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Developing Indicators of Inequality and Poverty Consistent with National Accounts

Richard Tonkin, Sean White, Sofiya Stoyanova, Aly Youssef, Sunny Valentineo Sidhu, and Chris Payne

20.1 National Accounts–Based Distributional Indicators

The national accounts, produced under the System of National Accounts (SNA 2008) framework, provide a range of measures of both household income and consumption. However, no distributional information is currently provided within the SNA framework, with these data instead providing only overall aggregates and simple per capita (or per household) averages. Despite these limitations, there is a clear interest in the development of measures of economic well-being, poverty, and inequality that are based on and consistent with the national accounts framework.

There are a number of reasons for this. First, such an approach aids international comparability. While there are relevant international standards and

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guidelines for income and consumption microstatistics, generally speaking, the approaches and concepts used can sometimes vary considerably across countries. By contrast, the SNA framework potentially offers greater coherence for making such comparisons. Second, the possibility of distributional indicators that are consistent with economywide totals is also beneficial in terms of coherence for users of statistics within countries. The regularity of national accounts is also beneficial for users, particularly in countries where there may be a number of years between surveys. Similarly, the timeliness of national accounts data is generally considerably greater than that of survey estimates, allowing for the potential of more timely measures of poverty and living conditions.

In recent years, there has therefore been a growing body of work seeking to produce distributional national accounts, including that coming out of the OECD-Eurostat Expert Group on Disparities within a National Accounts Framework (EG DNA, see, e.g., Tonkin and Wildman 2016; Zwijnenburg, Bournot, and Giovannelli 2017).

The EG DNA has developed a methodological framework to derive distributional estimates within the national accounts framework on the basis of microdata sources, consisting of five broad steps. The first of these is to adjust the national accounts totals so that they refer to the same population as the microdata by, for example, removing nonprofit institutions serving households (NPISH) and where possible removing the expenditures of nonresident households. In a second step, the relevant variables within national microdata which can be mapped onto the different national accounts income and consumption concepts are identified. The third step is concerned with bridging any gaps by imputing for missing elements and scaling the microdata to the adjusted national accounts totals. In the fourth step, on the basis of these aligned results, households are clustered into quintiles or other groups of interest, before relevant indicators are derived in the final stage.

20.1.1 Microdata Coverage

The microdata source used throughout this analysis is the Living Costs and Food Survey (LCFS), a cross-sectional survey with an achieved sample of approximately 5,000 households a year. The LCFS was chosen as it was considered desirable to use a single source of survey microdata for all income and consumption components, where possible, in order to ensure internal consistency. Out of the available sources, the LCFS is therefore preferable as it provides very detailed information on both income and expenditure, including social transfers in kind (STiK).

As described above, the second step of the EG DNA methodology is to map the variables within this microdata onto the different components of household income and consumption in the SNA framework. Doing so reveals sometimes substantial differences in recorded amounts between the two. As an example, figure 20.1 presents coverage rates for the main com-

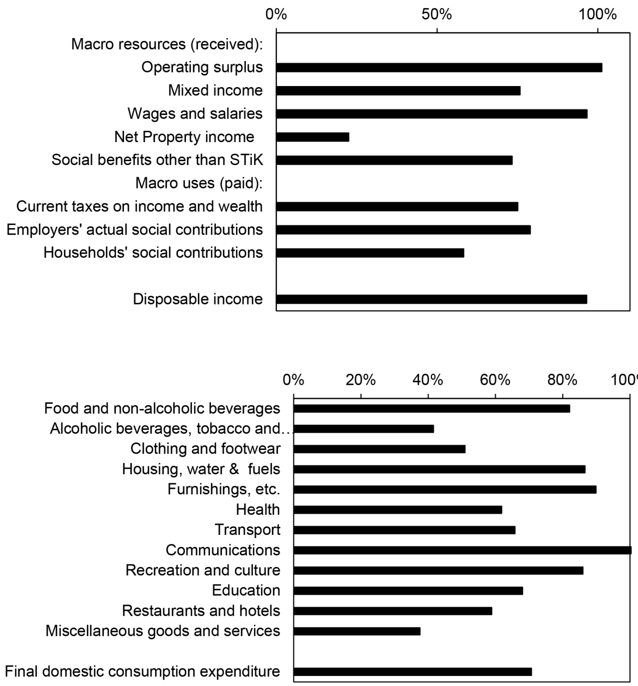

Fig. 20.1 Coverage of survey-based estimates of National Accounts aggregates, UK, 2017

Source: Office for National Statistics, Living Costs and Food Survey; National Accounts Blue Book, 2018.

ponents of income and expenditure for the UK in 2017, with microdata coverage expressed as a percentage of the macro figure.

Looking at these coverage rates, it is apparent there is considerable variation across the components, ranging from 23 percent to 101 percent for income, and 38 percent to 100 percent for consumption. The Atkinson Commission report (World Bank 2017) highlights two broad reasons why these differences between household surveys and national accounts can occur. The first is differences in recorded amounts, which may reflect issues with survey coverage, nonresponse and underreporting, as well as measurement error in the national accounts. The second is definitional differences, reflecting the different purposes to which the two sources are traditionally put. These factors are illustrated, for example, in the low microdata coverage for "net property income received" seen in figure 20.1.

The biggest single reason for this low coverage rate is that there are some components of the national accounts measure, such as investment income attributed to insurance policyholders and investment income payable on pension entitlements, for which there is no counterpart in household income microdata. Additionally, for those components where there are survey equivalents, such as interest and dividends received by households, the aggregate values in the micro sources are lower. This may reflect a combination of factors, including nonresponse at both the item and household level, and underreporting for those individuals and households who do report incomes from these sources.

On the consumption side, one of the main discrepancies is between reported expenditure on "alcoholic beverages and tobacco." This is largely explained by households underreporting their expenditure on these items in surveys. The UK National Accounts estimates for these items largely rely on administrative records from the tax authorities, which provide a better picture of overall expenditure (though they are unable to provide any distributional information).

These differences in coverage between the macro and micro totals are far from unique to the UK. Zwijnenburg, Bournot, and Giovannelli (2017), comparing data across 12 OECD countries (including the UK), showed both considerable differences in average coverage across the different components, but also a relatively high degree of similarities across countries for the same components, perhaps unsurprisingly given that many of the underlying issues will be applicable across most countries.

20.1.2 Imputation and Scaling

Low levels of microdata coverage are a particular issue for the production of distributional national accounts, and therefore poverty and inequality indicators based on that data, due to the large assumptions that they often necessitate. As highlighted above, the third step of the EG DNA methodology is to impute and scale the microdata to the adjusted national accounts totals. In some research, this has taken the form of proportionate scaling of the micro values to the national accounts aggregate, such that the distribution of each component remains unchanged. However, where the gaps between micro and macro figures are significant, the decisions taken around imputation and scaling can have a substantial impact on the final distribution, and for many components the available evidence does not support the assumptions inherent in such an approach. For this reason, proportionate scaling is something that Bourguignon (2015) and others have warned against, particularly when aiming to measure poverty and shared prosperity.

In particular, there is considerable evidence suggesting that, at least on the income side, a significant proportion of the difference between the micro and macro totals may be accounted for by underreporting toward the bottom of the distribution. Looking at the microdata, figure 20.2, taken from Stoyanova and Tonkin (2018), shows the distribution of disposable income and expenditure by income decile for the UK. Consistent with other studies in the UK and elsewhere, it shows relatively high levels of expenditure relative to income at the bottom of the distribution. While this in part may reflect

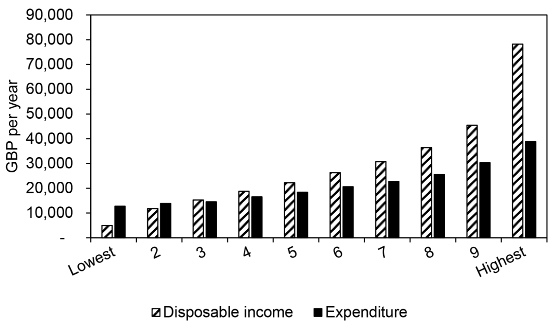

Fig. 20.2 Mean disposable income and expenditure by equivalized disposable income decile, UK, 2016/17

Source: Office for National Statistics, Living Costs and Food Survey.

consumption smoothing by those with temporarily low incomes, analysis from the UK and US indicates that a substantial component of this difference is explained by underreporting of incomes (e.g., Brewer, Etheridge, and O'Dea 2017; Meyer and Sullivan 2011). This underreporting may reflect people forgetting income they have received during the reference period from sources such as intrahousehold transfers, social transfers, or home-produced items they have sold. People may also be reluctant to disclose their full incomes for privacy reasons.

Further evidence comes from comparison of the value and number of recipients of different forms of social transfers with those reported in administrative data (figure 20.3). This reveals that in the UK, the level of coverage within survey microdata for some benefits can be pretty low, with the coverage rate for Pension Credit, Attendance Allowance and Industrial Injuries Disablement Benefit being less than 50 percent in terms of expenditure.

Figure 20.3 also highlights that, for most social security benefits in the UK, the survey microdata coverage rates are similar for both levels of expenditure and number of recipients. This suggests that the primary reason for the gaps is nonreporting of benefits received by some recipients, rather than those who do report receipt underestimating the amount.

While coverage rates for other benefits, such as the state pension, is a lot higher, their size in monetary terms means that they can still contribute significantly to the absolute difference between the micro and administrative figures. Figure 20.4 shows the benefits contributing the largest amount to the absolute gaps in benefit expenditure for 2017/18. Taken together, these 10 benefits account for a £44 billion difference between the level of social protection spending shown by administrative data for the UK for 2017/18 and the level recorded in the survey microdata.

Part of these differences can be accounted for by spending that goes to people who are either not resident in the UK (for example, pensioners living

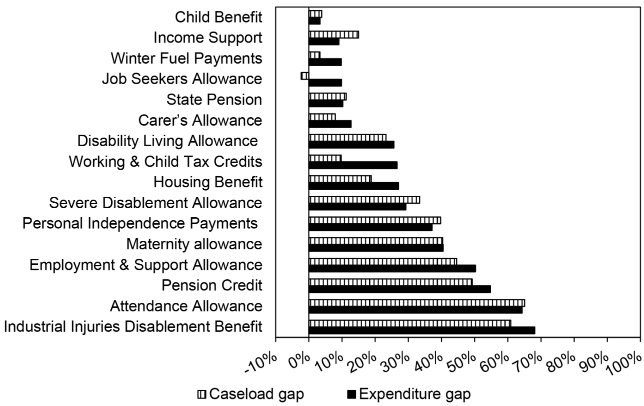

Fig. 20.3 Percentage coverage gap between microdata and administrative spending and caseload totals, UK, 2017

Source: Office for National Statistics, Living Costs and Food Survey; Department for Work and Pensions, benefit expenditure and caseload tables.

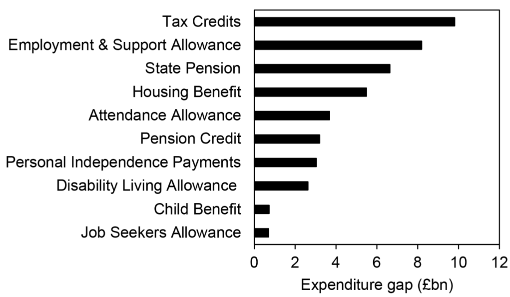

Fig. 20.4 Absolute expenditure gap between microdata and administrative data totals, UK, 2017/18

Source: Office for National Statistics, Living Costs and Food Survey; Department for Work and Pensions, benefit expenditure and caseload tables.

in other countries) or those living outside the private-household population (e.g., in care homes or other communal establishments). However, even when making adjustments to account for these factors, it is clear that a significant coverage issue remains.

Underreporting at the top of the distribution is also a problem for both income and consumption, particularly for some components (e.g., Bee, Gathright, and Meyer 2015; Burkhauser et al. 2018a). While this is of less relevance for poverty measurement, it is important where one wishes to assess inequality or measures such as the shared prosperity premium. Shared prosperity is measured in terms of whether per capita income (or expenditure) growth among the bottom 40 percent of the population exceeds that of the overall population. The growth rate of the total population may be

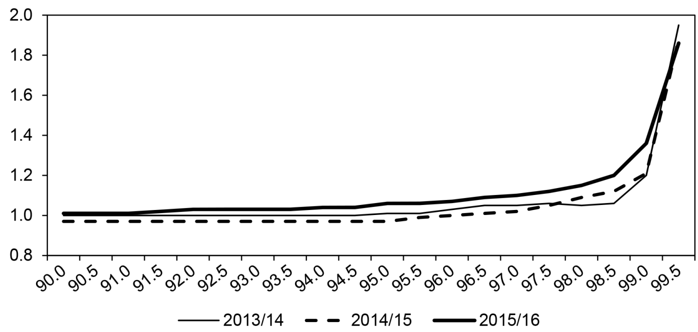

Fig. 20.5 Ratio of gross income of tax data to survey data, by quintile, UK, 2013/14 to 2015/16

Source: Office for National Statistics, Living Costs and Food Survey; HM Revenue and Customs, Survey of Personal Incomes.

heavily influenced by those at the top of the distribution, and underreporting of their incomes or expenditures may lead to misleading conclusions regarding progress toward the shared prosperity goal within a country.

There are several potential reasons for the undercoverage of top incomes (see Lustig 2018 for more information), the relative importance of which varies across countries and across surveys depending on the methods used. These include:

- frame or noncoverage error, where the frame used to select the sample for the survey does not fully cover the population of interest (in this case, households in the UK);
- unit nonresponse error, which may occur if individuals or households with higher incomes are less likely to participate in surveys than those in the rest of the income distribution;
- item nonresponse error, if those with higher incomes participating in surveys do not report all their sources of income;
- underreporting, where the levels of income received for some sources may be intentionally or unintentionally underreported by survey respondents;
- sparseness, where data on top incomes are limited due to the fewer number of observations within the dataset with very high incomes, making it difficult to estimate the true distribution.

Figure 20.5, taken from Webber, Tonkin, and Shine (2020), provides an indication of the extent to which individuals with the highest incomes appear to under-report their incomes in UK survey data. It uses data from Her Majesty's Revenue and Customs' (HMRC) Survey of Personal Incomes (SPI), a sample of anonymized records of individuals potentially liable to UK tax. The figure shows the ratio of the income of individuals in the SPI dataset to that of individuals in the survey microdata at different quantiles of the gross income distribution, for the three most recent years where full SPI datasets are available. Up to the 96th percentile, this ratio is generally close to one. It then starts to rise noticeably, increasing more sharply around the 98th percentile. At the 99th percentile and above, the income of individuals in the SPI is more than 1.2 times higher than in the survey, for all three years.

This indicates that, in line with the findings of Burkhauser et al. (2018a, 2018b), there is evidence to suggest that the largest challenge affecting top incomes in UK data is that of underreporting by survey respondents rather than undercoverage. It further suggests that any adjustment should focus primarily on the top few percentiles of the distribution.

20.2 Adjusting the Microdata

Given the above evidence, it is clear, as noted by the Atkinson Commission report (World Bank 2017), that proportionate adjustment of certain income components is not advisable, particularly when the intention is to use the data for analysis of poverty and shared prosperity. This chapter therefore takes a more sophisticated approach to addressing these issues of nonresponse and underreporting, making use of administrative data and other auxiliary information where possible, building on recent developments by Aitken and Weale (2018), Corlett et al. (2018), Shine et al. (2019), Webber, Tonkin, and Shine (2020), and others.

20.2.1 Correcting for Social Security Benefit Underreporting

In an ideal world, it would be possible to directly link administrative data on benefits to survey responses. While such an admin-data-first approach is a longer-term aim for ONS, as part of its Census and Data Collection Transformation Programme (CDCTP), more immediately, an alternative approach is necessary.

We therefore carried out an adjustment to the microdata for nearly every individual cash benefit, using a set of methods pioneered by Corlett et al. (2018). By using information contained within the microdata and comparing it with the administrative information, it was possible to allocate the missing government expenditure to appropriate individuals.

The first stage of this process was to calculate the gap between the administrative data and the survey microdata for each benefit, in terms of both number of recipients and total expenditure.[1] In this stage, some adjustments were made to the administrative totals to reflect pensions received by those

1. For some benefits, the DWP caseload and expenditure tables only contain information for Great Britain rather than the whole of the UK. For those benefits, adjustments are made to the GB survey data only.

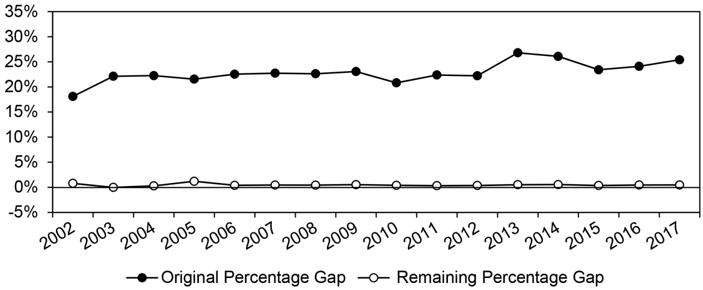

Fig. 20.6 Percentage coverage gap in social security benefits microdata, before and after adjustment, UK, 2002–17

Source: Office for National Statistics, Living Costs and Food Survey; Department for Work and Pensions, benefit expenditure and caseload tables.

living outside the UK and benefits received by those living in nursing homes or other forms of residential care.

Two potential methods were then chosen from to bring the total value for each benefit microdata in line with the adjusted administrative total, depending on whether the gaps appeared to reflect too few people receiving a benefit, underreporting of amounts by those in receipt, or a combination of both.

The most commonly used method was to allocate benefit income to people not reporting receipt of the benefit in the survey, but who appear likely recipients based on their characteristics. To do this, we first applied basic eligibility rules such as, for example, ensuring Pension Credit can only be received by people above the state pension age. For each benefit we then used a logistic regression model to look at the relationships between different characteristics and receipt. These models included variables including age, gender, employment status, household composition, housing tenure, region and income decile (excluding the benefit in question). These were then used to generate odds for people not reporting receipt, onto which a random element was added. The nonrecipients were then ranked by these adjusted odds with individuals then allocated the relevant benefit until enough cases were added to the microdata to bring the total in line with the administrative data. Each of these individuals was assigned the average amount of that benefit for the relevant year.

For any benefits where analysis of the caseload spending totals indicated that the undercoverage was primarily due to too little spending per recipient, the reported values for each individual in the microdata were scaled up such that the population total aligned with the adjusted admin data figure. In some cases, this method was used in conjunction with the previous approach of increasing caseload.

Figure 20.6 shows the results of applying these adjustments to the microdata. As can be seen, the difference between the microdata and the administrative data outturn figures for expenditure (adjusted to reflect the private household population) are virtually eliminated.

20.2.2 Correcting for Top Income Underreporting

As with social security benefits, it would be desirable to be able to use linked survey and administrative data in order to accurately capture incomes at the top of the distribution. However, an alternative methodology was devised. In seeking an approach, we focused on ensuring that it was methodologically sound, and based on academic research and existing best practice, as well as being relatively transparent and understandable by users. These criteria led us to building on methods described by Burkhauser et al. (2018a, 2018b) using the SPI data described above, which in turn are based on methods first developed by the Department for Work and Pensions (DWP 2015). The details of this approach, including analysis of the impact of various methodological choices, are set out in Webber, Tonkin, and Shine (2020).

In summary, individuals are first ranked in the survey data and SPI data by equivalent measures of gross income, separating for retired and nonretired individuals; in doing this, the SPI data also need to be adjusted to reflect that they contain only individuals who are potentially liable for UK tax in the current year, rather than the full population.

In the variant of the methodology used for this chapter, an adjustment is made at the 97th percentile and above, with the data above this point split into 0.5 percent quantile groups. The mean average gross income of each quantile group is then calculated and imputed onto individuals in the corresponding quantile group in the survey data. Once this is done, income components not present in the SPI data, such as tax-free savings and transfers between households, are added back to each observation.

Once these adjustments are made, income tax and social protection contributions are recalculated for individuals whose incomes have changed. Finally, individual incomes are reaggregated to the household level within the microdata and income quintiles recalculated.

20.2.3 Impact of Adjustments

Figure 20.7 shows the combined impact of these top income and social security benefit adjustments on the coverage rate of the microdata, using 2017 as an example. Together they have acted to improve the coverage of the microdata in a number of areas, including property income, wages and salaries, mixed income, social benefits, and current taxes on income and wealth. As a consequence, while some imputation and scaling are still necessary, the amounts of income involved are sometimes considerably smaller, thereby reducing the impact of the assumptions that need to be made.

Despite these adjustments, some coverage gaps clearly remain. However, the largest of these gaps reflect imputed and other items for which no micro-

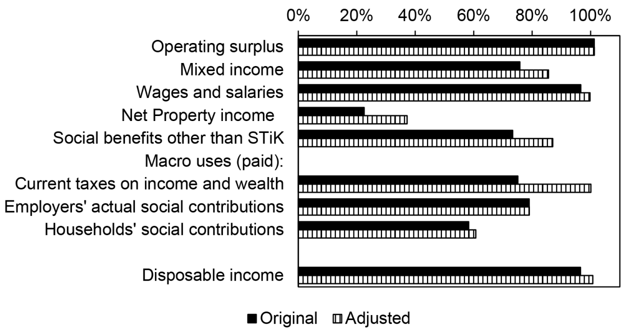

Fig. 20.7 Coverage of survey-based estimates of National Accounts aggregates, UK, 2017

Source: Office for National Statistics, Living Costs and Food Survey; National Accounts Blue Book, 2018.

data equivalents directly exist. For example, part of the mixed income coverage gap will be attributable to underground production, for which national accounts data is adjusted, but does not feature in the survey information. Similarly, a substantial component of the apparent undercoverage of net property income is attributable to investment income payable on pension entitlements, as well as investment income attributable to insurance policy holders, for which there is no microdata equivalent.

However, because a number of these larger imputed items net out in the calculation of disposable income, the overall coverage rate for disposable income is considerably closer than for some of the individual components.

Figure 20.8 shows the distribution of these different income components across quintiles of equivalized disposable income. It highlights that the relative value of compensation of employees compared to other income sources has by far the largest impact on the overall shares of income across the quintiles. Compensation of employees is the largest component of disposable income across all quintiles except for the bottom, where social benefits other than STiK form the biggest individual component.

20.3 Addressing Micro and Macro Conceptual Differences

As highlighted by the Atkinson Commission, a second key reason for the differences between surveys and the national accounts aggregates is the conceptual differences that exist between them. These definitional differences reflect to a large extent different purposes and user needs: Micro statistics on income and consumption, following UNECE (2011) and OECD (2013), view transactions from the perspective of households, whereas national accounts aggregates need to take a broader, macroeconomic perspective. For example, interhousehold transfers are important for many households and

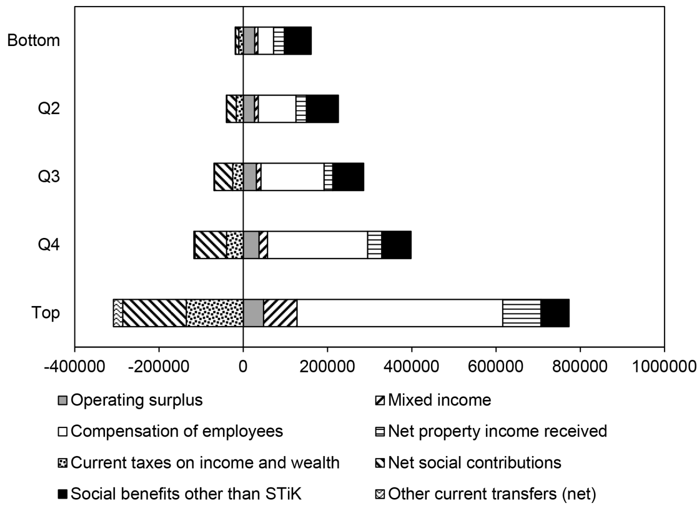

Fig. 20.8 Components of disposable income by equivalized disposable income quintile, UK, 2017

Source: Office for National Statistics, Living Costs and Food Survey; National Accounts Blue Book, 2018.

included in microstatistics but are not considered within a macro framework. By contrast, while important for National Accounts, FISIM is not directly relevant from the perspective of households considering their own economic well-being, so is excluded from income in microstatistics.

Whilst there are considerable advantages of using measures of inequality and poverty based on the national accounts, conceptually, it is the microstatistics framework, set out in OECD (2013), which arguably best reflects the household perspective and therefore provides the best reflection of their economic well-being. The analysis in this chapter therefore explores the development of distributional national accounts–based indicators that are as consistent as possible with the definitions and concepts used in microstatistics.

To create a measure of "cash disposable income," ONS (2018) has made a number of adjustments to disposable income, removing imputed transactions. First, gross operating surplus (B2g) was excluded, as it was composed almost entirely of imputed rental, which is not experienced directly by households.

Employers' social contributions (D12, as well as counterparts D611 and D612) were also removed, as these relate to the contributions made by employers toward social insurance schemes held by their employees and are not seen by households until they draw their pension. Similarly, income

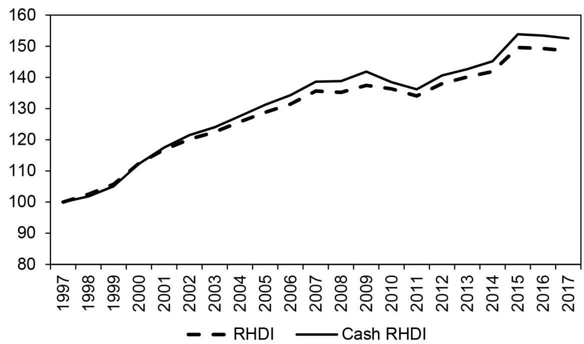

Fig. 20.9 Growth in real household disposable income (RHDI) and cash-basis RHDI, UK, 1997–2017

Note: Index 1997 = 100.

Source: Office for National Statistics; National Accounts Blue Book, 2018.

payable on pension entitlements (D442, and counterpart D614) and retained earnings attributable to collective investment fund shareholders (D4432) are all not seen directly by households and were therefore excluded.

FISIM (P119) refers to charges made by financial corporations acting as intermediaries that are implicitly included in the interest rates offered on loans and savings. Within the national accounts, FISIM adjustments are made to return these implicit charges back to households, however; as these charges are real, the adjustment was excluded from cash measure.

Finally, while non-life-insurance claims (D72) are treated as current transfers within the system of national accounts, they are not normally captured as income by micro sources, so have been removed from the cash-basis measure.

For the standard measure of real household disposable income (RHDI), the household final consumption expenditure implied deflator is normally used. To more closely reflect price changes experienced by households, the national accounts household expenditure deflator, less imputed rental and FISIM, was used to deflate the cash-basis measure.

Figure 20.9 shows growth in both the standard measure of RHDI and this new cash-basis measure since 1997 for the UK. Overall, the pattern of growth has been largely comparable, though there has been some divergence. Notably, cash-basis RHDI grew more quickly in the years leading up to the 2008 financial crisis, but also fell more sharply in the period 2009–11.

As highlighted in figure 20.10, cash-basis RHDI is slightly more unequally distributed than the standard measure of RHDI. In 2017, the cash-basis income share of the top quintile was 43 percent, compared with 8 percent for the poorest fifth of the population.

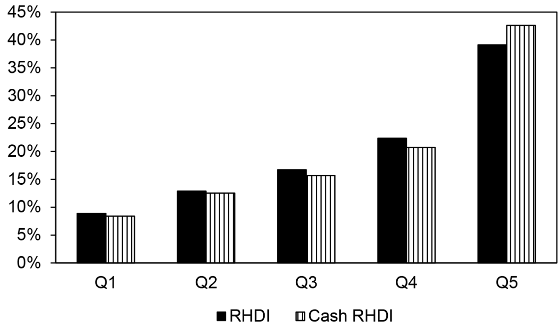

Fig. 20.10 Share of RHDI and cash-basis RHDI by equivalized disposable income quintile, UK, 2017

Source: Office for National Statistics, Living Costs and Food Survey; National Accounts Blue Book, 2018.

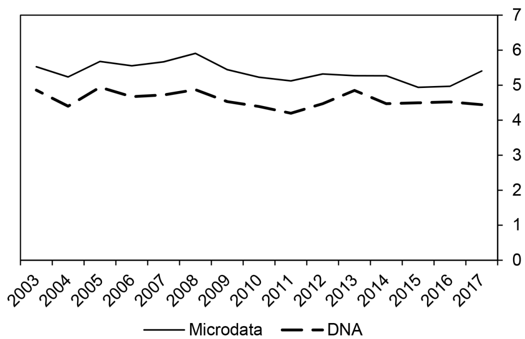

Fig. 20.11 S80/S20 ratio for equivalized disposable income (cash-basis): Survey microdata and national accounts–based measures, UK, 2003–17

Source: Office for National Statistics, Living Costs and Food Survey; National Accounts Blue Book, 2018.

20.4 National Accounts–Based Measures of Inequality, Shared Prosperity, and Poverty

Having created adjusted microdata which are consistent with the national accounts aggregates for each component of income and consumption, and created a cash-basis RHDI measure, it is possible to use these together to produce national accounts-based distributional measures of economic well-being.

As an example, figure 20.11 shows the S80/S20 ratio for equivalized disposable income over the 2003–17 period from both the original survey microdata and using the cash-basis national accounts–based measure described above. From this, it is clear that while the absolute level of inequality is lower in the distributional national accounts measure, both series show a similar

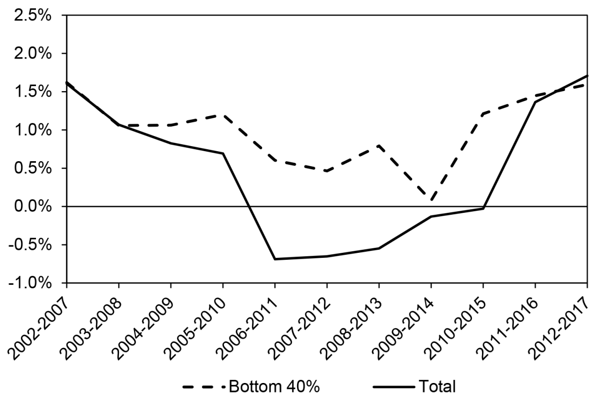

Fig. 20.12 Average annual growth rates of disposable income per capita among the bottom 40 percent of the population and total population: Survey-based measures, UK, 2002–7 to 2012–17

Source: Office for National Statistics, Living Costs and Food Survey.

trend with a fall in inequality in the years immediately following the Great Recession. In more recent years, the gap between the micro and macro series has narrowed, reflecting a slightly more pronounced bounce back in inequality levels in the national accounts measure.

In addition to basic measures of inequality such as the S80/S20 ratio, it is also possible to look at indicators such as shared prosperity, as set out in the second of the World Bank's twin goals and sustainable development goals (SDG) indicator 10.1.1. The shared prosperity measure is focused on improving the living standards of the bottom 40 percent of the population in each country, ensuring that the poorest in society are benefiting from broader economic growth and are not left behind. It is operationalized as having growth rates of household income per capita among the bottom 40 percent of the population that are higher than the national average.

Figure 20.12 provides a measure of this indicator for the UK, based on household survey data for both the bottom 40 percent and total population figures, and using annualized average growth rates over a five-year period. Figure 20.13 presents the same indicator, calculated in the same way, but using the distributional national accounts data and cash-basis RHDI measure described above.

As might be both expected and hoped, the trends in figures 20.12 and 20.13 display some clear similarities. In both, the growth rates for the bottom 40 percent and the total population are at similar levels at both the beginning and the end of the time period shown. Both show a fall in growth rates around the time of the Great Recession, particularly for the overall population, while the growth rates for the bottom 40 percent hold up slightly better over this period. However, there are differences too. Around the 2008–13

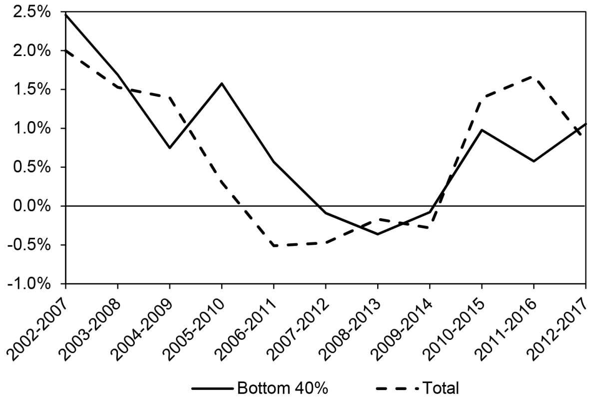

Fig. 20.13 Average annual growth rates of disposable income per capita among the bottom 40 percent of the population and total population—national accounts-based measures, UK, 2002–07 to 2012–17

Source: Office for National Statistics, Living Costs and Food Survey; National Accounts Blue Book, 2018

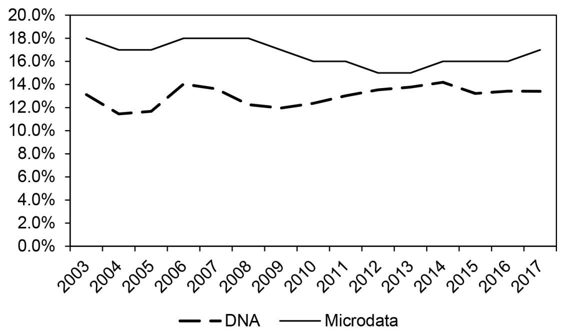

Fig. 20.14 Proportion of individuals with equivalized household disposable income (cash-basis) less than 60 percent of national median, microdata and national accounts-based measure, UK, 2003–2017

Note: The microstatistics from DWP's Households below Average Income series are on a UK financial year (April–March) rather than calendar-year basis.

Source: Office for National Statistics, Living Costs and Food Survey; National Accounts Blue Book, 2018; DWP, Households below Average Income.

period, the national accounts data suggest annual income growth for the bottom 40 percent was closer to that for the overall population (and lower) than indicated by the survey data. Similarly, in some of the most recent periods, the national accounts–based estimates suggest that income growth for the total population may have outstripped the bottom 40 percent.

As a further example, it is also possible to use the distributional national accounts data for monitoring poverty. Figure 20.14 compares the primary low-income statistics for the UK, the Households below Average Income

(HBAI) series produced by the DWP (2019), with a comparable measure produced using the national accounts–consistent cash-basis RHDI data. This shows, for the period 2003–9, despite the proportion of people considered to have relative low income being lower in the national accounts–based measure, the trend seen in the two series is broadly comparable, with a fall in the relative poverty rate between 2006 and 2009. However, in the following years, the two series diverge, with HBAI continuing to see falling relative low-income rates between 2009 and 2013, while the national accounts data suggest a small increase over the same period.

Which variants of these indicators should be prioritized for ongoing monitoring? As highlighted at the start of this chapter, survey income microdata often have issues with underreporting of certain income components both at the bottom and the top of the distribution, which may influence both the bottom 40 percent and the overall population. The national accounts–based indicators also have advantages of coherence both with macroeconomic statistics and comparability across countries. However, it must also be recognized that, despite the methodological developments presented in this chapter, these too are subject to measurement error, rely on a number of assumptions, are still very experimental in nature, and need further development. Ultimately, it may be sensible to consider the two approaches as complementary, recognizing that each has its own strengths and limitations, while together they can lead to a stronger understanding of shared prosperity, poverty, and other measures of material living standards.

20.5 Development of Timely Indicators

One of the opportunities of national accounts–based indicators is the potential for more timely and possibly more frequent monitoring. The ideal is the production of such indicators on a timely basis, ideally alongside or close to the release of national accounts aggregates, rather than having to wait for the collection and processing of survey-based estimates. However, to do this requires updated distributional information to accompany the macro figures.

In recent years there has therefore been growing interest in the production of flash estimates or "nowcasts" of income distribution and poverty statistics by both national statistical offices and international organizations, often with considerable success. For example, in the UK, ONS has been producing experimental nowcasts of measures such as median disposable income and the Gini coefficient for several years (Stoyanova and Tonkin 2016). This work uses a microsimulation model and involves uprating microdata to account for changes in financial variables such as growth in average wages; implementing changes to cash benefits and direct taxes resulting from changes to rates, thresholds, and more structural policy reforms; and adjusting for changes to labor market participation and the demographic structure of the population through calibration weighting. This development has allowed the publication of initial distributional measures less than four months after the end of the income reference period, compared with 10 or more months for the full microdata to become available.

Following the success of these annual nowcasts, we have started research into the potential for quarterly nowcasts (Mallett and Weale 2018). While this work is at a very early stage, it does indicate that quarterly microsimulation-based nowcasts are practically feasible and may have potential. If further developed and extended, it should be possible to apply the distributional information produced from these nowcasts to the existing quarterly national accounts aggregates, and in doing so, to provide a step-change in our ability to monitor economic well-being on a timely basis.

20.6 Conclusions and Next Steps

Taken together with the guidelines developed by the OECD-Eurostat EG DNA, the work presented in this chapter provides a framework for the production of indicators relating to shared prosperity, poverty, and inequality that can potentially draw strength from the national accounts in terms of coherence, comparability, and frequency, while also retaining the strengths of microstatistics-based measures in terms of their focus on distributions and concepts that more directly reflect the actual experience of households and individuals. While they should clearly be seen as a complementary to, rather than a replacement for, traditional microanalysis, the development and production of these and similar measures across countries have the potential to add significant value to the monitoring of the SDGs and beyond.

It is clear, however, that considerable practical challenges remain, particularly in terms of the reconciliation of micro- and macrostatistics. There is a need for national accountants and micro experts within both national statistical offices and international organizations to work together to first understand the inconsistencies between the two sets of statistics, and then to take steps to address them. As an example of development at the national level, ONS is seeking through its Transformation Programmes to make greater use of administrative data in both its micro- and macrostatistics on household income, which should lead to greater coherence in the estimates produced, as well as facilitating the production of distributional national accounts measures.

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