in Table 4, WIID estimates are based on net per capita income. Unfortunately, the KIHBS datasets (2005/06 and 2015/16) do not have information on taxes on income. If we assume that when workers are asked how much they earn, they respond by giving information on net income, then the income estimates from our data give disposable income. If the respondents provided gross income, then information on taxation is required to calculate net per capita income. However, it is not possible to know whether the information provided is net or gross income. Probably, some workers provided information on gross income while others provided information on net income. Most likely, long-serving workers could have provided information on net income in their responses while more recently employed workers could have given gross income, as that is what would be quoted in their employment contracts.

Table 4: The main concepts underlying inequality measures used in WIID

1. Employee income	Cash wages and salaries
2. Income from self-employment	• Profit/loss from unincorporated enterprise • Imputed income from self-employment • Goods and services produced for barter, less cost of inputs • Goods produce for home consumption, less cost of inputs
3. Income less expenses from rentals, except rent of land	
4. Property Income	• Interest received less interest paid • Dividends
5. Current transfers received	• Social insurance benefits from employers' schemes • Social insurance benefits in cash from government schemes o Universal social assistance benefits in cash from government o Means-tested social assistance benefits in cash from government • Regular inter-household cash transfers received
6. Total income	(Sum of 1 to 5)
7. Current transfers paid	Employees' social contributions: taxes on income
8. Disposable income	(6 less 7)
9. Other conceptual issues	• Household should be the basic statistical unit • Per capita incomes or consumption/expenditure should be measured • Person weights should be applied

Source: authors' construction based on UNU-WIDER (2022c: Table 1).

Furthermore, some dimensions of income for estimating net per capita income are missing in the KIHBS datasets. First, the income data underestimate the economic well-being of low-resourced households (see Bigsten et al. 2003; Meyer and Sullivan 2003) as it is not possible to estimate income for goods produced for home consumption. This underestimates income from subsistence farmers and may thus lead to high net per capita income inequality. Second, whereas there is information on interest received, there is no information on interest paid and this may overestimate this source of income for estimates based on KIHBS. Third, there is no information on dividends, and this could lead to an underestimation of household income. On current transfers received, there is no information on social insurance benefits from employers' schemes, social insurance benefits in cash from government schemes, universal social assistance benefits in cash from the government, and means-tested social assistance benefits in cash from the government. The current transfers variable captures only cash transfers. The total income computed without considering several key income concepts outlined in Table 4 can lead to underestimation of the income variable. In terms of the missing income concepts, the KIHBS 2005/06 data are much more affected than the KIHBS 2015/16 data.

If the KIHBS 2005/06 and KIHBS 2015/16 data had quality data on income, one would use the data to get income inequality directly and compare it with the WIID standardized inequality estimates. However for this to be done, we must ensure that the income data in the KIHBS 2005/06 and KIHBS 2015/16 datasets match the standard components of income outlined in the WIID guidelines to have an idea of whether the standardized measurements are close to what one can get *directly* (without adjustments) using net per capita income estimates from the household surveys. The KIHBS datasets do not have income components that reasonably match the suggested WIID income components. Given this and the discussion earlier on missing information that can possibly lead to serious measurement errors in estimating net per capita income, we do not attempt to use our survey dataset to estimate net per capita income inequality directly as it would obviously give wrong inequality estimates. This makes it difficult to assess the appropriateness of WIID standardized inequality related directly to income inequality measures obtained directly from the Kenyan survey data.

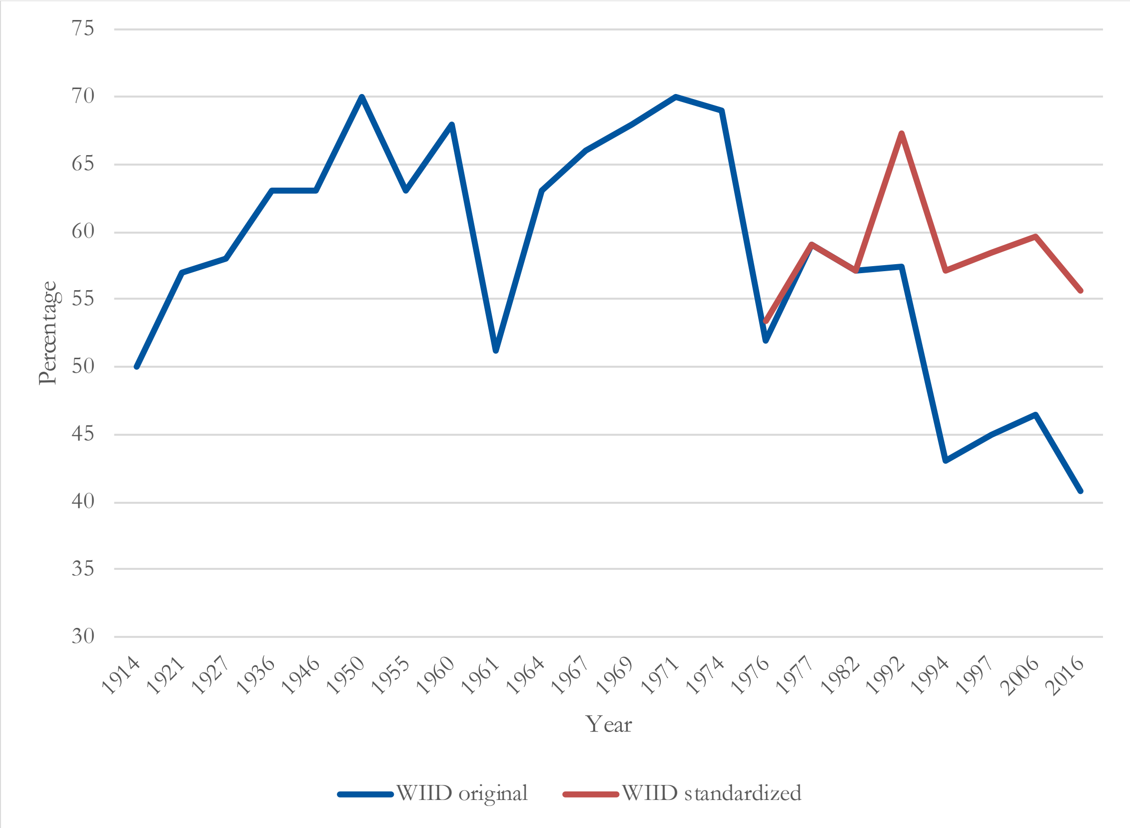
The three datasets, however, have very good information on household consumption expenditure and, therefore, the per capita consumption expenditure inequality estimates based on the datasets are fairly comparable over time despite the data shortcomings discussed. According to KNBS (2018) and Meyer and Sullivan (2003), the quality and reliability of consumption expenditure data for a developing country, such as Kenya, are better than that of net per capita income data. For instance, KNBS (2018) states that consumption is not strictly tied to short-term fluctuations as income is and that, over time, consumption expenditures are smoother and less variable than income. The report also states that rankings-based positions of household well-being based on consumption tend to be more stable for households whose income fluctuates a great deal from one year to the next or even within the year. Moreover, Meyer and Sullivan (2003) find that consumption-based measures better capture the incomes of disadvantaged individuals or households than measures based on income because consumption-based measures account for savings usage, ownership of durable goods, access to credit, and the use of anti-poverty programmes.

3 Comparison of inequality measures from WIID original, WIID Companion, and measures from other study sources

Figure 1 depicts Kenya's income distribution statistics based on the WIID and WIID Companion for the period 1914–2016. The WIID coefficients are available for some years starting from 1914 to 2016; the WIID Companion, which provides standardized measures based on net per capita income, is also available for some years and runs from 1961 to 2016. Based on the WIID, represented by the blue line in Figure 1, the graph shows that inequality generally increased most of the time from 1914 to 1950, then declined in 1961, increased until 1971, and thereafter it generally declined between 1971 and 2016. Most of the Gini coefficient inequality estimates for the period 1914–76 are from one source (i.e. Bigsten 1986) and estimates for the remaining period up to 2016 are from the Poverty and Inequality Platform (World Bank 2023) and KNBS (2007) (see Appendix Table A1). Except for 1976, 1977, and 1982 when the estimated Gini inequality measures for the WIID and WIID Companion are similar, the WIID Companion Gini measures from 1992 to 2016 are much higher than those in the WIID. It is worth noting that the Bigsten data series are not combinable with the recent nationally representative KNBS series, to form one long dataset, covering a century (i.e. the 1914–2016 period). The Bigsten dataset is from national income accounts, records of firms, government documents, such as population censuses, labour force surveys, economic surveys, and statistical abstracts, among other sources. The Bigsten income data are derived from gross domestic product estimates. More importantly, data are not available for every year in the series. Still, the Bigsten (1986) data series is the best dataset on Kenyan poverty and inequality for the period 1914–76. However, the poverty rates and inequality measures were computed using pre-Foster–Greer–Thorbecke poverty measures and pre-Atkinson methodologies. Thus, the Bigsten metrics for poverty and inequality are not fully comparable with recent measures (KNBS and University of Nairobi 2022).[2] For example, the poverty indices comprise only the headcount ratios, and the inequality index is just the one due to Gini.

In the next section, we compare the WIID Companion estimates, those in the WIID, and estimates of the Kenyan inequality diagnostics study, among others. The comparable statistics for the period 1994–2016 are documented in the WIID and the Companion, in the Kenyan inequality diagnostics study and the Companion fiscal incidence study (KNBS 2020; KNBS and University of Nairobi 2022).

Figure 1: Gini coefficients in WIID original and WIID Companion, 1914–2016



Source: authors' illustration based on the WIID Excel database.

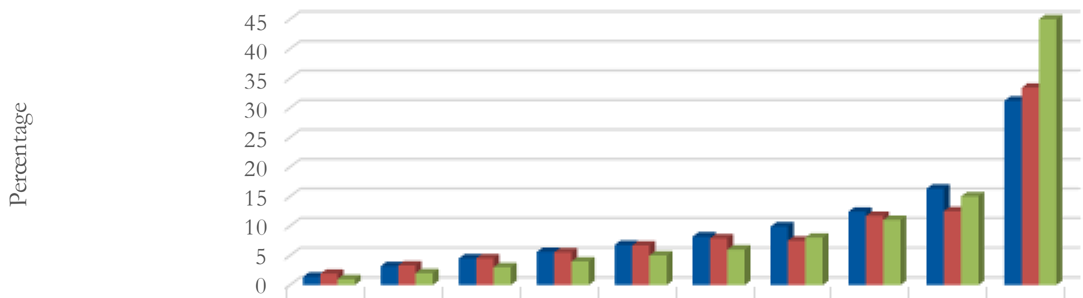
3.1 Comparison of expenditure and income shares by population deciles for 1994, 2006, and 2016

First, it is important to mention that estimated shares for the 3 years for the WIID and the Kenyan ACEIR study on inequality trends and diagnostics are based on per capita consumption expenditure while those for the WIID standardized inequality estimates are adjusted to net per capita income inequality estimates based on regression coefficient predictions as outlined in Machemedze and Wittenberg (2023). Figures 2, 3, and 4 show the expenditure and income shares by deciles for the three years. The figures show that the expenditure shares for the WIID and the Kenyan ACEIR study on inequality trends and diagnostics based on per capita consumption expenditure have similar distributions across the deciles with minor differences. The shares in the WIID standardized inequality estimates are lower than those of the WIID and the Kenyan ACEIR study on inequality trends and diagnostics for the lower eight deciles but much higher for the top

[2] For different versions of the KNBS and University of Nairobi (2022) study, see Manda et al. (2020a, 2020b).

deciles. For instance, for the top decile the shares for the WIID standardized measures are 44–48 per cent in the three years compared with WIID that ranges from 31.6 per cent to 36.8 per cent and 29.8 per cent to 41.6 per cent for the Kenyan ACEIR study on inequality trends and diagnostics. This distribution difference is one of the reasons why inequality based on income is much higher than inequality measure based on per capita consumption expenditure.

Figure 2: Expenditure and income shares by deciles of the population for 1994

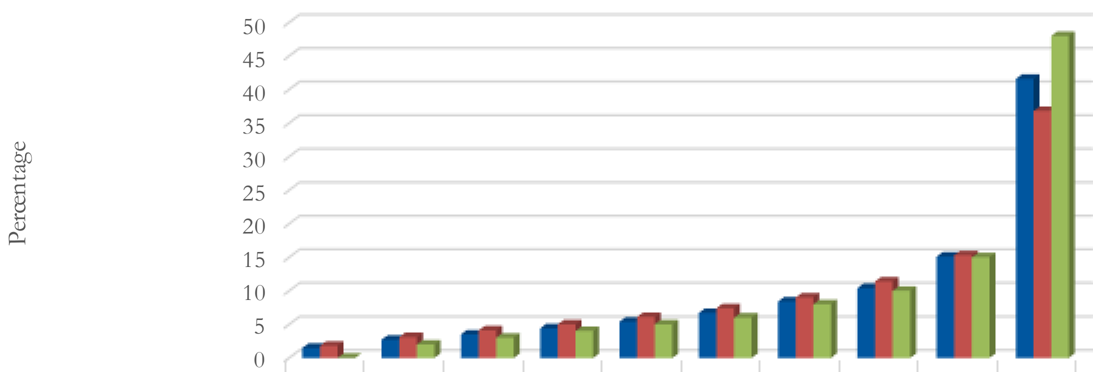


	1	2	3	4	5	6	7	8	9	10
ACEIR diagnostics study	1.4	3.2	4.5	5.6	6.8	8.2	9.9	12.4	16.3	31.2
WIID original	1.9	3.3	4.5	5.5	6.7	7.9	7.5	11.7	12.5	33.4
WIID standardized	1	2	3	4	5	6	8	11	15	45

ACEIR diagnostics study WIID original WIID standardized

Source: authors' construction based on UNU-WIDER (2022a, 2022b) inequality Excel data and KNBS (2020).

Figure 3: Expenditure and income shares by deciles of the population for 2006

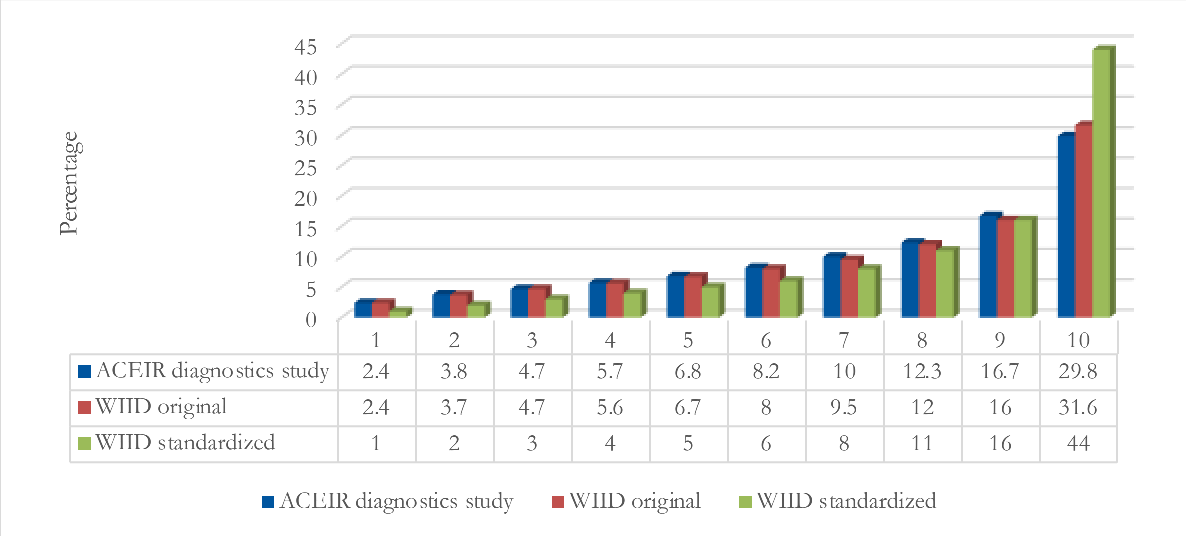


	1	2	3	4	5	6	7	8	9	10
ACEIR diagnostics study	1.5	2.7	3.5	4.4	5.4	6.7	8.4	10.4	15.1	41.6
WIID original	1.8	3.1	4.1	5	6.1	7.4	9	11.4	15.3	36.8
WIID standardized	0	2	3	4	5	6	8	10	15	48

ACEIR diagnostics study WIID original WIID standardized

Source: authors' construction based on UNU-WIDER (2022a, 2022b) inequality Excel data and KNBS (2020).

Figure 4: Expenditure and income shares by deciles of the population for 2016



Source: authors' construction based on UNU-WIDER (2022a, 2022b) inequality Excel data and KNBS (2020).

It is clear from the distribution that when using per capita income to measure inequality, the incomes of the population in lower deciles may be underestimated while those in the top deciles may be much higher than when one is using per capita consumption. We try to explain these differences later in this section.

Table 5 shows the share of per capita net income/per capita consumption expenditure based on the WIID, WIID standardized measures, and the Kenyan inequality diagnostics study. The table shows that the poorest 10 per cent and 20 per cent of the population received about 2 per cent and 6 per cent or less of the income in each of the 3 years, respectively, whereas the poorest 40 per cent of the population received 17 per cent or less of the income in each of the years.

Table 5: Share of income/consumption expenditure for the lower and upper deciles

	Lower 10%	Lower 20%	Lower 40%	Top 20%	Top 10%
1994					
ACEIR diagnostics study	1.4	4.6	14.7	47.5	31.2
WIID original	1.9	5.2	15.2	48.9	33.4
WIID standardized	1.0	3.0	10.0	60.0	45.0
2006					
ACEIR diagnostics study	1.9	4.2	14.6	56.7	41.6
WIID original	1.8	5.0	14.1	52.2	36.8
WIID standardized	0	2.0	9.0	63.0	48.0
2016					
ACEIR diagnostics study	2.4	6.2	16.6	46.5	29.8
WIID original	2.4	6.3	16.4	47.5	31.6
WIID standardized	1.0	3.0	10.0	60.0	44.0

Source: authors' construction based on UNU-WIDER (2022a, 2022b) inequality Excel data and KNBS (2020).

On the other hand, Table 5 shows that the top 10 per cent of the richest population received between 30 and 48 per cent of the income each year while the top 20 per cent of the richest population received between 47 and 64 per cent of the income each year. However, there are differences depending on whether the measure used in the analysis is per capita net income or per capita consumption expenditure. For instance, using the WIID standardized measures and the Kenyan inequality diagnostics study estimates based on per capita consumption expenditure, the poorest population (the poorest 10 per cent, 20 per cent, and 40 per cent) receive a higher proportion of the income compared with WIID standardized measures that are based on predicted net per capita income. Also, for estimates based on per capita consumption expenditure, the richest population (the top 10 per cent and 20 per cent) receive a lower proportion of the income compared with the WIID standardized measures that are based on net per capita income. Thus, using per capita consumption expenditure to measure inequality is likely to yield a relatively lower inequality than when using net per capita income. This could be in line with the observation by Meyer and Sullivan (2003) that income for low-resourced households is underreported, specifically incomes associated with self-employment earnings, private transfers, and public transfers, because that income seems to be a more sensitive topic in the administration of household surveys and, thus, easier to hide. In Kenya, given the large number of self-employed people and non-monetized economic activities, there are real measurement difficulties in estimating household income, particularly for low-resourced households in self-employment and informal activities (Bigsten et al. 2003; ILO 2003; KNBS 2018; Meyer and Sullivan 2003), and this could explain these differences.

3.2 Comparison of inequality measures for WIID standardized estimates, WIID original, and those for the Kenya ACEIR study on inequality trends and diagnostics

This section starts by comparing the WIID Gini coefficient estimates with the WIID standardized Gini coefficient for Kenya as presented in the WIID Companion (see Table 6). As shown in Table 6, from 1961 to 1982 the difference between the WIID standardized Gini estimates and the original estimates of the Gini coefficients is very small, ranging from 0 to 2 percentage points. However, the same differences for the period 1992–2016 are very large, ranging from 10 to 15 percentage points.

Table 6: Differences between the original and standardized WIID Gini coefficients

Year	WIID original Gini coefficients (%)	WIID Companion standardized Gini coefficients (%)	Difference between WIID original and WIID standardized Gini coefficients (%)
	(A)	(B)	(B−A)
1961	48.80	51.17	2.37
1976	52.00	53.43	1.43
1977	59.00	59.00	0.00
1982	57.30	57.16	−0.14
1992	57.46	67.30	9.90
1994	43.11	57.21	14.10
1997	44.98	58.52	14.41
2006	46.45	59.56	15.11
2016	40.78	55.57	14.79

Source: authors' construction based on UNU-WIDER (2022a, 2022b) inequality Excel data.

Table 7 shows the differences between the Kenyan inequality diagnostics study Gini coefficient estimates and the WIID and the WIID standardized Gini coefficient estimates reported in the WIID Companion. As shown in the table, the differences between the estimated Gini coefficients in the Kenyan diagnostics study and the WIID Gini coefficient estimates are small, hovering around 0–3 percentage points, whereas the differences in Gini coefficient estimates for the Kenyan inequality diagnostics study and the WIID standardized Gini estimates are large, ranging from 11 to 15 percentage points.

Table 7: Differences between the Kenyan inequality diagnostics study Gini coefficient estimates and the WIID original and standardized Gini coefficients reported in the WIID Companion

Year	Diagnostics Gini coefficients	WIID original Gini coefficients	WIID standardized Gini coefficients	Difference 1 (percentage points)	Difference 2 (percentage points)
	(A)	(B)	(C)	(B−A)	(C−A)
1994	46.00	43.11	56.97	−2.89	10.97
2006	47.00	46.45	59.22	−0.55	12.22
2016	40.40	40.78	55.30	0.38	14.90

Source: authors' construction based on UNU-WIDER (2022a, 2022b) inequality Excel data and KNBS (2020).

Table 8 shows the comparison of other alternative measures of inequality that include general entropy (GE) and Atkinson index (A) for 3 years (i.e. 1994, 2006, and 2016). The comparison is done only for estimates in the WIID Companion and the Kenyan inequality diagnostics study as these estimates are not reported for the WIID original data on Kenya. It is only done for GE(0), GE(1), A(1), and A(2), which are in the Kenyan inequality diagnostics study.

Table 8: Differences in general entropy and Atkinson index measures of inequality in WIID standardized estimates and the Kenya ACEIR study on inequality trends and diagnostics

Year and alternative inequality measures	WIID standardized (A)	Kenya inequality diagnostics (B)	Difference (A−B)
1994			
GE(0)	66.0	38.6	27.4
GE(1)	65.0	44.6	20.4
A(1)	48.0	32.1	15.9
A(2)	82.0	69.8	12.2
2006			
GE(0)	73.0	38.7	34.3
GE(1)	71.0	45.4	25.6
A(1)	52.0	32.1	19.9
A(2)	84.0	52.9	31.1
2016			
GE(0)	56.0	27.9	28.1
GE(1)	61.0	29.1	31.9
A(1)	43.0	24.4	18.6
A(2)	67.0	43.2	23.8

Source: authors' construction based on UNU-WIDER (2022b) inequality Excel data and KNBS (2020).

As shown in Table 8, the differences between the estimated general entropy and Atkinson index inequality based on net per capita income, as in the WIID standardized measures, and those based on per capita consumption expenditure, as in the case of the Kenyan diagnostics study, are very large. For 1994 the difference ranges from 12 to 27 percentage points; for 2006 it ranges from 20 to 35 percentage points; for 2016 the difference ranges from 19 to 32 percentage points. The differences estimated for this measure are much higher than those estimated based on the Gini coefficients as shown in Table 8. What can be said about the differences in this table being different for measures that focus on the bottom end of the distribution GE(0) or A(1)? The answer to this question, *which lies in the absence of tax data in Kenyan surveys*, lends support to our earlier argument that differences in ACEIR and WIID inequality indices arise mainly from use of consumption expenditure in the former and of income in the latter, when computing inequality measures. People at the bottom of the income distribution are likely to be recipients of targeted public transfers, which boost their consumption, and this has the tendency to reduce inequality. More fundamentally, income responses to survey questionnaires at the bottom income deciles are at risk of suffering behavioural biases, which encourage reporting of gross rather than net income, which has a tendency to increase inequality. The reason for over-reporting is that people suffer a disutility from mentioning or revealing an income lower than a previous or reference income. This is because they are essentially reporting an income loss. In contrast, people derive utility from reporting an income greater than a previous level because they are basically reporting an income gain. Moreover, the disutility from reporting an income loss should roughly be twice the utility gained from reporting an income gain of the same magnitude. Since people can be assumed to be averse to losses (Thaler 1980), we can conclude that they have an incentive to report gross rather than net income. This tendency should be stronger at the bottom of the income distribution where the risk of an individual falling below a previous level of income is high. That this risk is real is evident from the following observation by Fields (2000: 2) on the employment problem in South Africa: 'Once the issue is defined as an employment problem—comprising not only those who are unemployed by standard international definitions but also those with low labour market earnings by South African standards—different policy analysis and prescriptions follow. The goal is no longer merely to create jobs. The goal is to create *good* jobs. It is as important to raise the earnings of the working poor as it is to get the poor working.'

Empirically, we address the above-mentioned issue by first discussing how the inequality measures are estimated and whether the differences in measures used to estimate them can explain the noted variations. Second, we look at how the WIID standardized measures for Kenya are arrived at and whether this could partly explain the differences in the measures. Finally, we try to compare the WIID standardized income measures with those in the Commitment to Equity (CEQ) Institute's fiscal incidence study on Kenya, which are based on income.

3.3 Inequality estimates in the Kenyan diagnostics study, WIID original, and WIID Companion

We use the period 1992–2016 for which data are available to discuss the inequality estimates in the Kenyan inequality diagnostics study and in WIID original and the WIID Companion. Over the period 1992–2016 the WIID original Gini coefficient estimates and those for the Kenyan inequality diagnostics study are computed on the basis of per capita consumption expenditure. The estimated per capita consumption expenditure inequality for WIID original and those for the Kenyan inequality diagnostics study are similar, with only minor differences, arguably because they are both derived from per capita consumption expenditure. On the other hand, the WIID Companion income inequality estimates are predicted based on regression coefficient on net income (disposable income) from a sample of countries in the Luxembourg Income Study (LIS) database (see Machemedze and Wittenberg 2023). As shown earlier, the WIID Companion predicted Gini estimates for Kenya are much higher than the WIID original Gini estimates and those in the Kenyan inequality diagnostics study based on per capita consumption expenditure. So, why are the predicted Gini estimates for Kenya based on net income much higher than those based on per capita consumption expenditure? What explains the large differences between the two measures of inequality?

First, probably, the differences between the two is due to the differences in the measures used in the estimation of the two inequality measures. It is clear from theory that part of disposable income can be consumed or saved. Individuals with low incomes are likely to spend a high proportion of their disposable income on consumption while those with high incomes spend a small fraction of their disposable income on consumption with a possibility of saving the remaining fraction. If this is the case, then per capita consumption expenditure does not capture the savings part for individuals or households whose incomes are high and who only spend a small portion of their income on consumption. This is likely to result in lower Gini coefficient estimates based on per capita consumption expenditure. On the other hand, the net per capita income includes savings that are not captured in the per capita consumption for those households with high income and would most likely give rise to a higher Gini coefficient based on net per capita income estimates. However, because domestic savings in Kenya are very low (at about 12.4 per cent) it is uncertain that it will lead to such a huge difference in inequality measures based on per capita consumption expenditure and per capita income.

Second, the difference could be due to the difficulties in measuring the income of low-resourced households involved in informal activities, subsistence agriculture, and other activities. Given the large sizes of self-employment and non-monetized economic activities in Kenya, there are real measurement difficulties in estimating household income, particularly for low-resourced households in self-employment and informal activities (Bigsten et al. 2003; ILO 2003; KNBS 2018; Meyer and Sullivan 2003). For instance, according to Meyer and Sullivan (2003) income for low-resourced households is underreported, specifically incomes associated with self-employment earnings, private transfers, and public transfers, because income seems to be a more sensitive topic in the administration of household surveys and, thus, easier to hide. If these income measurement difficulties were encountered in the LIS data used to estimate per capita income for the sample countries that we used to run the regression coefficients, then they are likely to lower the income of the low-income groups, most of whom are self-employed and engaged in informal activities, and could lead to overestimation of inequality measures if not taken into account in the calculation of household income. On the other hand, as mentioned earlier, the consumption-based inequality measure of household well-being captures better the permanent income of households and individuals, and better reflects the insurance value of government programmes and credit markets. The consumption-based measure also better accommodates remunerations from illegal activities and captures price changes, and is more likely to reflect benefits derived from private and government transfers. For instance, the quality and reliability of consumption expenditure data for a developing country, such as Kenya, are better than that of net per capita income data (see KNBS 2020; Meyer and Sullivan 2003). Estimations based on per capita consumptions are likely to yield lower inequality. For instance, Figures 2, 3, and 4 on Kenya seem to support this as the distribution of income across the population based on the WIID Companion projection based on net per capita income estimates underestimates income for the poor compared with estimates based on per capita consumption, as in the case of the Kenyan inequality diagnostics study and WIID original.

Briefly, while we can believe more in the Gini coefficients based on per capita consumption expenditure and also accept that they are likely to be less than the coefficients based on net per capita income, we are not so certain that the difference between the two should be as high as reported in the datasets reviewed. If we had data on household savings, then we would add it to consumption expenditure and use this to estimate the Gini coefficients and verify whether the calculation yields results closer to those based on per capita income. However, we do not have information on household savings in the survey data collected in Kenya. In fact, in the WIID datasets, income based on WMS 1992, 1994, and 1997 is described as being of low quality whereas income from KIHBS 2005/06 and KIHBS 2015/16 is described as being of moderate quality, which is in line with our earlier discussion on the datasets. Due to this, the WIID does not use income from the surveys to directly estimate income inequality in the WIID Companion. The WIID standardized Gini measures are obtained regression predictions as explained in the next subsection. Thus, while we know that inequality measures based on per capita consumption expenditure will be less than those based on per capita income, we are not sure that those based on net per capita income will be as high as those provided in the WIID Companion. Next, we attempt to understand how the WIID Companion's standardized measures of inequality for Kenya are obtained.

3.4 Estimation of standardized inequality for Kenya (1994–2014) in the WIID Companion

Understanding how the WIID standardized inequality for Kenya are derived can boost confidence in using the estimated inequality measures and also help in explaining the differences outlined earlier. According to Machemedze and Wittenberg (2023), the WIID standardized inequality measures for Kenya and other countries are imputed using regressions coefficients estimated using net per capita income inequality data for a sample of countries in the LIS dataset and the available consumption inequality measures. The African countries included in the LIS sample data used to estimate the regression are South Africa, Sudan, Somalia, and Côte d'Ivoire. The dependent variable in the regression is per capita net income Gini coefficient while explanatory variables include the other measured Gini (e.g. per capita consumption), the associated type of income concept (e.g., consumption), the form of equivalization, and interactions between these variables and country dummies, income group and region.

For countries like South Africa, the regression coefficients are used to predict net per capita income inequality from the measured series (i.e. per capita consumption inequality). In the case of Kenya, the conversion makes use of income group and region but is more complicated and has several issues emanating from the data used in the conversion process not being all of the same type (Machemedze and Wittenberg 2023). For instance, according to Machemedze and Wittenberg (2023), the 1976 and 1982 data points are not adjusted yet; they ought to be converted but cannot be because of empty data. Also the original data points and imputed series suggest that there is a major break in the inequality data series between 1992 and 1994, but the WIID Companion series suggests that 1992 may be a once-off outlier so that, ignoring that point, there has been a slow rise in inequality over the period. Furthermore, the 95 per cent confidence interval shows that there is considerable uncertainty about the accuracy of the imputed values. With the drop in inequality between 1992 and 1994 appearing to be statistically significant. However, it is hard to believe that a major change in the level of inequality could be concentrated into such a short time period (Machemedze and Wittenberg 2023). Nevertheless, if the original measures are inaccurate, then the degree of uncertainty about the imputed values will be much higher than reflected in the confidence intervals.

Another issue is that Kenya is not part of the sample used in the estimation of the regression model that was relied on to predict the standardized inequality measures because it is not one of the countries in the LIS dataset and had poor data on household income. Given the vast differences in sub-Saharan African countries, if these countries are not well represented in the LIS dataset and/or if Kenya is not part of the sample as is the case, then using the regression parameters based on the estimation sample is likely to give biased inequality measures. This is in line with the conclusion by Machemedze and Wittenberg (2023), that there is likely to be considerable measurement error in the underlying information, as revealed by huge changes in Gini coefficients in very short time periods so that the process of adjustment or conversion can introduce new errors that are likely to be large enough to create doubt about the overall direction of change in the level of inequality. Given this, it is likely the big difference between the WIID standardized inequality measures and those of the WIID original and the Kenyan inequality diagnostics study could be partly due to measurement errors. Therefore, as a second best option, in the next subsection we assess how the standardized WIID Companion inequality measures compare with income inequality measures in the Kenyan fiscal incidence that uses an approach developed by the CEQ Institute to measure net income.

3.5 Inequality measures using CEQ income concepts and standardized WIID measures

The ACEIR fiscal incidence study for Kenya (see KNBS and University of Nairobi 2022), which estimates inequality and poverty based on various income concepts using a combination of KIHBS 2015/16 and administrative data, shows that when taxation, pensions, and cash transfers are taken into account in the construction of household income, the magnitudes of measured income inequality and poverty change noticeably. However, in measuring the income, it is assumed that household savings are equal to zero. The study shows variations in inequality and poverty measures, as the household well-being indicator is shifted from market income (pre-tax income) to gross income (market income plus transfers), and eventually to consumable income (disposable income less indirect taxes plus indirect subsidies). The study shows that income inequality is highest for the market income at Gini coefficient of 45 per cent while inequality among the poor is highest for the consumable income at 10.9 per cent. Income inequality is lowest for the final income (consumable income plus in-kind benefits less user fees) at a Gini of 35.7 per cent. Across the various income concepts income inequality ranges from 35.7 per cent to 45 per cent while inequality among the poor ranges from 8.8 per cent to 10.9 per cent (see KNBS and University of Nairobi 2022).

The findings in this study (KNBS and University of Nairobi 2022) are aligned with the WIID Companion inequality statistics as it shows how the components that constitute income determine the magnitudes of income inequality. In particular, the total reduction in the Gini coefficient when the measure of household well-being is shifted from market income to final income is 9.3 percentage points. A comparison of the WIID Companion Gini coefficients for 2016 at 55.57 per cent with the Gini statistics in KNBS and University of Nairobi (2022) shows that the WIID standardized inequality measures are much higher than the ones for the Kenyan fiscal incidence study. The measures from the incidence study are roughly within the same range as the Gini coefficients reported in the WIID and in the Kenyan diagnostics study. This finding suggests that taxation and savings might not be the only factors driving the differences between the WIID standardized inequality measures and those in the Kenyan inequality diagnostics study measures, as both the WIID standardized measures and the Kenyan fiscal incidence study use per capita consumption to obtain the inequality measure based on income (see KNBS and University of Nairobi 2022).

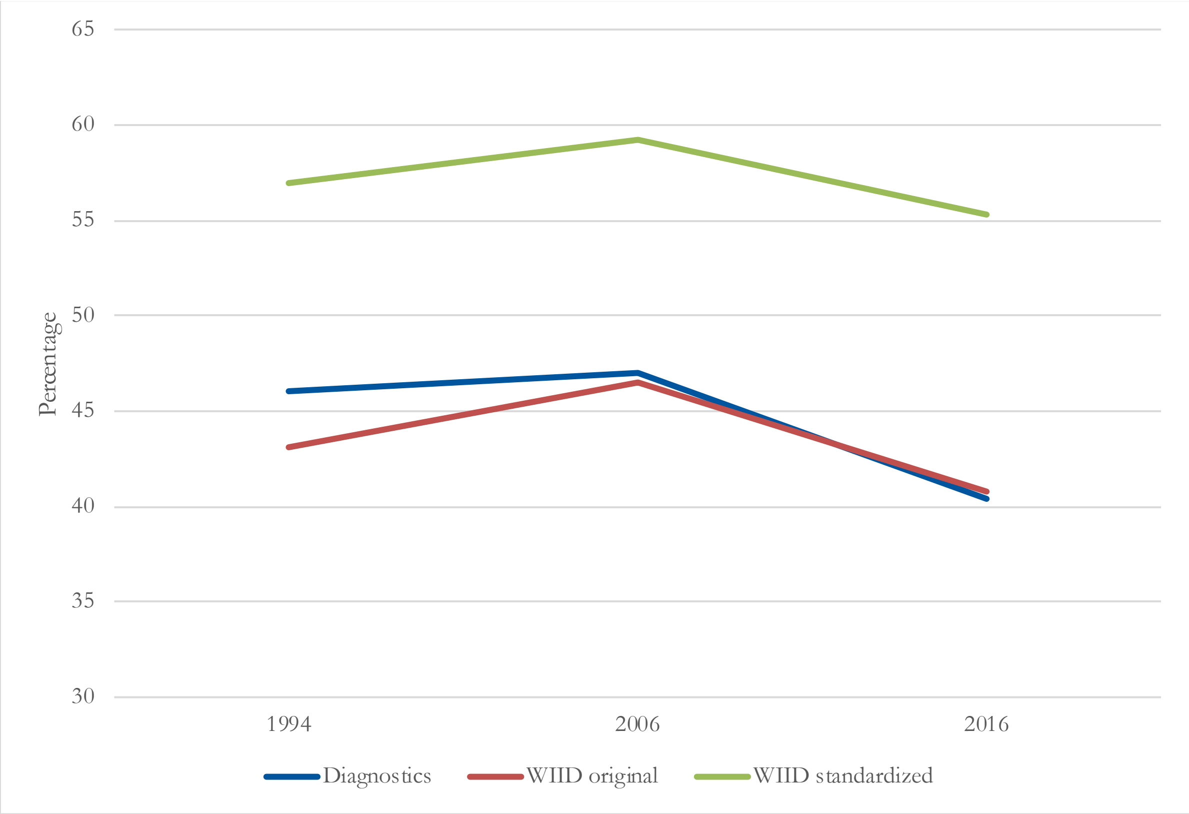
KNBS and University of Nairobi (2022) also bring out some policy value in comparing the distribution statistics on Gini coefficient and poverty gap. The comparison shows that the Gini (0.450) is higher for market income than for consumable income (0.402) as a result of the inequality reduction effect of taxation. However, the contrary is the case for change in the poverty gap, where taxation increases poverty. It is evident that taxation (value-added tax) in the Kenyan fiscal incidence study worsens the distribution of income among the poor as the income gap among the poor widens with the move from market income to consumable income, suggesting that the Gini is increasing.

The analysis in this paper shows that in the case of Kenya, inequalities in household well-being that are measured using locally available survey and/or administrative data are similar irrespective of whether they are based on household income or on household consumption expenditure. That is, the Gini coefficients computed using locally available household income data (Kenyan fiscal incidence study) and the Kenyan inequality diagnostics study are in the same range as the Gini measures obtained using the WIID. However, the standardized inequality measures derived from the WIID *Companion* are substantially different from those computed using household income or consumption expenditure variables generated from locally available survey data. This could be partly due to adjusting or converting the series in the WIID Companion and introducing new errors to the extent that they are likely to be large enough to create doubt about the overall direction of change in the level of inequality, even if we were to believe the baseline data (see Machemedze and Wittenberg 2023). Next, we assess the trends in the WIID standardized inequality measures compared with the measures based on per capita consumption expenditure.

3.6 Trends in the WIID standardized inequalities and the WIID and diagnostics study inequality measures

First, we look at trends in Gini coefficient estimates. Figure 5 shows trends in the Gini inequality measure for the ACEIR diagnostics study for Kenya and for the WIID original and standardized inequality measures. As shown in the figure, the Gini coefficient estimates increase from 1994 to 2005/06 and then decline between 2005/05 and 2015/16. This applies to estimates for the inequality trends and diagnostics study as well as for the WIID original and standardized inequality measures. The only difference is that WIID standardized estimates are much higher than those for the inequality trends in the Kenyan ACEIR study and for WIID original. Another worthwhile observation is the slight difference between the Gini estimates for the Kenya diagnostics study and for the WIID original; however, the estimates for the two seem to be similar for the period 2005/06 and 2015/16.

Figure 5: Trends in Gini inequality measures for the Kenyan diagnostics study, WIID original, and WIID standardized for 1994–2016

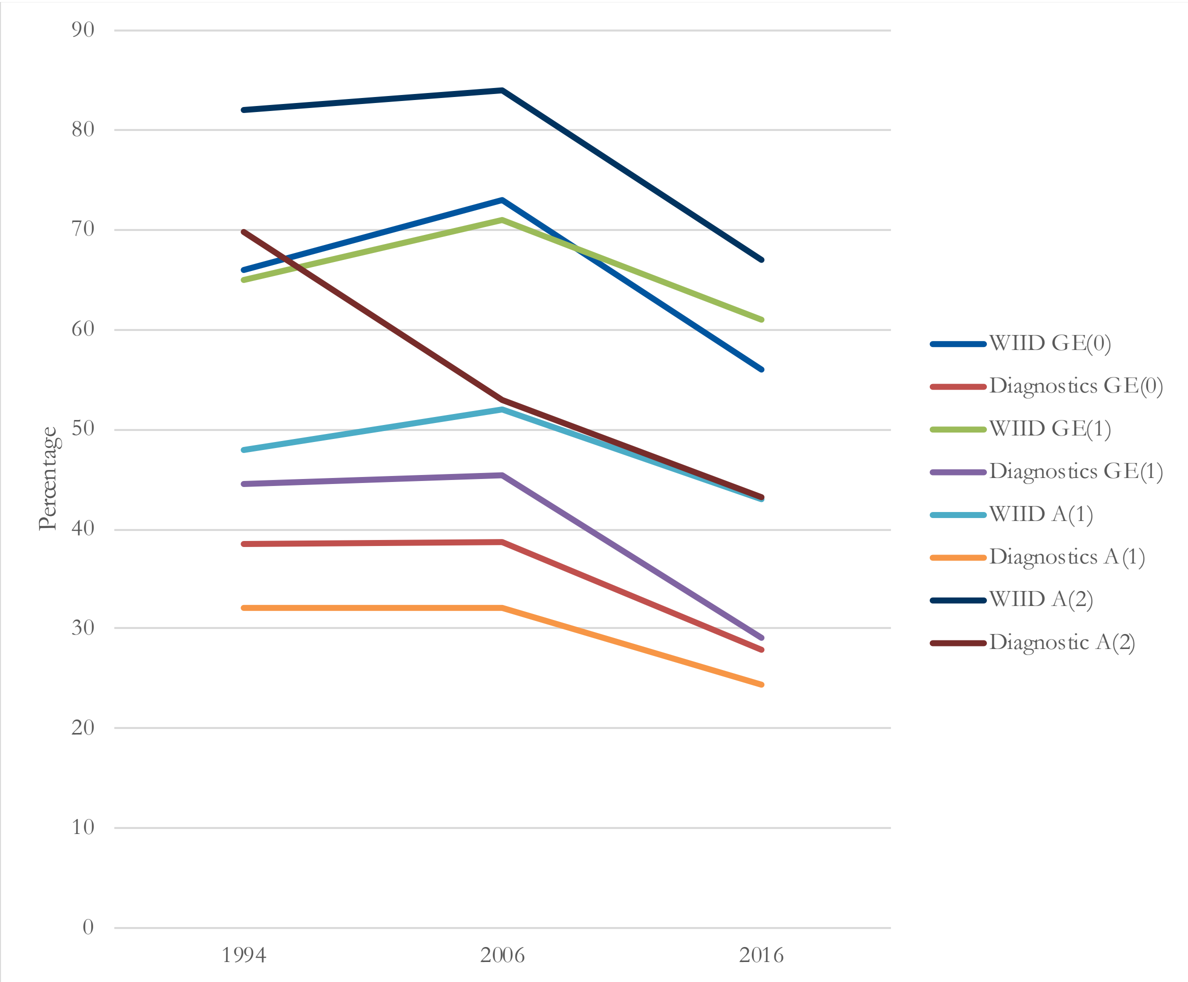


Source: authors' construction based on UNU-WIDER (2022a, 2022b) inequality Excel data and KNBS (2020).

Figure 6 shows trends in general entropy and Atkinson index measures of inequality in the WIID Companion and the Kenyan ACEIR study on inequality trends and diagnostics for the years 1994, 2006, and 2016. As shown in the figure, the WIID standardized measures, which are based on net per capita income, are generally much higher than those in the Kenyan inequality diagnostics study, which are based on per capita consumption expenditure. The figure shows some differences in the trends of the various measures in the period 1994–2006, with standardized WIID measures rising at different rates over the period and some of the Kenyan diagnostics study measures declining.

However, over the period 2006–16, all the measures decline at varying rates. The trends for these measures are much more consistent over this period than in the period 1994–2006. Thus, as in the case of the Gini coefficient trends, the inequality estimates (general entropy and Atkinson index) seem to show similar trends over the period 2006–16 but in terms of magnitudes, the estimates for the WIID Companion are much higher than those reported in the Kenyan ACEIR study on inequality trends and diagnostics.

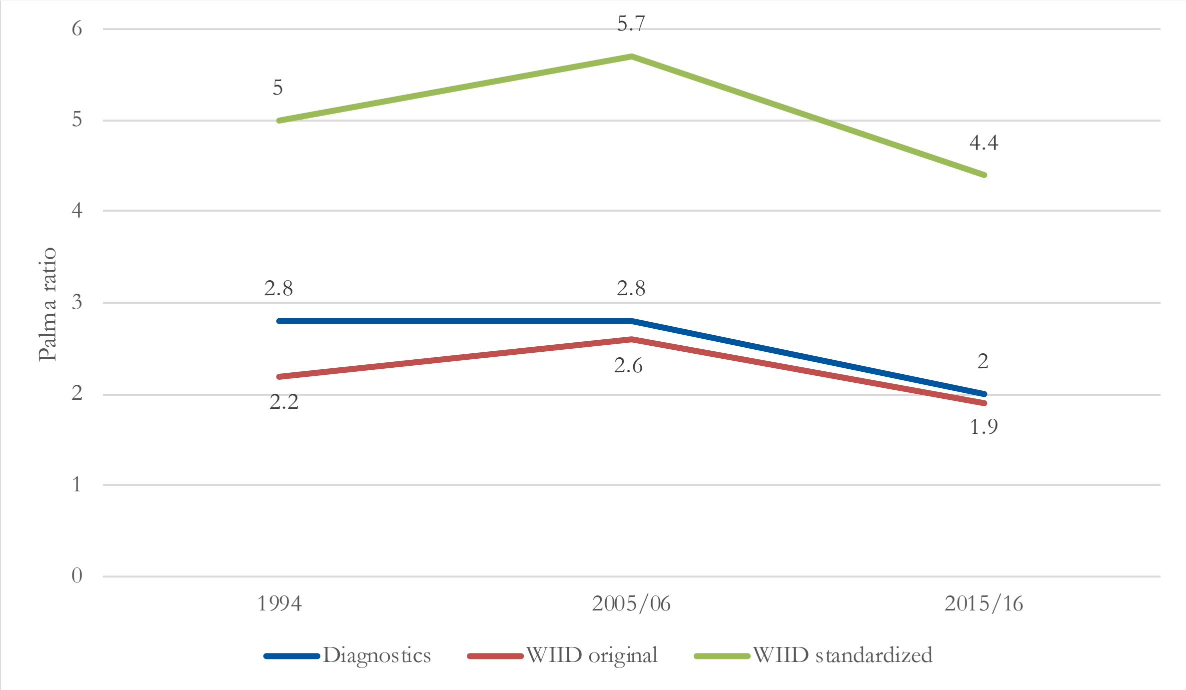
Figure 6: Trends in general entropy and Atkinson index inequality measures for WIID standardized and Kenyan diagnostics study for 1994–2016



Source: authors' construction based on UNU-WIDER (2022b) inequality Excel data and KNBS (2020).

Figure 7 shows trends in the Palma ratio measures of inequality trends based on data for the diagnostics study for Kenya, for the data comprising the WIID, and for the WIID Companion. As shown in the figure, the WIID standardized measure of the Palma ratio is much higher than the Palma ratio derived from the data underlying the diagnostics study and the WIID. In terms of trends, like the Gini estimates, except for the Kenyan inequality diagnostics study where the Palma ratio remains the same at 2.0, between 1994 and 2016, the Palma ratio for the WIID and its Companion is higher than that for the Kenyan diagnostics study. The Palma ratio in all three datasets declined between 2005/06 and 2015/16. The estimates in the inequality trends and diagnostics study for Kenya are slightly higher than those for the WIID. Thus, the estimates seem to show similar trends but in terms of magnitudes, the estimates for the WIID Companion are much higher than those reported in inequality trends and diagnostics studies for Kenya and those based on the WIID. However, since it has been difficult to confirm the inequality magnitudes in the WIID Companion because of poor data on household income, it is not advisable to use this particular dataset to analyse or compare income inequality trends within or across countries.

Figure 7: Trends in Palma ratio estimates for the Kenyan diagnostics study, the WIID, and WIID standardized measures for 1994–2016



Source: authors' construction based on UNU-WIDER (2022a, 2022b) inequality Excel data and KNBS (2020).

4 Summary and conclusions

In East Africa, Kenya has moderately high inequality compared with the neighbouring countries of Uganda, Tanzania, and Ethiopia, but has relatively lower inequality compared with South Africa, Namibia, Rwanda, and Nigeria, which are among the continent's most unequal countries. Over time inequality in Kenya increased slightly between 1994 and 2005/06 and then declined considerably at the national level, in rural and urban areas, and across social strata between 2005/06 and 2015/16. Globally, following the adoption of the SDGs (particularly SDG 10) and the need to monitor progress towards achieving it, there has been growing interest in inequality, with several initiatives being undertaken to ensure data are readily available. Among the leading initiatives on this front is the UNU-WIDER WIID, with the WIID Companion standardized inequality measures being an attempt to provide inequality measures that can be used to analyse, describe, or compare levels of inequality between countries or over time. This study has explored how well the UNU-WIDER WIID standardized inequality measures for Kenya relate to those of other Kenyan studies with a focus on the Kenyan inequality diagnostics and the fiscal incidence studies undertaken by ACEIR. Based on our analysis, we make observations on the appropriateness of using WIID standardized measures to analyse, describe, or compare levels of inequality between countries or over time.

Our assessment shows that all the datasets with information that can be used in the analysis of income inequality are available in Kenya and are reflected in the WIID analysis. First, the datasets are collected with a gap between the surveys ranging from 2 to 10 years, making it difficult to have a longer run series of inequality estimates in Kenya. The WIID estimates for Kenya face the same difficulty, as it is not possible to obtain a systematic annual series of inequality measures. Second, the income information in the datasets is of varying quality, ranging from poor quality income information in WMS 1992, 1994, and 1997 to moderate quality information for KIHBS 2005/06 and 2015/16. As a result of missing information, the KIHBS datasets do not have all income components that reasonably match the suggested WIID income components for estimating standardized income inequality. This makes it difficult to estimate net per capita income inequality directly from the Kenyan surveys for comparison with the standardized measures in the WIID Companion that are imputed based on regression estimates. Without this, it is not possible to assess how well the WIID standardized inequality relates to similar estimates based on Kenyan survey data. Finally, the survey datasets for the period 1992–2016 have very good information on household consumption expenditure and are used to estimate the per capita consumption expenditure inequality estimates in the WIID and in the Kenyan inequalities studies. The WIID Companion standardized inequality measures use regression estimates to adjust the per capita consumption inequality measure for this period to obtain income inequality measures for Kenya. However, some of the Kenyan inequality measures (i.e. for 1976 and 1982) are not adjusted using this method even though they should have been adjusted. Moreover, even when data from well-designed surveys are available, they cannot be fully trusted because people at the bottom of the income distribution have strong incentives to over-report income, thus biasing inequality measures upwards.

Our analysis also shows that the WIID standardized inequality measures are much higher than those in the WIID and the Kenyan studies on inequality diagnostics and fiscal incidence. We demonstrate that inequality measures based on per capita consumption expenditure are generally lower than the WIID standardized measures for Kenya that use regression coefficients based on income to impute the estimates. The difference between them is partly from per capita consumption expenditure underestimating household income for high-income earners by not capturing the savings portion of disposable income in the per capita net income. It is also partly because the income measure is likely to underestimate income for low-resourced households involved in informal activities, self-employment, and subsistence agriculture due to measurement problems. Furthermore, the difference could be due to measurement errors arising from the way the standardized measures for Kenya are imputed using regression coefficient estimates, or because Kenyan data are not part of the sample used in the estimation of the regression coefficient, or because sub-Saharan Africa countries are not being well represented in the sample.

As a result of poor quality data on income in the Kenyan survey data, we cannot use the data to estimate income inequality metrics that we can directly compare with the WIID standardized inequality estimates. Using poor quality data to estimate income inequality will give biased estimates of inequality, but also the WIID standardized inequality measures based on regression interpolation has a weakness as outlined earlier. It is difficult, therefore, to assess the appropriateness of how the WIID standardized inequality measures would relate to income inequality measures obtained directly from the Kenyan survey data. Thus, the adjustments and assumptions in the WIID Companion are hard to verify. This means that even if the WIID Companion measures are to be used, caution to the user and the reader is warranted because the reliability of the measures remains an issue.

On the other hand, although the estimated WIID standardized estimates are higher than those based on per capita consumption expenditure, their trends to some extent mimic those of the per capita consumption expenditure, especially in the period 2006 and 2016. Thus, when inequality based on per capita expenditure is increasing, the WIID standardized measure is also increasing and vice versa. However, this could be because the WIID standardization based on regression coefficient estimates upscales the inequality based on per capita consumption expenditure without much altering of the trend. However, since it has been hard to confirm the accuracy of inequality magnitudes in the WIID Companion, it makes it equally difficult to use the WIID Companion estimates to show trends in inequality. This is because one needs to refer to the increasing or decreasing magnitude of this measure when describing inequality dynamics.

In conclusion, quality data on income are not available in Kenya and possibly in other African countries to authenticate how well the WIID standardized inequality measure relates to the per capita income inequality index. This issue needs to be investigated further as better data become available. The collection of better and quality information on income at the household level in household budget surveys in Kenya and elsewhere is key to ensuring accurate inequality estimates based on net per capita income. However, an important contribution of this study is the finding that the WIID Companion inequality measures are higher than the inequality indices derived from the per capita consumption expenditure, despite the uncertainty as to why this is so. There is evidence suggesting that this uncertainty will diminish as better concepts to unravel biases in the reporting of income in household surveys are invented and applied.

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Appendix A

Table A1: Gini coefficients for Kenya from the WIID Excel database, 1914–2016

Year	WIID original	WIID Companion		Coverage	Source
		(WIID original)	WIID standardized		
1914	50.00			All	Bigsten (1986)
1921	57.00			All	Bigsten (1986)
1927	58.00			All	Bigsten (1986)
1936	63.00			All	Bigsten (1986)
1946	64.00			All	Bigsten (1986)
1950	70.00			All	Bigsten (1986)
1955	63.00			All	Bigsten (1986)
1960	68.00			All	Bigsten (1986)
1961	48.80	48.80	51.17	All	Cromwell (1977)
1964	63.00			All	Bigsten (1986)
1967	66.00			All	Bigsten (1986)
1969	47.90			Urban	Jain (1975)
1969	63.70			All	Jain (1975)
1969	68.00			All	Bigsten (1986)
1969	60.40			All	Lecaillon et al. (1984)
1971	70.00			All	Bigsten (1986)
1974	69.00			All	Bigsten (1986)
1976	52.00	52.00	53.43	All	ILO (1984)
1976	68.00			All	Bigsten (1986)
1977	59.00	59.00	59.00	All	van Ginneken and Park (1984)
1977	59.00			All	van Ginneken and Park (1984)
1982	57.30	57.30	57.16	All	Milanovic (1994)
1992	57.46	57.46	67.30	All	World Bank (2023)
1994	43.11	43.11	57.21	All	World Bank (2023)
1997	44.98	44.98	58.52	All	World Bank (2023)
1999	62.50			All	Society for International Development (2004)
1999	57.00			All	Society for International Development (2004)
2006	45.90			All	Kenya National Bureau of Statistics (KNBS 2007)
2006	38.00			Rural	Kenya National Bureau of Statistics (KNBS 2007)
2006	44.70			Urban	Kenya National Bureau of Statistics (KNBS 2007)
2006	46.45	46.45	59.56	All	World Bank (2023)
2016	40.78	40.78	55.57	All	World Bank (2023)

Source: authors' construction based on UNU-WIDER (2022a, 2022b) inequality Excel data.