Office for National Statistics

Compendium

Economic review: February 2020

An analysis of economic statistics development and trends. Economic review articles are now published separately. There is a link to the articles in the Notice in this compendium.

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Notice

27 April 2020

The Economic review will be no longer be published as a compendium. Newer releases will be published as separate articles to make them easier to find.

Chapters in this compendium

Compendium

Child poverty and education outcomes by ethnicity

An exploration of how child poverty and educational outcomes vary for different ethnic groups, including a look at whether there is a relationship between these variables that is consistent across ethnic groups.

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1 . Main points

- Children in Bangladeshi and Pakistani households were the most likely to live in low income and material deprivation out of all ethnic groups, while children in Indian households were the least likely.

- Children in Asian households were 2.5 times as likely, compared with the national average, to be in persistent low income during the period from 2013 to 2017.

- Pupils eligible for free school meals (FSM) made less progress between 11 and 16 years old than those not eligible for FSM, with national average Progress 8 scores of -0.53 and 0.06 respectively.

- Educational outcomes for Bangladeshi and Pakistani children did not follow this trend; Bangladeshi and Pakistani children who were eligible for FSM had higher Progress 8 scores than the national average.

- London had the highest Progress 8 scores for Asian, White and Mixed pupils. White pupils in the North East had the lowest Progress 8 score of all pupils (-0.28), and Chinese pupils in the East Midlands had the highest (1.22).

2 . Introduction

Child poverty in the UK is a growing issue and affects more than 4 million children. Growing up in poverty can have negative consequences for children's well-being and future life prospects, such as employment and earning opportunities (HM Government, 2014).

Young adults who suffer financial hardship as children have significantly greater than average chances (PDF, 113.95KB) of earning lower wages, being unemployed, spending time in prison (men) or becoming a lone parent (women).

There is a clear pathway from childhood poverty to reduced employment opportunities, with earnings estimated to be reduced by between 15% and 28%, and the probability of being in employment at age 34 years reduced by between 4% and 7%.

To understand the scale of child poverty, we can analyse the income that a family has available to spend or save (that is their disposable income). One commonly used measure of child poverty is children living in households in relative low income (also referred to as relative poverty). Relative low income helps us to understand the variances between low- and middle-income households at a specific point in time.

The relative low income measure provides a snapshot of the number of children living in poverty at a point in time, but does not tell us how long someone experiences poverty. To understand how long children experience poverty, persistent low income measures can be used to estimate the proportion of children living in low-income households in at least three of the last four years.

Income alone may not always reflect the extent to which a family can afford items and activities considered typical in society at a given point in time. The combination of a low-income threshold and an assessment of whether households are able to access essential goods and services (material deprivation), allows for a more holistic measure of children living in poverty.

Children living in poverty are more likely to have lower levels of educational outcomes (PDF, 930.61KB). The relationship between deprivation and education is crucial for understanding the significant impact deprivation has on later outcomes in adulthood. We measure this relationship by looking at the educational outcomes of children who were eligible for free school meals (FSM). Eligibility for FSM is related to receipt of income support benefits, such as Universal Credit. FSM-eligible children are more likely to be in low-income families than children who are not eligible.

The relationship between poverty and education outcomes is complex, and affected by multiple factors, including geography. For this reason, we will explore educational outcomes in smaller geographical areas in the context of the proportion of children living in low income locally. For example, regions in the North of England tend to have higher poverty rates (before accounting for housing costs) than regions in the South of England.

The aim of this article is to explore how both child poverty and educational outcomes vary for different ethnic groups, and to look at whether there is a relationship between these variables that is consistent across ethnic groups. In doing so, we will look at how children from different ethnic groups experience:

- poverty at a fixed point in time
- poverty that persists over time
- the inability to afford necessities

We will then assess the relative progress pupils from different ethnic groups make in education when compared with their peers who start at a similar level of educational attainment. We will use pupil-based and area-based proxies for child poverty to explore the relationship between child poverty and educational outcomes by ethnicity.

3 . Child poverty and ethnicity

There are a number of ways of measuring poverty, and no single definition is universally accepted. This section focuses on three measures of child poverty:

- relative poverty (living in a low-income household)
- persistent poverty (living in a household in persistent low income)
- low income and material deprivation

Children living in low-income households

A household is defined as being "low income" if it has an equivalised income below 60% of the UK's median household income, before housing costs. Household income includes income from earnings, benefits, pensions and investments (and other sources), and is adjusted to take account of the household size and composition. In the financial year ending (FYE) 2018, the UK's median equivalised household income was £26,000 for a couple with no children, and £37,000 for a couple with two children under 14 years of age (before housing costs).

Children in Pakistani and Bangladeshi households were the most likely to live in low-income households. They were 2.8 and 2.4 times as likely, respectively, to live in low-income households, compared with children living in White British households, during the three-year average ending in FYE 2018.

Figure 1 shows that 47% of children living in Pakistani households, and 41% of children living in Bangladeshi households were living in low income. This was 30 and 24 percentage points higher, respectively, than children living in White British households and 27 and 21 percentage points higher than the national average.

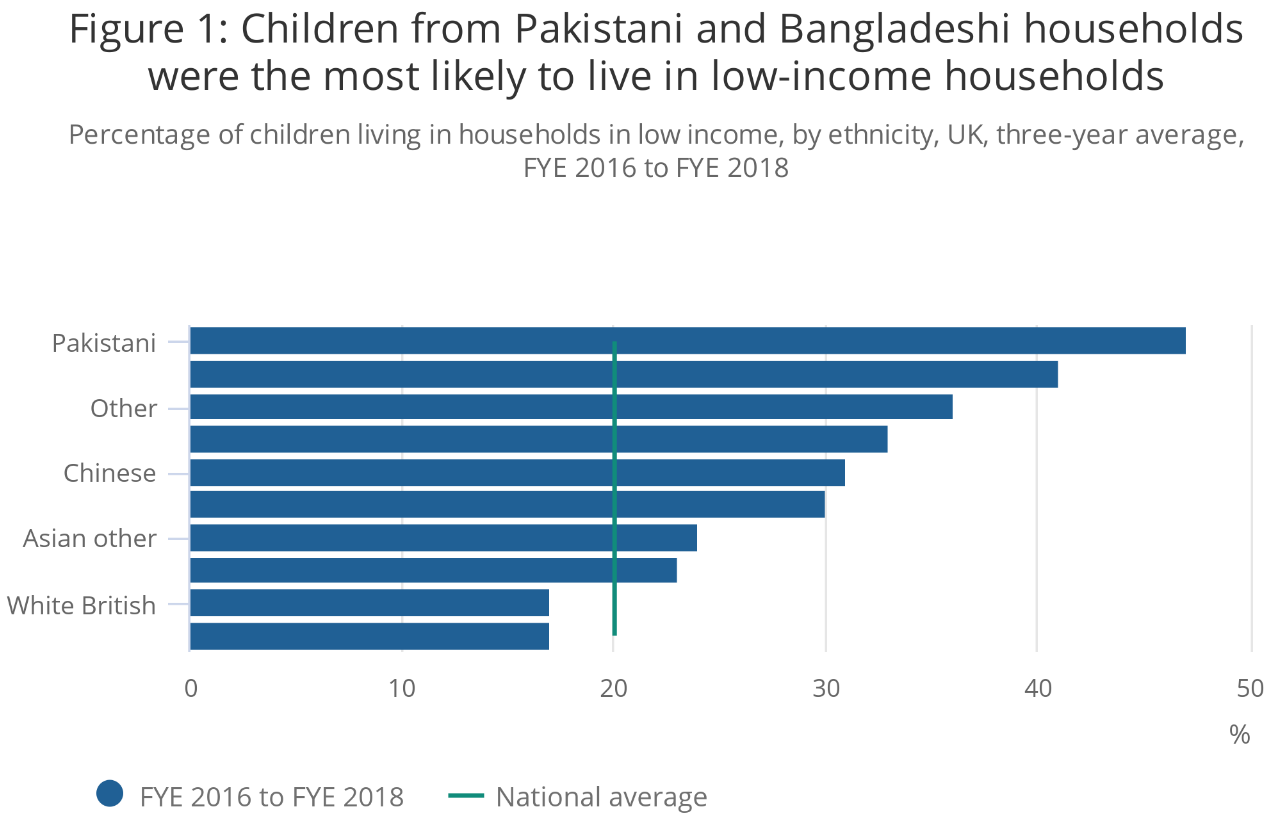
In 2018, the Pakistani and Bangladeshi population had a higher rate of unemployment (8%) and the highest rate of economic inactivity (38%). This may explain their higher likelihood of living in low income.

In contrast, Indian and White British children were the least likely to live in low-income households; 17% of children living in Indian and White British households were living in low-income families, three percentage points lower than the national average.

The Other (36%), Mixed (33%) and Black (30%) high-level ethnic groups all have a higher percentage of children living in low-income households than the national average. This may be, in part, because these ethnic groups have unemployment rates higher than the national average (4%), at 8%, 7% and 9% respectively. In addition, the Black and Mixed ethnic groups were the most likely to have gross household income (the income that a household has available for spending after taxes and benefits are taken into account) of less than £400 per week.

Figure 1: Children from Pakistani and Bangladeshi households were the most likely to live in low-income households

Percentage of children living in households in low income, by ethnicity, UK, three-year average, FYE 2016 to FYE 2018



Source: Department for Work and Pensions –Households Below Average Income: 1994/95 to 2017/18

Figure 2 shows how child poverty has changed between the three-year averages for FYE 2012, 2015 and 2018 for some specific ethnic groups. During this period, the national average increased slightly from 18% to 20%, and children in White British households were the least likely to live in low-income households.

During the same period, the largest decrease in the percentage of children living in low-income households was among children living in Indian households - a decrease of six percentage points, from 23% to 17%. This may be because of the decrease of Indian households having a weekly income of less than £400, from 33% to 25% for the same time period.

The largest increase was among children living in households from the Other White ethnic group, an increase of seven percentage points, from 16% to 23%.

Children living in Pakistani and Bangladeshi households were the most likely to live in low-income households through the period FYE 2012 to FYE 2018.

Figure 2: Child poverty has fallen most for children from Indian households in recent years

Percentage of children in households in low income, by ethnicity, UK, three-year average, FYE 2012 to FYE 2018

Data download

Children living in households in persistent low income

Children live in persistent low income if they live in a household that has been recorded as being in low income (an income below 60% of the median income, before housing costs are taken into account) in at least three out of the last four consecutive years.

The proportion of children living in persistent low income is dependent on the proportion of children in relative poverty in the current year, and the three previous years. Therefore, a reduction in the proportion of children in relative poverty in one year will not immediately translate to a fall in the proportion in persistent poverty. However, if the fall in relative child poverty is sustained, then this should gradually result in a fall in persistent child poverty.

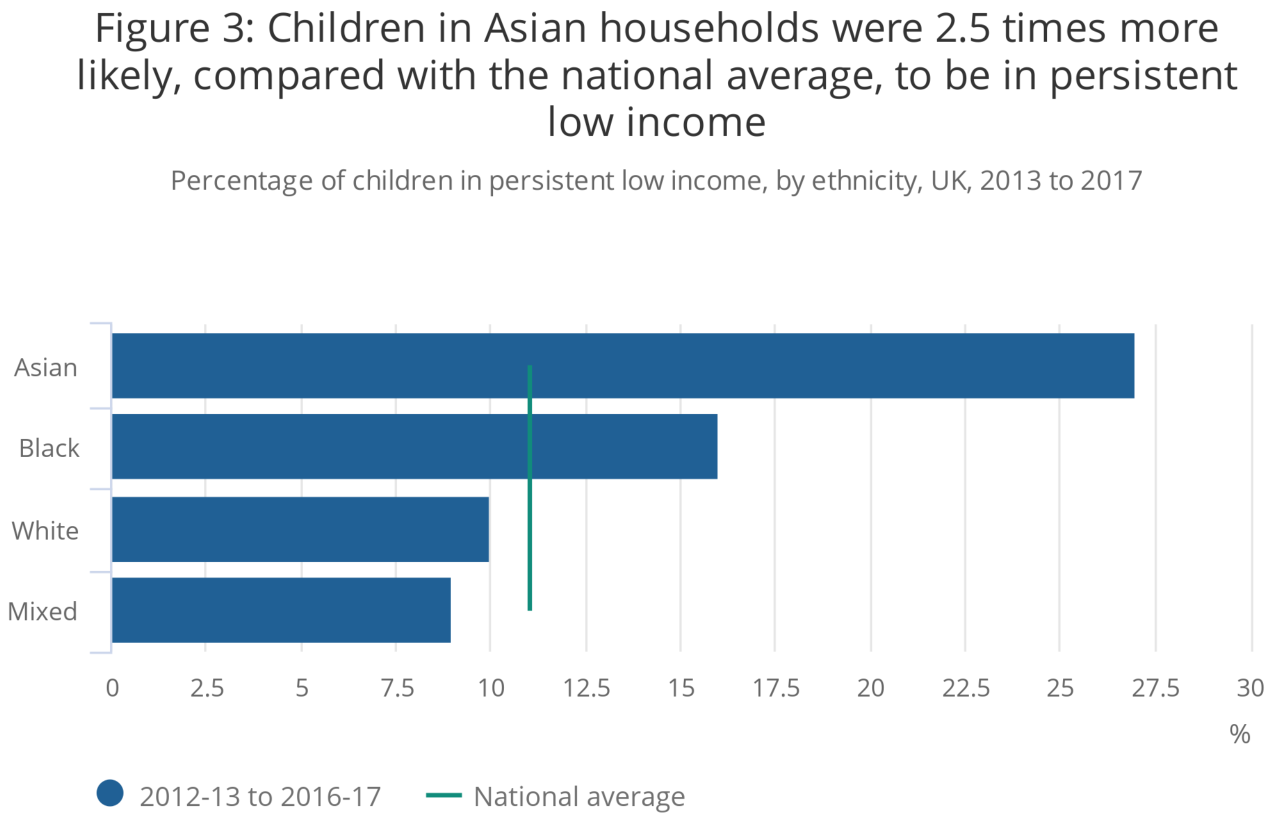
Figure 3 indicates that 11% of children were living in households in persistent low income during the period between 2013 and 2017. Children are more likely to be in persistent low-income households if they are in a workless family (that is, no one in the family was working). During the same period, 37% of children in workless families were living in households in persistent low income.

Children in Asian households were 2.5 times as likely, compared with the national average, to be in persistent low income during this period. The high percentage of Asian children living in households in persistent low income may be driven by the Pakistani and Bangladeshi ethnic groups, who are the most likely to be living in low-income households.

The percentage of children in Black households living in persistent low income was six percentage points higher than the percentage of children in White households living in persistent low income.

Figure 3: Children in Asian households were 2.5 times more likely, compared with the national average, to be in persistent low income

Percentage of children in persistent low income, by ethnicity, UK, 2013 to 2017



Source: Department for Work and Pensions – Income Dynamics, 2010 to 2017

Notes:

1. Data for the Other ethnic group have been withheld because of its small sample size (although they are included within the national average).

2. There are public available data only for the main 5 ethnic groups (Asian, Black, Mixed, Other and White).

Low income and material deprivation

Material deprivation is an additional way of measuring living standards, and refers to the self-reported inability of individuals or households to afford [21 particular goods and activities (PDF, 1.76MB)]() that are typical in society at a given point in time, irrespective of whether they would choose to have these items, even if they could afford them. This includes items such as warm coats for children and keeping accommodation warm in winter.

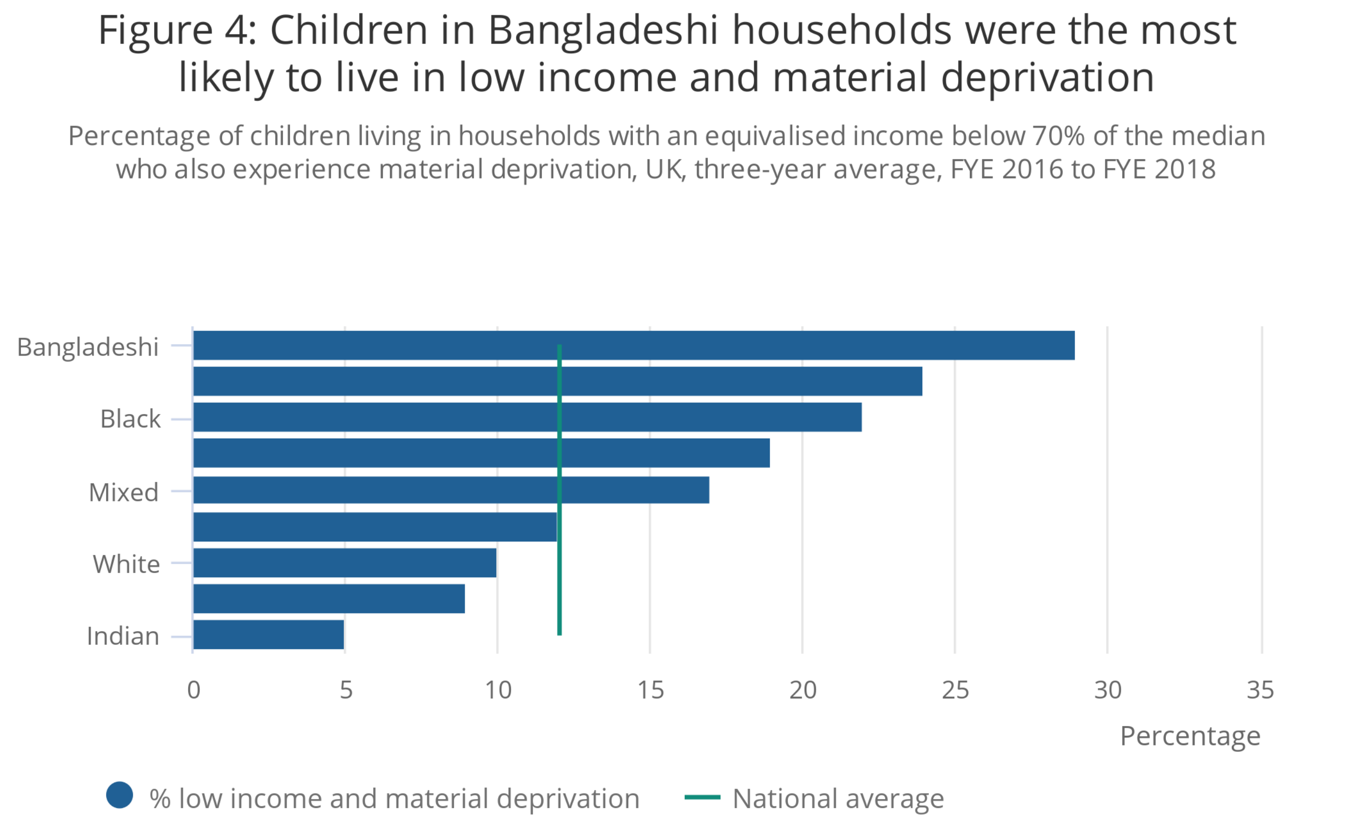
A child is considered to be in low income and material deprivation if they live in a household that has a final score of 25 or more out of 100 in the material deprivation questions, and equivalised household income below 70% of contemporary median income, before housing costs. In FYE 2018, 12% of children fell below the threshold of low income and material deprivation in the UK.

During this period, children in Bangladeshi households were the most likely out of all ethnic groups to live in low income and material deprivation, at 29%. This was almost three times as high as White households (10%), and was followed by 24% of children living in Pakistani households and 22% of children living in Black households.

Conversely, children in Indian households were the least likely to be in material deprivation and low income (5%) out of all ethnic groups.

Figure 4: Children in Bangladeshi households were the most likely to live in low income and material deprivation

Percentage of children living in households with an equivalised income below 70% of the median who also experience material deprivation, UK, three-year average, FYE 2016 to FYE 2018



Source: Department for Work and Pensions –Households Below Average Income: 1994/95 to 2017/18

4 . Education and ethnicity

To measure education, we use the "Progress 8" measure collected by the Department for Education (DfE). Progress 8 measures how much progress students make between 11 and 16 years, compared with other students with similar starting points. The starting points are calculated using assessments of Maths and English at the end of primary school (Key Stage 2 results), when children are usually 11 years old. Each pupil's progress is then worked out by comparing their "Attainment 8" score with the national average score for pupils who started at a similar level to them. Attainment 8 is a measure of a pupil's performance at the end of Key Stage 4 across eight core subjects, including Maths and English.

If a student's Progress 8 score is equal to the national average, their progress is in line with that of other students who started at a similar level. A score above the national average means the student has made more progress than other students who started at a similar level to them. A score below the national average means they have made less progress than other students who started at a similar level to them.

Group averages of Progress 8 scores can be calculated, for example, within schools or ethnic groups, in order to see how a group has progressed as a whole. In this article, we present averages within ethnic groups.

The average Progress 8 score for all ethnic groups during the academic year 2018 to 2019 was negative 0.03. Information on how this is calculated is available in section 7: About the data.

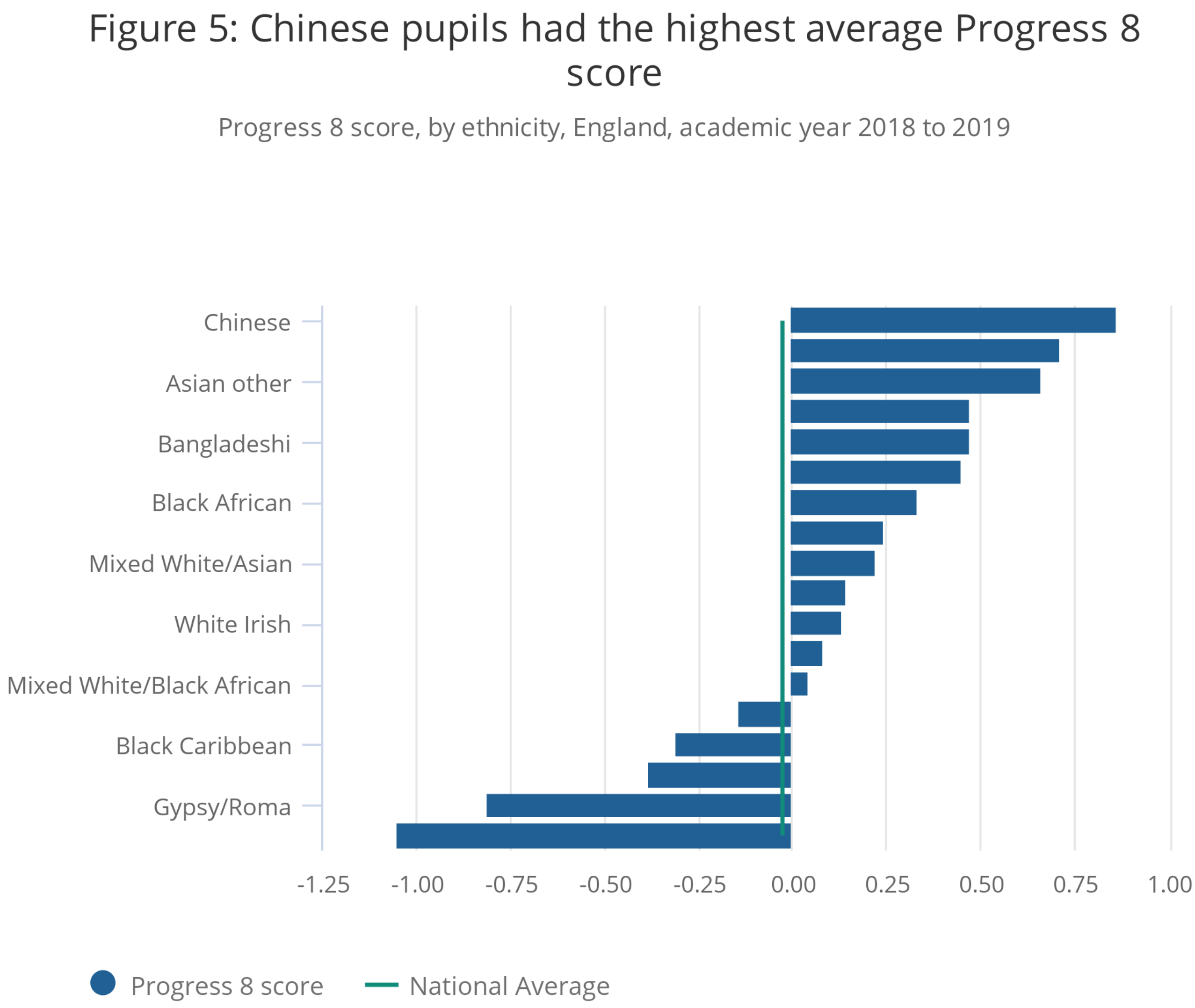
Figure 5 provides an overview of the average Progress 8 scores for each ethnic group. Chinese pupils were the highest performers, achieving an average Progress 8 score of 0.86.

The second highest Progress 8 score was achieved by Indian pupils (0.71) - the ethnic group least likely to experience both low income alone, and low income and material deprivation combined. Conversely, Bangladeshi and Pakistani pupils had higher Progress 8 scores than the national average, despite tending to have higher prevalence of poverty than other ethnic groups.

Traveller of Irish Heritage and Gypsy/Roma pupils made the least progress between 11 and 16 years, achieving scores of negative 1.05 and negative 0.81 respectively. Some caution should be taken when interpreting these percentages as they are based on a small number of pupils. For example, there were 141 pupils from Traveller of Irish Heritage backgrounds in the academic year 2018 to 2019.

Figure 5: Chinese pupils had the highest average Progress 8 score

Progress 8 score, by ethnicity, England, academic year 2018 to 2019



Source: Department for Education – Key Stage 4 performance, 2019 (revised)

5 . Child poverty, education and ethnicity

Evidence has suggested that [poverty and social deprivation in children is linked to educational underachievement](). Furthermore, the relationship is somewhat circular, with educational attainment the [most influential factor (PDF, 5.97MB)](), surpassing child poverty, for poverty in future life stages. Given that deprivation varies for different ethnic groups, it is important to consider how educational outcomes may vary as a consequence.

To analyse the relationship between poverty and education, we use two measures of poverty that are used widely in educational analysis: free school meal (FSM) eligibility - a pupil-based measure, and the Income Deprivation Affecting Children Index (IDACI) - an area-based measure. The previously used measures of child poverty cannot be explored in the context of education but FSM and the IDACI provide reasonable proxies with which to compare average Progress 8 scores.

The percentages of each ethnic group that were eligible for FSM in academic year 2018 to 2019 were broadly similar to the proportions experiencing low income, persistent low income, and low income and material deprivation.

In the academic year 2018 to 2019, 14% of all pupils were eligible for FSM. The Chinese and Indian ethnic groups had the lowest percentages of students who were eligible for FSM, at 7%.

The highest percentages of FSM eligibility were seen in White minority groups - 56% of Traveller of Irish Heritage pupils, and 39% of Gypsy/Roma pupils were eligible for FSM. 26% of Bangladeshi and 20% of Pakistani pupils were eligible for FSM, respectively 12 and six percentage points higher than the national average.

Education outcomes by ethnicity and eligibility for free school meals

This section focuses on [FSM eligibility] as an indicator of poverty. FSM eligibility demonstrates child poverty at the pupil level, and has the advantages of being easily collected and familiar to schools, parents and local authorities. FSM eligibility is a good indicator of child poverty, as it captures the majority of children living in poverty, however there is a small but significant group of children who live in poverty [who are not captured by FSM eligibility (PDF, 831.01KB)].

Pupils eligible for FSM made less progress between 11 and 16 years than those not eligible, with average Progress 8 scores of negative 0.53 and 0.06 respectively. This was also the case within every ethnic group.

Chinese pupils achieved the highest Progress 8 scores out of all ethnic groups. When looking at the progress made by pupils eligible for FSM only, this was still the case. Among FSM-eligible pupils, those from the Chinese ethnic group made the most progress out of all ethnic groups, with an average score of 0.66. The Chinese group also had the second smallest gap between the Progress 8 scores of pupils eligible for FSM and those not eligible (0.22), although this difference is based on a very small number of pupils; 123 Chinese pupils were eligible for FSM.

When taking into account gender too, as collected and defined in the school census by the Department for Education (DfE), girls from the Chinese ethnic group who were not eligible for FSM had the highest Progress 8 score (1.01) out of all combinations of ethnic groups, FSM-eligibility status, and gender. Figure 7 shows how Progress 8 scores vary according to these three variables.

The previous exploration of child poverty indicated that Bangladeshi and Pakistani children were the most likely to live in poverty out of all ethnic groups. Bangladeshi and Pakistani pupils who were eligible for FSM progressed higher than the average, with Progress 8 scores of 0.30 and 0.03 respectively. The gap between average Progress 8 scores for FSM-eligible pupils and those not eligible was 0.24 for Bangladeshi pupils and 0.27 for Pakistani pupils, narrower than for most ethnic groups.

By contrast, the lowest progress was seen among White pupils. Among those eligible for FSM, the least progress was made by Traveller of Irish Heritage pupils, with an average score of negative 1.16. This pattern was seen in the previous analysis of ethnic groups, before accounting for FSM eligibility. When taking into account gender too, boys from the Traveller of Irish Heritage ethnic group who were eligible for FSM had the lowest Progress 8 score (negative 1.51) out of all combinations of ethnic groups, FSM-eligibility status, and gender. In addition, among pupils eligible for FSM, the biggest gap between boys and girls was seen in the Traveller of Irish Heritage pupils, where girls achieved an average Progress 8 score 0.80 points higher than boys.

The White Irish ethnic group had the biggest gap between the average Progress 8 scores of FSM-eligible pupils (negative 0.51) and those not eligible (0.23). This may be driven by gender; among pupils eligible for FSM, the second biggest gap between boys and girls was in the White Irish group, where girls scored an average of 0.77 points more than boys.

White British children, who were less likely to live in poverty than children from other ethnic groups (as indicated in the previous measures of poverty), progressed less than average if they were FSM eligible (negative 0.78). In addition, White British pupils had the second largest gap in average Progress 8 between FSM-eligible pupils and those not eligible, at 0.73 points.

Gender plays an important role in the progress that pupils make between 11 and 16 years. As can be seen in Figure 6, in most ethnic groups, FSM-eligible girls made more progress than boys who were not eligible, with the exception of the White Irish, White British and some Mixed ethnic groups. Among pupils eligible for free school meals, girls made more progress (negative 0.28) than boys (negative 0.77), and this was also the case within every ethnic group.

The previous analysis showed that one-third of children in Black households lived in low income, and 22% of children in Black households lived in low income and material deprivation. Among Black children who were eligible for FSM, the average Progress 8 score was negative 0.08, however when looking at specific Black ethnic groups, there is some variation. Black African pupils achieved Progress 8 scores higher than average (0.17), while the progress made by Black Caribbean and Black other students was lower than average (negative 0.54 and negative 0.23 respectively).

Figure 6: Bangladeshi and Pakistani pupils who were eligible for FSM progressed higher than the national average of all pupils

Average Progress 8 score by ethnicity, gender and eligibility for free school meals, England, academic year 2018 to 2019

Data download

Education outcomes by geography and ethnicity

It is important to consider the geographical impact on child poverty and educational outcomes, as local resources, prosperity and subsequent geographical sorting effects mean that both poverty and education can vary at low levels of geography. By looking only at national estimates of child poverty and education, the data smooth over outlying performers.

The lowest average Progress 8 score for Asian pupils (0.24) was in Yorkshire and The Humber. For the Black (0.08) and Mixed (negative 0.14) pupils, it was in the West Midlands. The lowest average Progress 8 score of all was seen in White pupils in the North East (negative 0.28). Within every ethnic group, the region with the lowest average Progress 8 score was in the North or Midlands.

When looking at the highest average Progress 8 scores, London stands out as the region with the highest average Progress 8 scores for Asian (0.62), White (0.07) and Mixed (0.1) pupils. However, the highest average Progress 8 score for Black pupils was in the North East, and Chinese pupils in the East Midlands had the highest average Progress 8 score of all ethnic groups and regions (1.22).

Nationally, during the three-year average in the financial year ending (FYE) 2018, 31% of children in England were estimated to live in relative low income (60% below the median after housing costs) but the estimate varies by region. London had the highest percentage of children living in low income after housing costs (37%), followed by the North East (35%) and the West Midlands (34%).

The lowest percentages of children living in low income were seen in the South East and South West (25%). London housing market aside, the data suggest a North-South variation in children experiencing low income that is only somewhat suggested in regional average Progress 8 scores.

The remainder of this section focuses on the average local authority scores from the [Income Deprivation Affected Children Index (IDACI, 2019)] as an indicator of poverty. The IDACI is a supplementary metric to the Indices of Multiple Deprivation, which estimates the proportion of children aged 0 to 15 years living in income-deprived families (as defined by receipt of various benefits or tax credits with an income below 60% of the national median before housing costs).

IDACI scores and ranks are calculated at Lower layer Super Output Area (LSOA) level, but in this article, we are using the local authority summary statistics in order to match average Progress 8 data published by local authority.

The strength of the relationship between academic progress and income deprivation (as measured by the IDACI) varies for the different ethnic groups, but is negative in direction for some. There is a moderate negative correlation (negative 0.55) between White average Progress 8 scores and the IDACI local authority average scores. This means that as a local authority's IDACI score increases, the average Progress 8 score of White pupils decreases.

Similar but weaker correlations are seen for Mixed and Asian pupils (negative 0.33 and negative 0.19 respectively). There is no correlation between Black or Chinese average Progress 8 scores and average local authority IDACI scores (0.09 and negative 0.02 respectively). Average Progress 8 scores remain consistent regardless of average local deprivation.

Many local authorities with the lowest average Progress 8 scores for different ethnic groups also had high average local authority IDACI scores, estimating that higher proportions of children live in income-deprived families.

Knowsley ranked third out of all upper tier local authorities by average IDACI score (30.3% of children estimated to live in income-deprived families) and had average Progress 8 scores of negative 0.7, negative 0.82 and negative 0.9 for Mixed, White and Black pupils respectively. This made it the local authority with the lowest average Progress 8 scores for these ethnic groups.

Similarly, Blackpool ranked second by average IDACI score (30.7% of children estimated to live in income-deprived families) and had average Progress 8 scores of negative 0.65 and negative 0.69 for White and Mixed pupils respectively.

Middlesbrough, and Manchester also have higher proportions of children estimated to live in income-deprived families, and similarly appear in the bottom 10 average Progress 8 scores for an ethnic group.

Figure 7: Many local authorities with high proportions of children living in income-deprived families also had lower average Progress 8 scores

Average Progress 8 scores, by ethnicity, England, academic year 2018 to 2019, and average Income Deprivation Affecting

[Data download]

6 . Conclusion

Looking at estimates of child poverty and educational progress by ethnicity, as well as specific proxies for child poverty within education, there is no clear, consistent relationship between child poverty and progress from Key Stage 2 to Key Stage 4. Where there does appear to be a link, it cannot be ruled out that it may be related to variables not considered in this work, and the educational resilience of different ethnic groups when living in poverty.

Children from Pakistani and Bangladeshi households consistently appear as being more likely to live in poverty compared with other ethnic groups. They are most likely to live in low-income households, with nearly half of children in Pakistani households considered to be living in low income. When factoring in material deprivation, they continue to be the most likely out of all ethnic groups to live in poverty. Despite this, Pakistani and Bangladeshi children who are eligible for free school meals (FSM) - the proxy for poverty in educational analysis - achieve Progress 8 scores higher than average, indicating that they make more progress than pupils from other ethnic groups who started at a similar level to them.

The likelihood of experiencing poverty for children in Black households is also notable; 30% are considered to live in low-income households, and 22% live in low income and material deprivation. There is a mixed picture for educational progress for specific Black ethnic groups; Black African and Black Other pupils make more progress than peers starting at a similar level, but Black Caribbean pupils make less progress than their peers.

Children living in Indian households are some of the least likely to be living in child poverty and the likelihood has decreased over time. Indian pupils have the second largest average Progress 8 score after Chinese pupils.

Across the board, pupils who are eligible for FSM have lower average Progress 8 scores than pupils that do not, but there is variation seen between the ethnic groups. White Irish and White British pupils have the largest gaps between average Progress 8 scores for FSM-eligible students and those not eligible, while Chinese, Black African, Bangladeshi and Pakistani students have the smallest gaps.

Looking at regional estimates of children living in low income and material deprivation, there appears to be variances between the north and south of Britain in the likelihood of poverty, but this pattern is not so clearly reflected in regional average Progress 8 scores. In the North East, for example, 17% of children are estimated to live in low income and material deprivation, and White pupils achieved an average Progress 8 score of negative 0.27, the lowest score out of all combinations of ethnic groups and regions. However, the North East is also the region in which Chinese, Black and Mixed pupils had their highest average Progress 8 scores.

There is a moderate negative relationship between local authority average IDACI scores and average Progress 8 scores for White pupils, but this relationship is either weak or null for other ethnic groups.

Many local authorities with the lowest average Progress 8 scores for different ethnic groups also had high average local authority IDACI scores, most often for the Mixed and White ethnic groups.

7 . About the data

A child is an individual under 16 years, or someone who is 16 to 19 years, and all of the following:

- not married, in a civil partnership or living with a partner
- living with their parents or a responsible adult
- in full-time education or unpaid government training

Child poverty

In the analysis of child poverty outcomes, the ethnic background reported is that of the "household reference person", who is usually the person with the highest income. This means a child living in a Black household is not necessarily from the Black ethnic group. The definition of Household reference person may differ between data sources. More details can be found in the ONS glossary.

Details about the equivalisation of households can be found in the Households Below Average Income (HBAI) Quality and Methodology Information Report (PDF, 1.76MB).

Children in low income

This uses the Households Below Average Income: 1994/95 to 2017/18, published by the Department for Work and Pensions (DWP). These statistics come from the Family Resources Survey (FRS), which is a representative survey of around 19,000 private households in the UK.

The statistics for children in low-income households are presented as three-year averages (financial years ending (FYE) 2016 to 2018).

The ethnic groups presented are broken down into the Office for National Statistics (ONS) 2011 5 broad groups, and into the following detailed groups:

- Asian: Indian, Pakistani, Bangladeshi, Chinese, Asian Other
- Black
- Mixed
- White: White British, White Other
- Other

Details about statistical uncertainty over time can be found in the Households Below Average Income (HBAI) Quality and Methodology Information Report (PDF, 1.76MB).

Children in persistent low income

This uses the Income Dynamics, 2010 to 2017 Experimental Statistics published by the DWP. These statistics come from the Understanding Society (USoc) survey, Waves 2 to 8, 2010 to 2017. In 2016 to 2017 (Wave 8), the sample for USoc was of over 35,000 individuals in the UK.

The statistics for children in persistent low-income households are presented for a four-year consecutive period, 2013 to 2017.

The ethnic groups presented are the Asian, Black, Mixed and White. Statistics for the Other ethnic group are not presented because of small sample size.

Low income and material deprivation

This uses the Family Resources Survey (FRS), financial years ending (FYE) 2016 to 2018.

The statistics for children in low income and material deprivation are presented as three-year averages (FYE 2016 to 2018).

The ethnic groups presented are broken down into the ONS 2011 5 broad groups and into the following detailed groups:

- Asian: Indian, Pakistani, Bangladeshi, Chinese, Asian Other
- Black
- Mixed
- White
- Other

A suite of questions designed to capture the material deprivation experienced by families with children has been included in the Family Resources Survey (FRS) since FYE 2005. Respondents are asked whether they have 21 goods and services, including child, adult and household items.

Together, these questions form the best discriminator between those families that are deprived and those that are not. If they do not have a good or service, they are asked whether this is because they do not want them or because they cannot afford them. More details can be found in the Households Below Average Income (HBAI) Quality and Methodology Information Report (PDF, 1.76MB).

For each question, a score of 1 indicates where an item is lacking because it cannot be afforded. If the family has the item, the item is not needed or wanted, or the question does not apply then a score of 0 is given. This score is multiplied by the relevant prevalence weight. The scores on each item are summed and then divided by the total maximum score; this results in a continuous distribution of scores ranging from 0 to 1. The scores are multiplied by 100 to make them easier to interpret. The final scores, therefore, range from 0 to 100, with any families lacking all items which other families had access to scoring 100.

Income Deprivation Affecting Children Index (IDACI)

This uses data on receipt of various benefits and tax credits, as at August 2015, as an indicator of income deprivation.

Further detail on the exact indicators used is available in the Indices of Deprivation technical report.

The IDACI measures the proportion of children within a geography that are considered to be in low-income families. A score of 0.30 equates to 30% of children.

The IDACI is calculated at Lower layer Super Output Area (LSOA) level, from which local authority summary statistics are calculated. This research uses the average score local authority summary. Further detail on the higher area summaries measures is available in the Indices of Deprivation technical report.

Education

Progress 8 statistics come from the Department for Education (DfE) Key Stage 4 performance 2019 (revised) publication.

The ethnic groups presented in the Progress 8 statistics are broken down into six broad groups and the following detailed groups:

- Asian: Indian, Pakistani, Bangladeshi, Other Asian
- Black: Black African, Black Caribbean, Other Black
- Mixed: Mixed White/Black Caribbean, Mixed White/Black African, Mixed White/Asian, Other Mixed
- White: White British, White Irish, Irish Traveller, Gypsy/Roma, Other White
- Chinese
- Other

Some of the statistics quoted here are based on very small numbers of pupils and can change a lot from year to year. For example, only 97 pupils in the Chinese ethnic group were eligible for free school meals (FSM) in the academic year 2017 to 2018, meaning that the average score for this group can be heavily influenced by one pupil either performing exceptionally, or getting a very low score.

Progress 8 measures how much progress students make between 11 and 16 years. Each pupil's progress is worked out by comparing their Attainment 8 score with the national average score for pupils who started at a similar level to them. The higher a pupil's Progress 8 score, the more progress they have made in comparison with pupils who started at a similar level. The starting level is calculated using assessments from the end of primary school, when children are usually 11 years old.

The average Progress 8 score for all ethnic groups during the academic year 2018 to 2019 was negative 0.03. This average is not an exact "0" because:

- the national average for protected characteristics (such as ethnicity) refers to "All state-funded schools", which includes special schools, while the national average for schools is taken for "All state-funded mainstream schools", which excludes special schools
- it includes adjustments of extremely negative scores

The school census collected by DfE includes a gender variable, recording a pupil's gender as either male or female. The definition of this variable within the school census does not necessarily match the definition used for collection of a gender variable elsewhere. More information on this variable and others is available in the 2018 to 2019 school census guide.

Pupils are included in the figures for free school meals (FSM) if their families claimed eligibility for FSM at the time of the annual spring school census. This definition includes all pupils who were FSM eligible, not only those who actually received free school meals.

A child may be able to get FSM if their family receives any of the following:

- Income Support
- income-based Jobseeker's Allowance
- income-related Employment and Support Allowance
- support under Part VI of the Immigration and Asylum Act 1999
- the guaranteed element of Pension Credit
- Child Tax Credit (provided the recipient is not also entitled to Working Tax Credit and has an annual gross income of no more than £16,190)
- Working Tax Credit run-on - paid for four weeks after the recipient stops qualifying for Working Tax Credit
- Universal Credit

Children who get paid these benefits directly, instead of through a parent or guardian, can also get FSM.

A child may also get FSM if their family receives any of these benefits and the child is both:

- younger than the compulsory age for starting school
- in full-time education

8 . Authors

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Compendium

Analysing regional economic and well-being trends

How UK regions and countries vary in performance on economic and wellbeing indicators, and how this trend has changed over time.

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25 February 2020

Next release:
To be announced

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1 . Main points

- London and the South East outperform other UK regions and countries in terms of productivity, human capital and wages, with little indication of the other regions and countries catching up.

- Once housing costs are considered London is only slightly above the UK average level for household income, while the South East has the highest household income.

- London tends to underperform on socio-economic variables such as cost of living, wealth inequality, and the personal well-being indicators.

- The South East is the least unequal region of UK in terms of within-region wealth inequality using the Gini coefficient.

- The South West and Northern Ireland ranked the highest for personal well-being indicators such as life satisfaction, feeling worthwhile and happiness.

2 . Introduction

Typically the economy is considered at an aggregate level to judge the economic experience of individuals within a country. While aggregate measures like gross domestic product (GDP) provide valuable insights, they often mask the disparities between the experience of individuals living in different regions and countries of the UK. In this respect regional indicators give us more insight. Within the UK, [Nomenclature of Territorial Units for Statistics (NUTS) areas and local administrative units (LAUs)] can be used to identify regions and countries of the UK at a different level of detail.

In this article, we look at the regional picture for the UK at the NUTS 1 level[1], to give an understanding of how UK regions and countries vary in economic performance with respect to each other, and how this trend has changed over time. There is also an interactive tool for users to look at some personal well-being indicators such as life satisfaction, feeling worthwhile, happiness, and anxiety at a local area level.

With the government focusing on addressing regional disparities, such analysis is useful for identifying the lagging regions and countries. This analysis is valuable in helping us understand the economic and social experiences of the individuals living in different parts of the UK, and can ultimately help reduce the disparities within and between regions and countries.

Notes for Introduction

1. NUTS 1 refers to the 9 regions of England (North East, North West, Yorkshire and The Humber, East Midlands, West Midlands, East of England, London, South East, South West), and the countries of Scotland, Wales, and Northern Ireland.

3 . Macroeconomic variables

The macroeconomic variables we will consider are:

- estimates of productivity (in terms of output per hour)
- average (median) earnings
- an indicator for human capital
- household costs
- household income

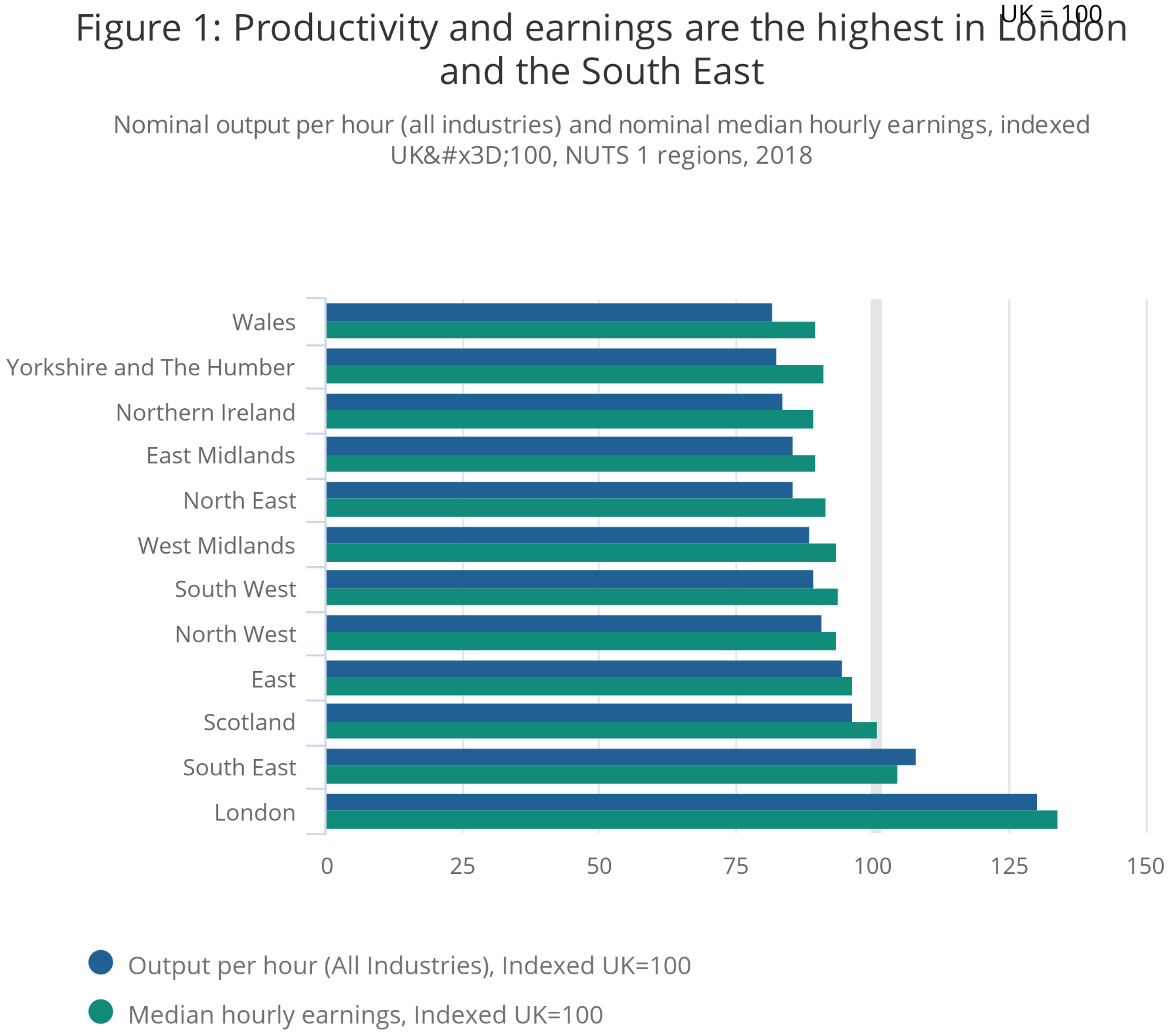
London is by far the most productive and best-paid region

Gross value added (output) per hour gives an estimate for productivity across the NUTS 1 regions. That is, the greater the output per hour estimate for a region or country, the more productive it is. Economic theory stipulates that, all things being equal, higher productivity is associated with higher wages. A possible explanation for this is that, theoretically, an increase in worker productivity can lead to an increase in the demand for labour (all else constant) which should ultimately lead to an increase in wages (marginal productivity theory of wages[1]).

This positive correlation can also be explained by the efficiency wage hypothesis. This hypothesis claims that firms will offer a wage greater than that of the labour market clearing wage to incentivise workers to increase their labour productivity. One potential driver for output per hour is capital investment. When considering the neoclassical production function, a greater stock of capital will increase the marginal productivity of labour, all else being equal. In practice, the relationship between productivity and wages is less straightforward.

Figure 1: Productivity and earnings are the highest in London and the South East

Nominal output per hour (all industries) and nominal median hourly earnings, indexed UK=100, NUTS 1 regions, 2018



Source: Office for National Statistics

Notes:

1. Figures are based on where people work and not where they live. There will be people working in London who will not live there and will not necessarily be commuting from the South East.

2. This chart compares regional performance with the UK average for two different concepts that have different collection and compilation methods. Please take caution when comparing the measures within each particular region.

London and the South East were the top performers for output per hour and median hourly earnings.

The performance of regions and countries relative to the UK has generally stayed steady between 1998 and 2018. This means that the other regions and countries are not catching up with London and the South East. Some other points to note are:

- productivity and wages in London have been continuously higher (relative to the UK) than all other regions or countries, with the highest relative performance occurring in 2007 (36% above the UK average) and the highest relative median hourly earnings in 2011 (40% above the UK average)
- between 1998 and 2018, the NUTS1 regions with the lowest productivity and earnings were Wales and Northern Ireland
- the largest ratio between the highest (London) and lowest (Northern Ireland) annual estimates of productivity was in 2007, at 1.69, and for median hourly earnings was in 2010, at 1.58
- productivity in London (relative to the UK) increased between 1998 and 2007, and then gradually stalled following the 2008 economic downturn
- between 1998 and 2018, productivity in the East of England, relative to the UK average, declined from 96.7 to 95.0
- productivity in Scotland, relative to the UK average, increased from 89.7 in 1998 to 96.8 in 2018.

Figure 2: The gap between the regions and countries for productivity and wages has remained steady over time

Output per hour (all industries), constant price (CVM) (2016), and median hourly earnings, indexed UK=100, NUTS 1 regions, 1998 to 2018

Notes

1. Because we do not have figures for regional prices, we have used the UK level consumer price indices to deflate earnings. Indexing means that both the real and nominal values are the same.
2. The data represent relative performance, so an increase in productivity in one region over time does not necessarily reflect growth in productivity for that region, but an improvement in performance relative to the UK.

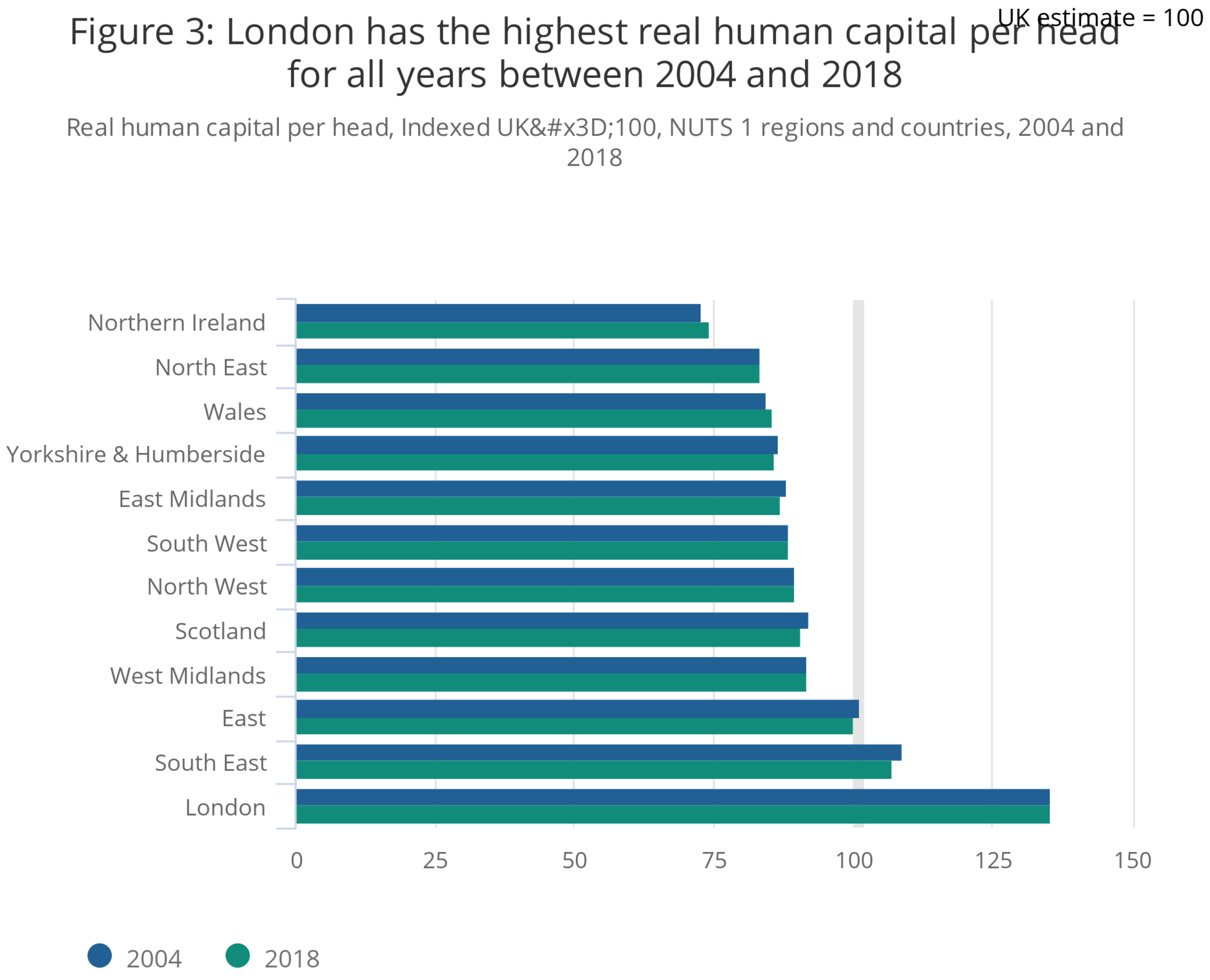
Data download

London has the highest human capital per head across all regions and countries of the UK

Human capital is defined as the stock of skills, knowledge and experience of an individual or population, which can productively be applied in the economy; it is widely referred to as one of the main drivers of economic growth. The methodology for calculating human capital can be found in the Human capital estimates, UK: 2004 to 2018 release. We are in the process of expanding our measure of human capital following the consultation launched in September 2019.

Figure 3: London has the highest real human capital per head for all years between 2004 and 2018

Real human capital per head, Indexed UK=100, NUTS 1 regions and countries, 2004 and 2018

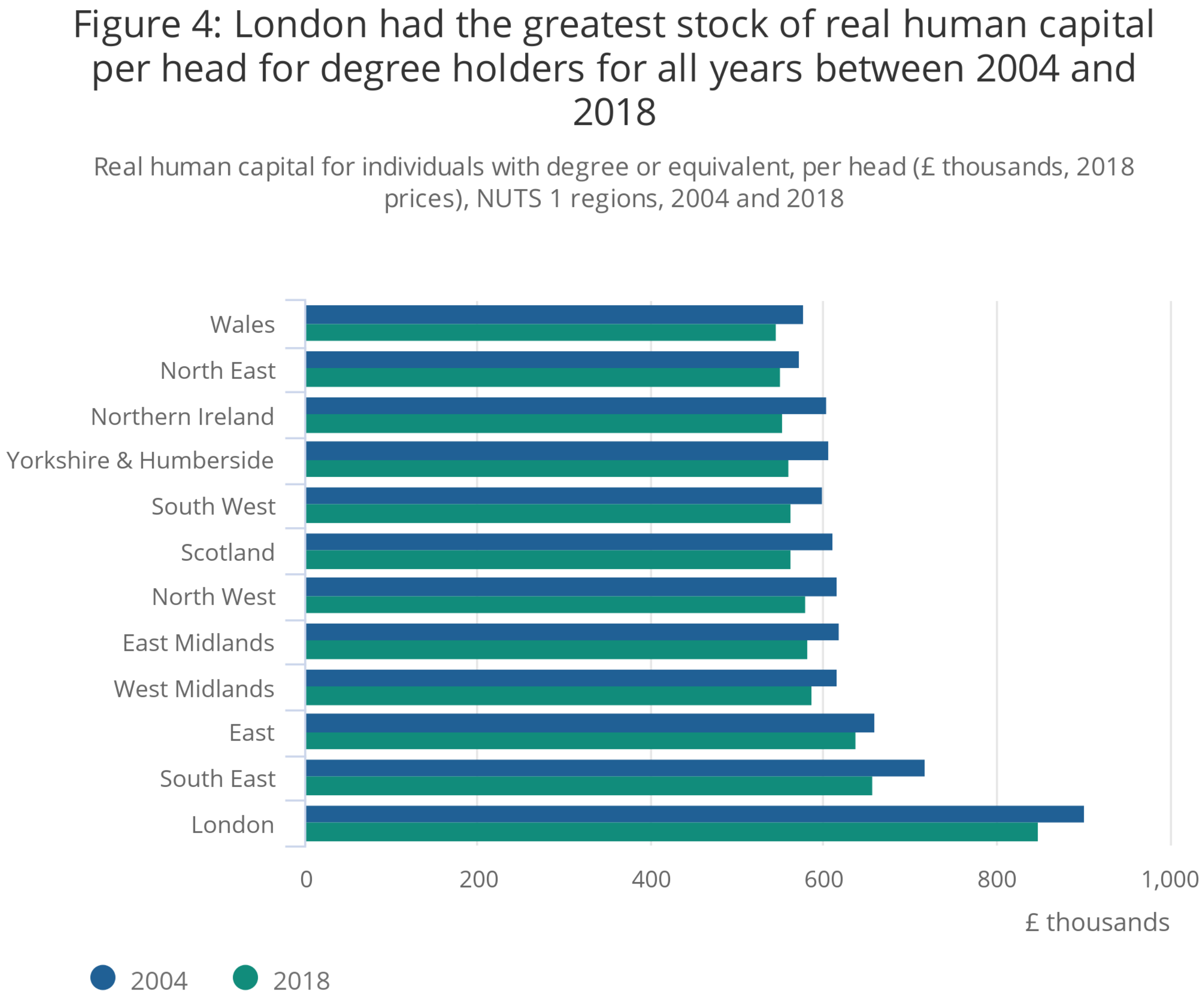


Source: Office for National Statistics

London and the South East have the highest human capital per head compared with all other regions and countries of the UK. Given that the UK's high-skill service industries, such as financial services and technology, are concentrated in London, it attracts both domestic and international skilled labour to the region. As skilled labour is mobile, it is likely that people with a higher stock of human capital relocate to regions and countries that pay more and have better job opportunities. Over time, real human capital per head has generally increased for each NUTS1 region.

Figure 4: London had the greatest stock of real human capital per head for degree holders for all years between 2004 and 2018

Real human capital for individuals with degree or equivalent, per head (£ thousands, 2018 prices), NUTS 1 regions, 2004 and 2018



Source: Office for National Statistics

London also has the highest real human capital per head estimate for people with a degree or equivalent qualification. The real human capital per head estimate for these individuals was lower in 2018 compared with 2004 for all regions and countries of UK. The differences across regions and countries in Figures 3 and 4 may be partially attributed to differences in the population composition, such as the average age of the economically active population in each region and country, and the amount of occupational mismatch for those with differing qualifications.

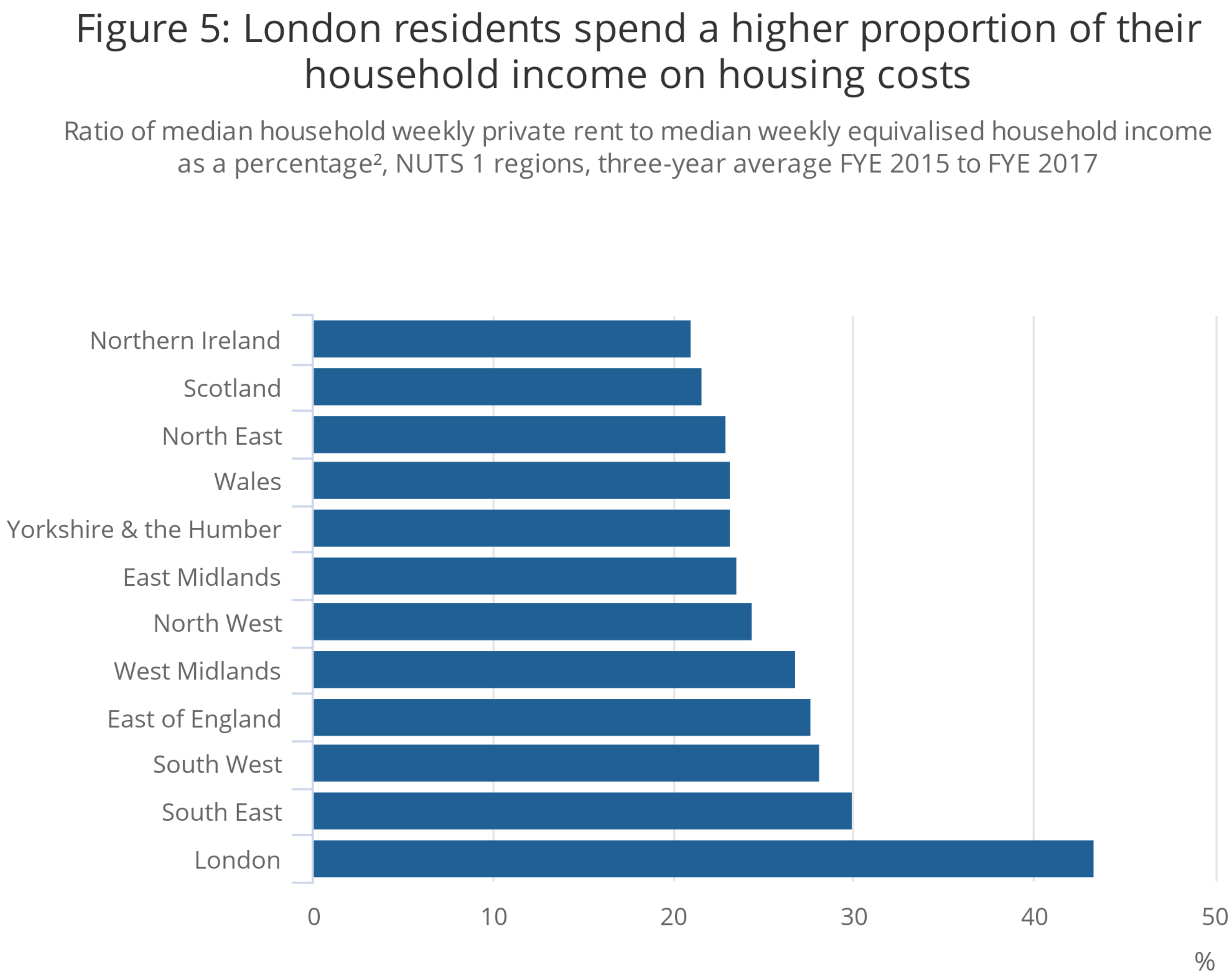
London residents spend a higher proportion of their household income on housing costs

Regions and countries with higher household income are also likely to have a higher household consumption[3]. This positive relationship is well established within economic theory, represented for example, by the Keynesian consumption function (Keynes, 1936). However, if the households in a certain region experience a higher cost of living, their residual income after housing costs will reduce, despite the higher income.

While London ranks top in performance of macroeconomic variables such as productivity, wages and human capital, the residents pay a higher proportion of their household income on housing costs. Between financial years ending (FYE) 2015 and 2017, housing costs (as measured by the median household weekly private rent) accounted for 43% of median weekly equivalised household income in London, compared with 21% in Northern Ireland.

Figure 5: London residents spend a higher proportion of their household income on housing costs

Ratio of median household weekly private rent to median weekly equivalised household income as a percentage[2], NUTS 1 regions, three-year average FYE 2015 to FYE 2017



Source: Department for Work and Pensions

Some other things to note are:

- household weekly private rent in London was lower in FYE 2017 (£230), than FYE 2016 (£247) and FYE 2015 (£239)
- between FYE 2015 and 2017, weekly private rent rose in the South West, South East, West Midlands, North East, Scotland, and Northern Ireland, possibly because of strong growth in the housing market

The fall in median household weekly private rent in London between FYE 2017 and FYE 2016 could be partly explained by a steady fall in the growth in the House Price Index (HPI) and the Index of Private Housing Rental Prices (IPHRP) during this period. The volume of sales also declined during this period, partly the result of changes in stamp duty introduced in April 2016, and a slowdown in the buy-to-let market. For more details on the London housing market please see the Exploring recent trends in the London housing market article.

London is no longer the region with the highest household income, once housing costs are considered

The Department for Work and Pensions (DWP) publishes the Households below average income release. This contains information on equivalised disposable household income adjusted for household size and composition (called equivalisation), estimated on both a before and after housing costs basis. A better way to look at the difference in income between regions and countries is to use this equivalised household income and compare estimates both before and after housing costs.

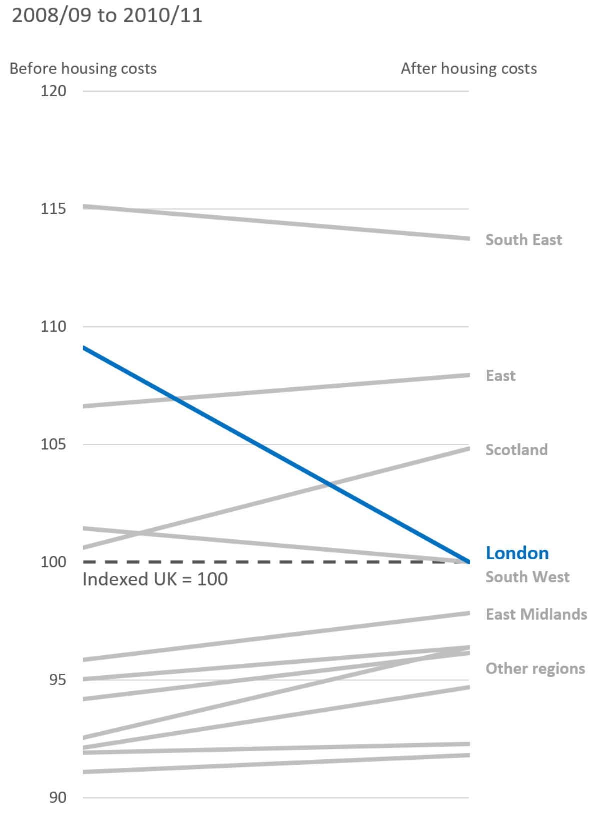
Figure 6 shows that before housing costs are accounted for, London has the highest median weekly household income, but after housing costs are considered, the South East overtakes it. London is only slightly above the UK average household income after considering housing costs, while the South East, East of England, Scotland, and South West regions or countries are above the UK average.

The East Midlands is below the UK average in terms of equivalised household income before housing cost, but is just above the average when housing costs are considered. Northern Ireland, Yorkshire and The Humber, the North West, West Midlands, Wales, and the North East remain below the UK average even after taking housing costs into consideration.

The difference between household income before and after housing costs has worsened for London between FYE 2009 to FYE 2011 and FYE 2016 to FYE 2018. An increase in housing costs can be partially explained by a shortage of housing supply relative to the demand. This shortage was much greater in London and the South East resulting in higher housing costs in these regions. Despite growth in the amount of homes supplied (PDF, 1.49MB) in recent years, housing demand has remained strong and continued to outstrip housing supply in these regions.

Figure 6: London is only slightly above the UK average household income after considering housing costs

Median weekly equivalised household income for all individuals in average FYE 2018 prices, indexed UK=100, NUTS 1 regions, FYE 2009 to FYE 2011 and FYE 2016 to FYE 2018



Source: Department for Work and Pensions

[Data download](#)

This analysis does not include commuting costs. Both housing and commuting costs are important for the South East as London is a big employment centre for the region.

Notes for Macroeconomic Variables

1. Pullen, J (2009), 'The Marginal Productivity Theory of Distribution: A Critical History', June 2009

2. Assuming marginal propensity to consume is constant across the NUTS 1 regions.
3. $$\frac{\textit{Median household weekly private rent}}{\textit{Median weekly equivalised household income}} \times 100$$

4. Keynes, J M (1936), 'The General Theory of Employment, Interest and Money', February 1936

4 . Economic and personal well-being indicators

The [Wealth and Assets Survey](#) calculates the total wealth in Great Britain, which can shed some light on the wealth inequality within the different regions and countries. Data for Northern Ireland is unavailable, so the analysis focuses on Great Britain. Aggregate total net wealth is an estimate of the value of wealth held by all private households in Great Britain, including net property, net financial, private pension and physical wealth.

London is the most unequal region of Great Britain for wealth inequality

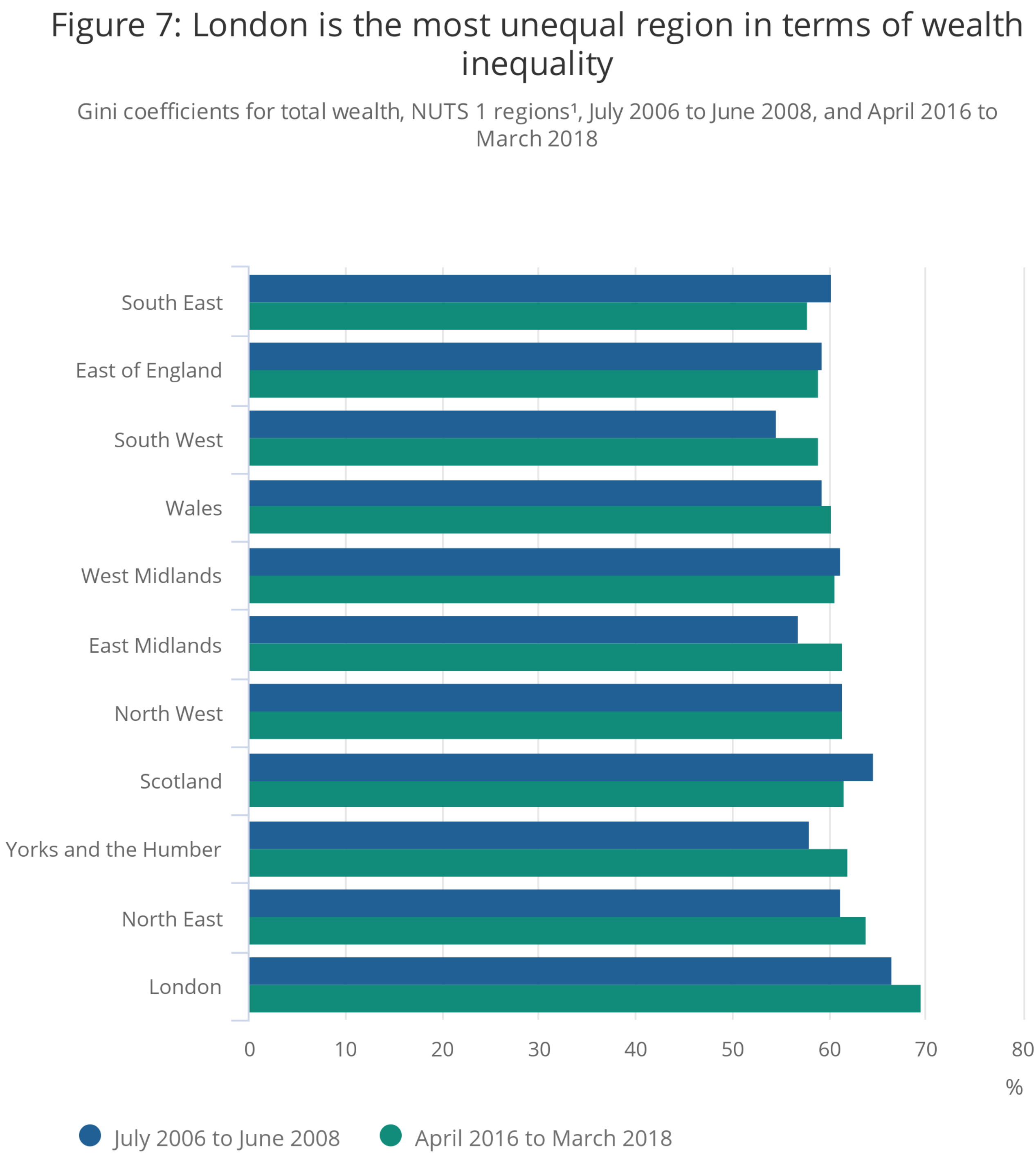
A common measure of calculating inequality within regions and countries is the Gini coefficient. The Gini coefficient can have a value between 0% (no inequality) and 100% (total inequality). Figure 7 shows, that for April 2016 to March 2018, London had the highest Gini coefficient (70%) in Great Britain and as such was the most unequal region in terms of wealth. In the same period, the South East had the lowest (58%) Gini coefficient and so is the least unequal region of Great Britain.

One thing to note is that the Gini coefficient does not reveal the source of inequality. Many factors, including demographic variations by region, can result in higher inequality. Other things to note in Figure 7 are:

- for the periods shown, the Gini coefficient varies for UK regions and countries, from 54% to 70%
- the North East had the second highest Gini coefficient (64%), while having the lowest value for aggregate total wealth from April 2016 to March 2018
- although the South East had the highest aggregate total wealth from April 2016 to March 2018, it was the least unequal region in Great Britain
- in contrast, London had the second highest aggregate total wealth and yet was the most unequal region in Great Britain
- Scotland and the South East, and to a lesser extent the West Midlands and the East of England, are the only NUTS 1 regions to have a lower Gini coefficient in April 2016 to March 2018 than when previously measured in July 2006 to June 2008
- the gap in Gini coefficients between London and the rest of the regions and countries of Great Britain has increased between July 2006 to June 2008, and April 2016 to March 2018

Figure 7: London is the most unequal region in terms of wealth inequality

Gini coefficients for total wealth, NUTS 1 regions[1], July 2006 to June 2008, and April 2016 to March 2018



Source: Office for National Statistics

Notes:

1. Data for Northern Ireland are unavailable

While London outperformed other NUTS1 regions of the UK in terms of macroeconomic variables such as productivity, human capital, and wages, once housing costs are considered, and looking at socio-economic variables like wealth inequality, London underperforms.

London underperforms on personal well-being indicators compared with other regions and countries of the UK

Our personal well-being explorer tool in Figure 8 allows you to observe well-being in one local area and compare it with other areas. Some of the most insightful comparisons may relate to how specific areas have progressed over time. For more information on well-being please see the Personal and economic well-being in the UK: February 2020 bulletin.

Figure 8: Personal well-being interactive map

Average ratings, UK, years ending March 2012 to March 2019

Data download

It is possible to rank local authorities based on their average scores alone but this may be misleading for various reasons, such as different sample sizes, different confidence intervals and mode effects, and not comparing like with like (for example, we know that people in rural areas tend to rate their well-being more highly than people in urban areas). Comparisons between areas should be made with caution.

Focusing only on the NUTS 1 regions, the ratings for life satisfaction, feeling worthwhile, and happiness have generally increased between 2012 and 2019, while anxiety has generally decreased. In 2019, London ranked the lowest for life satisfaction and feeling worthwhile, and the highest for anxiety, while the South West and Northern Ireland ranked the highest for life satisfaction, feeling worthwhile and happiness.

London's underperformance on well-being indicators such as life satisfaction, feeling worthwhile and anxiety maybe because residents face a relatively high cost of living, higher commute times with an overcrowded transport network, and experience relatively higher levels of atmospheric pollution. In recent years London’s performance on life satisfaction has increased.

Notes for Economic and personal well-being indicators

1. Calculated from the Lorenz curve (plot of the cumulative share of household income against the cumulative share of households). The Gini coefficient is the area between the Lorenz curve of the income distribution and the diagonal line of complete equality, expressed as a proportion of the triangular area between the curves of complete equality and inequality.

5 . Authors

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Top income adjustment in effects of taxes and benefits data: methodology

Analysis of a recently introduced approach to addressing survey under-coverage of the highest earners in effects of taxes and benefits data, using tax record information.

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To be announced

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1 . Important points

- This article concludes two years of joint research with the Department for Work and Pensions to explore new methods of addressing under coverage of the highest incomes in household finance surveys, thereby improving our understanding of trends and levels of income inequality in the UK.

- The methods explored in this research involve replacing survey responses for the richest respondents in the Living Costs and Food Survey – the principal source for ONS' income inequality statistics - with information from a sample of administrative tax records produced by HM Revenue and Customs, known as the Survey of Personal Incomes.

- The introduction of a top income adjustment increases estimates of income inequality by an average of 1.9 percentage points over the period covering financial year ending 2002 to financial year ending 2018.

- The adjustments allow for new analyses of income inequality, for example the income share of the richest 1% of people, which has remained fairly stable at around 7% since financial year ending 2010.

- The introduction of a top income adjustment increases the coherence of estimates of levels of income inequality reported by ONS and DWP, while the trends seen in both series remain comparable.

- The ONS will introduce its new income adjustment for the income inequality statistics for the financial year ending 2019 (to be published 5 March 2020) and create an adjusted time series going back to the financial year ending 2002.

2 . Introduction

The Office for National Statistics (ONS) and its predecessors have published statistics on the distribution and redistribution of household income since 1961. This began with 'The incidence of taxes and social service benefits', which was one of the first publications in the world to give such a complete examination of these issues.

The primary source of data for the ONS's official statistics on household income inequality is the Living Costs and Food Survey (LCF), a sample survey of private households in the UK, collecting detailed data on household income and expenditure and currently covering approximately 5,000 households. The household income dataset produced from the LCF is often known as the effects of taxes and benefits (ETB) data.

While household surveys have several important advantages over relying solely on administrative records, there is a well-recognised challenge: they do not fully capture the incomes of the richest individuals and households, particularly those among the so-called "top 1%". There are several potential reasons for this (see, for example, Lustig, 2018), the relative importance of which varies across countries and across surveys depending on the methods used. These include:

- frame or non-coverage 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 non-response 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 non-response error, if those with higher incomes participating in surveys do not report all their sources of income

- under-reporting, where the levels of income received for some sources may be intentionally or unintentionally under-reported by survey respondents

- sparseness, where data on top incomes are limited because there are fewer observations within the dataset with very high incomes, making it difficult to estimate the true distribution

This article examines the nature and scale of under-coverage of top incomes in ONS statistics on income inequality derived from the LCF. It then explores different approaches to dealing with these issues, in particular focussing on methods developed first by the Department for Work and Pensions (DWP) (2015) and then by Burkhauser et al. (2018); these make use of the Survey of Personal Incomes (SPI), a microdata set containing taxable incomes based on a sample of administrative records from UK tax payers. Building on this research, this article contrasts two top income adjustment approaches, exploring their relative impacts on headline measures of income inequality published by the ONS.

3 . The under-coverage of richest households in the survey data

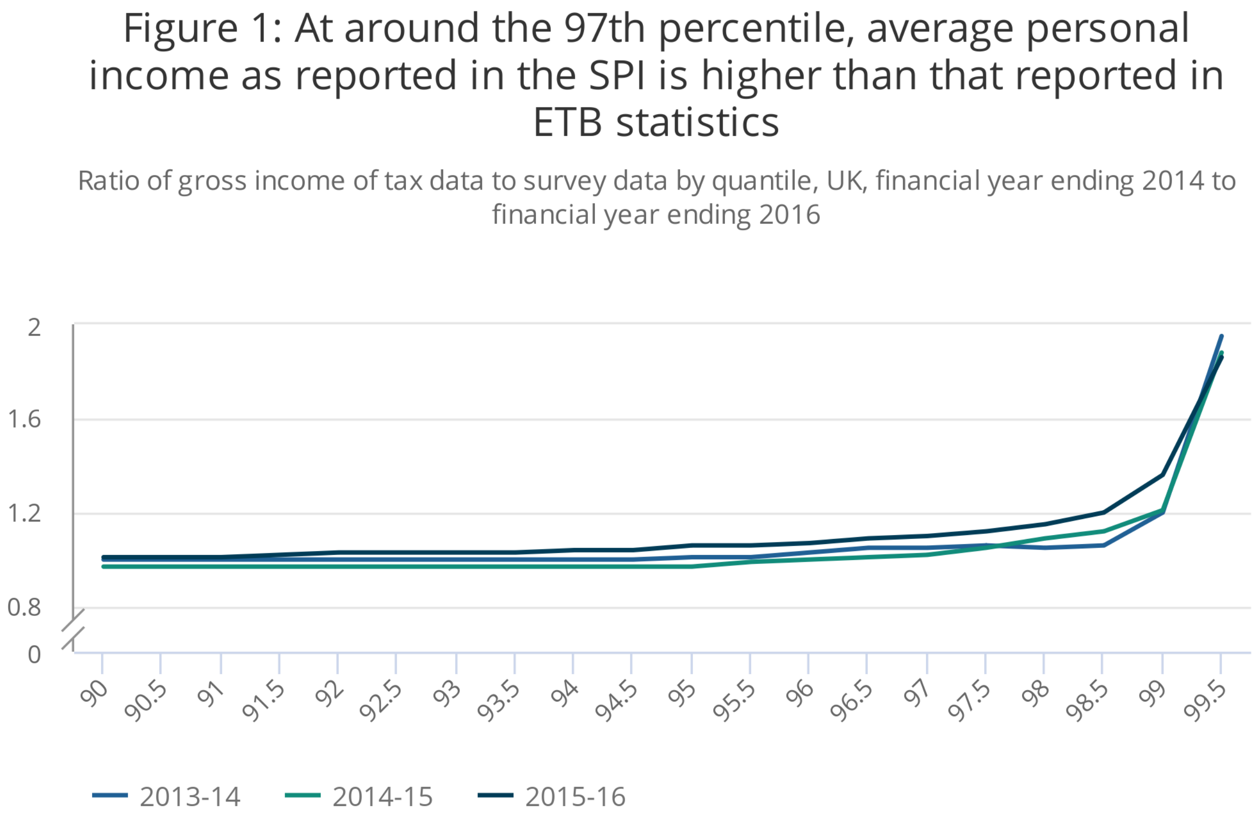
We can make an assessment of the accuracy with which the Living Costs and Food Survey (LCF) data capture personal income by comparing it to the Survey of Personal Incomes (SPI), an individual-level dataset produced from tax records by HM Revenue and Customs (HMRC), based on a sample of individuals potentially liable for UK tax.

Examining the three most recent years where full SPI datasets are available, Figure 1 highlights that at around the 97th percentile, average personal income as reported in the SPI is higher than that reported in effects of taxes and benefits (ETB) statistics. This shows that survey under-coverage is an issue for ETB statistics, and therefore measured estimates of income inequality are potentially lower than they should be.

That the ratio becomes close to 1.0 below the top few percentiles of the distribution suggests that the greatest challenge affecting top incomes in UK survey data is that of under-reporting by survey respondents rather than lower survey participation. If the primary issue was that of unit non-response, it might be expected that the ratio would remain above 1.0 considerably further down, owing to the misalignment of the two distributions resulting from those with the highest incomes being absent from the survey.

Figure 1: At around the 97th percentile, average personal income as reported in the SPI is higher than that reported in ETB statistics

Ratio of gross income of tax data to survey data by quantile, UK, financial year ending 2014 to financial year ending 2016



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

4 . Approaches to addressing survey under-coverage of top incomes

Economic research has employed a variety of methods to address the issues outlined in the previous section. While a more detailed taxonomy is provided in Lustig (2018), broadly speaking, these can be divided into three groups:

- methods that use survey data only
- those using tax data only
- those that combine survey and administrative data

Recognising our role as producers of official statistics, our approach needs to be methodologically robust, based on academic research and existing best practice, as well as being transparent and understandable by users. In addition, the value of effects of taxes and benefits (ETB) microdata to academics and researchers needs to be reflected, with any approach continuing to enable the replication of headline measures using the data. This means the method needs to be applied to the underlying microdata rather than to the headline measures themselves.

The adjusted data should also permit the reporting of income on a household, rather than individual, basis reflecting the greater insight this measure provides because of, for example, intrahousehold sharing of resources. Finally, the selected approach needs to be feasible considering the current availability of source data.

This final reason leads us away from approaches that rely on the direct use of linked survey and administrative data at this stage of the research. In the longer term, this is our ambition as more record-level administrative data become available within the Office for National Statistics (ONS) under the Digital Economy Act 2017. This will help to improve the quality of estimates of income both at the bottom and top of the income distribution while maintaining the detailed information about people and households (such as intrahousehold relationships, spending and health status) that is not so readily available in administrative data. However, there still remains a clear need to develop and introduce a method of bringing together the survey and administrative data that does not rely on direct record linkage, that can be applied now, and that allows for the production of historical data.

These criteria have led us to the set of methods first implemented in the UK by the Department for Work and Pensions (DWP) for the households below average incomes (HBAI) statistics, which are based on the Family Resources Survey (FRS). This method, often referred to as the "SPI adjustment" owing to its use of HM Revenue and Customs' (HMRC's) Survey of Personal Incomes (SPI) data, involves replacing the incomes of the richest 0.32% and 1.16% of working-age people and pensioners, respectively, with cell-mean imputations based on corresponding observations in tax return data. The SPI adjustment also stratifies separately for Great Britain and Northern Ireland.

The groundbreaking work of the original SPI adjustment is recognised by Burkhauser et al. (2018), but they argue that with the increasing interest in income inequality and the income shares of specific groups such as the so-called "top 1%", the SPI approach requires "new scrutiny". They outline several recommendations for optimising the SPI adjustment, setting out a so-called "SPI2" methodology.

First, they demonstrate that survey under-coverage of top incomes in HBAI data tends to become more of an issue from around the 95th percentile upwards, becoming particularly acute from the top 2%. As highlighted in Figure 1, similar results are demonstrated in ETB data, making a case for adjusting incomes at a lower threshold than that currently set by the SPI1 adjustment.

Burkhauser et al. also compare the ratios of adjusted HBAI data with SPI data at different quantile groups towards the top of the distribution. They highlight that the gap between the mean incomes of HBAI and SPI quantile groups is reduced for the top 2% to 1% group as well as for the top 1% to 0.5% group. However, they further highlight that the correspondence between adjusted-HBAI data and SPI data remains low towards the very top of the distribution (in the top 0.5% to 0.1% group and the top 0.1%). They argue that this stems from the fact that cell means from the original SPI adjustment are calculated from a wide range of incomes. Therefore, the adjustment tends to impute incomes that are too low for the 0.5 to 0.1 percentile group and too small for the top 0.1%. They conclude that more granular adjustments could lead to improved measures of income inequality for the top incomes.

Aside from applying a lower threshold and increased granularity, the SPI2 adjustment differs in two important ways from the original SPI methodology. First, the SPI2 methodology contains no stratification for pensioner and non-pensioner individuals or for Great Britain and Northern Ireland. Secondly, the SPI2 does not involve reweighting of the data, instead simply replacing survey incomes for each quantile group with the SPI mean for the same quantile group.

This paper therefore builds on the work of both the DWP and Burkhauser et al., through exploring different methodological choices with the aim of identifying a perceived optimum variant for use with the ONS's household income statistics, considering the various constraints that exist.

5 . New approaches: quantile and reweighting methods

In determining the optimal approach to adjust for under-coverage of top incomes in effects of taxes and benefits (ETB) statistics, two underlying methods are used and tested. The first, which we term the "quantile" approach, closely resembles the so-called "SPI2 approach" developed by Burkhauser et al. The second - "reweighting" - brings together elements of both the SPI2 and the original Survey of Personal Incomes (SPI) adjustment adopted for households below average income (HBAI) statistics.

Under the quantile approach, the mean gross income for each SPI quantile group is imputed onto individuals in the equivalent quantile groups in the survey data. More specifically:

1. estimate personal taxable income for individuals on ETB data
2. add a dummy case to the SPI data to account for individuals who do not pay tax; their personal taxable income is set to zero, and their weight reflects the difference in population totals between the ETB and SPI datasets
3. rank individuals in ETB and SPI data by personal taxable income
4. allocate individuals at the top of both the ETB and SPI distributions to quantile groups, depending on the threshold and granularity selected (for example, at the 97th percentile and 0.5% levels of granularity, there will be six groups of individuals at the top, each representing 0.5% of the population)
5. calculate the mean personal taxable income for each quantile group in the SPI data
6. replace the income of each case within the ETB quantile groups with the mean SPI income from the corresponding group
7. add back several income components to the ETB cases not represented in SPI data, such as individual savings accounts (ISAs) and intrahousehold transfers
8. re-calculate Income Tax and National Insurance contributions for the adjusted ETB cases based on new estimates of personal pre-tax income
9. aggregate personal-level income across household members to estimate adjusted household disposable income

By contrast, the reweighting methodology replaces steps four to six with the following:

4a. allocate individuals at the top of the SPI distributions to quantile groups, depending on the threshold and granularity selected (for example, at the 97th percentile and 0.5% levels of granularity, there will be six groups of individuals at the top, each representing 0.5% of the population)

4b. calculate the lower income boundaries for each of these quantile groups on the SPI data and create bands in the ETB data using these boundaries

5. calculate the mean personal taxable income for each quantile group in the SPI data and impute this onto individuals in the equivalent survey bands

6a. reweight the ETB bands so that their weights are the same as the SPI quantiles

6b. reweight the unadjusted ETB data so that overall population totals for each weighting variable are maintained

Where the primary challenge affecting top incomes is that of under-reporting rather than lower survey participation of the richest households, the effects of the two methods should be largely equivalent in practice. However, where lower participation also has a significant impact, the second "reweighting" method should prove more effective.

The combination of two different SPI adjustment methods (reweighting and quantile), many possibilities in both the threshold and granularity of adjustments, as well as the decision on whether to adjust pensioners and non-pensioners separately means that there are many choices to be made in selecting a preferred approach. In determining this, we have sought to address the following questions:

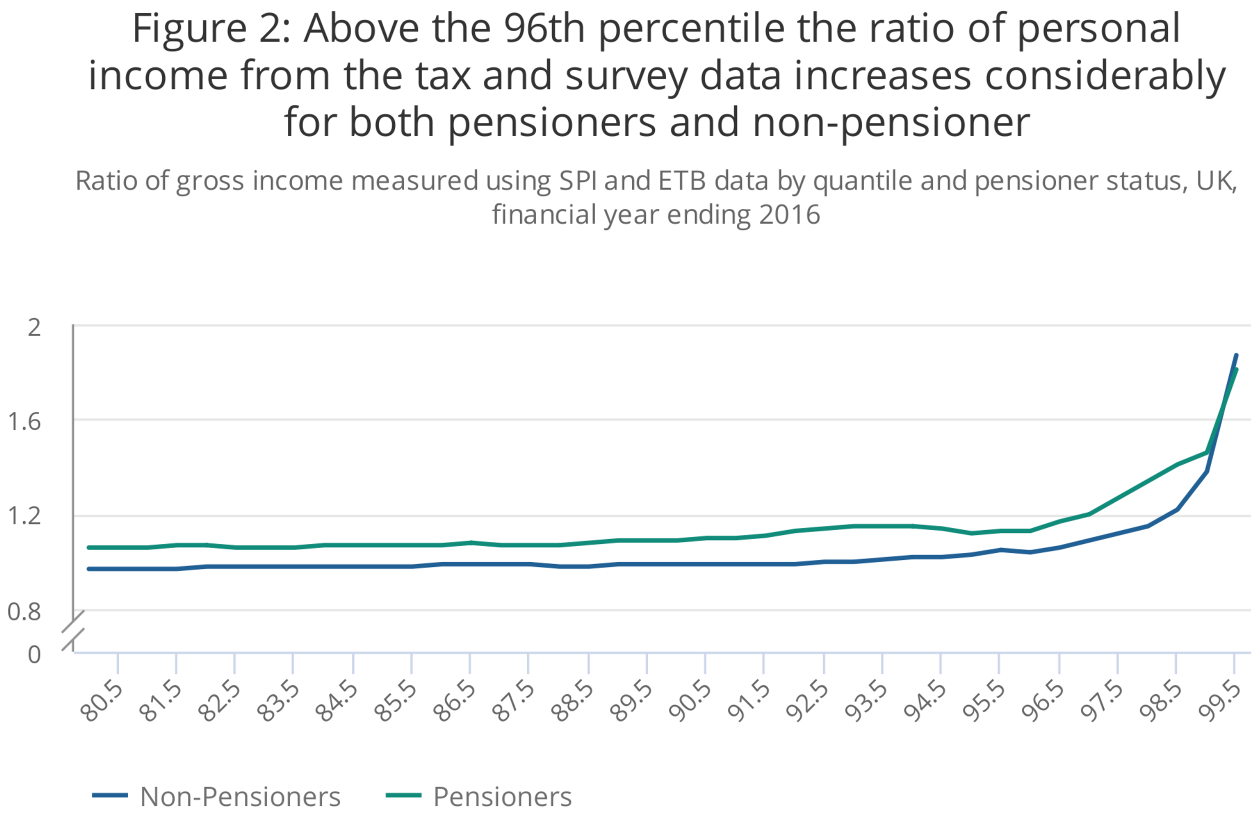
- Should the richest pensioners and non-pensioners be adjusted separately?
- How low should the threshold be?
- How granular should the adjustment be?
- Should the quantile or reweighting method be chosen?
- Should estimates be revised once final outturn data are available?

Recommendation to adjust richest pensioners and non-pensioners separately

The SPI adjustment currently implemented in HBAI statistics involves separately adjusting the income of the richest pensioners and non-pensioners. Considering this approach, Burkhauser et al. (2018) question whether there is a clear rationale for doing so. Exploring these issues in more detail, Figure 2 presents the ratio of average (mean) personal taxable income by quantile group reported on ETB and SPI data, for both pensioner and non-pensioner distributions.

Figure 2: Above the 96th percentile the ratio of personal income from the tax and survey data increases considerably for both pensioners and non-pensioner

Ratio of gross income measured using SPI and ETB data by quantile and pensioner status, UK, financial year ending 2016



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

The ratio of taxable income measured on ETB and SPI data for working-age people closely resembles the whole population average shown in Figure 1, hovering around 1.0 before sharply increasing at the 96th percentile. We see a similar observation in the distribution of pensioners, where the ratio also increases at the 96th percentile. In contrast with the non-pensioner distribution, the ratio remains above 1.0 during the entirety of the portion of the distribution shown in this chart, suggesting that the income distribution for pensioners is affected by both under-reporting and unit non-response.

These findings confirm that survey under-coverage of top incomes affects both the non-pensioner and pensioner distributions. Only 1.7% of pensioners have a personal taxable income high enough to feature in the top 5% of the overall income distribution. This means that an adjustment applied just to the overall distribution would be unlikely to fully adjust for under-coverage of the incomes of pensioners. Given this is an important breakdown in the analysis produced by the Office for National Statistics (ONS), there is a clear rationale for stratifying by pensioner and non-pensioner, as is currently done by the Department for Work and Pensions (DWP).

Recommended income threshold for adjustments

In considering the threshold to use, there is a balance that needs to be struck. Too high, and there is a risk that the adjustment does not fully account for survey under-coverage. Too low, and survey data are being unnecessarily discarded in exchange for averages from the SPI.

As demonstrated in Figure 1, under-coverage of top incomes in the Living Costs and Food Survey (LCF) becomes an issue at around the 96th percentile. On this evidence, thresholds ranging from the 95th to 99th percentile are explored and tested, using both the quantile and reweighting methods. In testing these different thresholds, the quantile group sizes were held constant at 0.5%.

Over the period considered, differences between the various adjustments, based on different thresholds, are relatively small, under both the quantile and reweighting methods. By far the largest difference is that between having any adjustment and not having one at all.

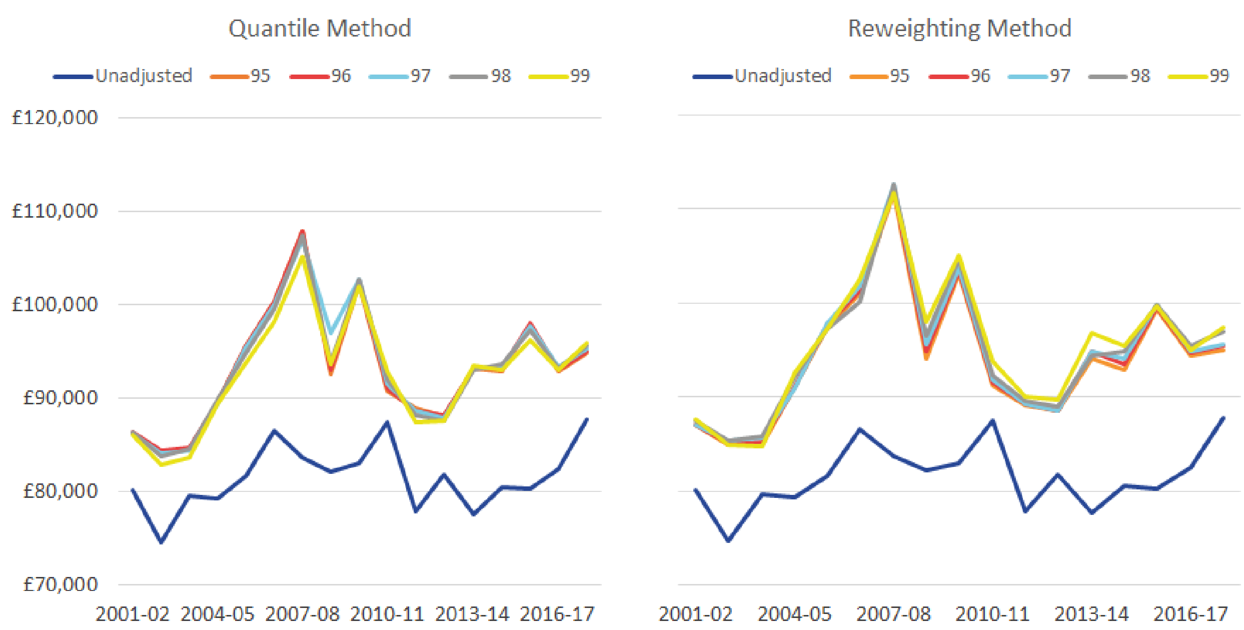
For instance, Figure 3 looks at the mean of the richest 10% (Figure 3), across the 5 adjustments, and over the period financial year ending 2002 to financial year ending 2018. It shows that under the quantile method, the average absolute deviation of the five adjustments from their mean is 0.4%, compared with the 14.2% average difference between each adjusted estimate and the unadjusted amount. Similarly, under the reweighting approach, these figures are 0.5% and 16.2% respectively.

The same is also true when examining the Gini coefficient (Figure 4). Under the quantile method, the average absolute deviation of the 5 adjustments from their mean is 0.1 percentage points, compared with the 1.8 percentage point average absolute difference between each adjusted estimate and the unadjusted amount. Similarly, under the reweighting approach, these figures are 0.1 and 2.0 percentage points respectively.

The gap between the adjusted and unadjusted is greatest during the period between the financial year ending 2006 and the financial year ending 2010 where, according the reweighting method, the average income of the richest 10% increased by 28.5% between the financial year ending 2002 and the financial year ending 2008, before falling 20.8% by the financial year ending 2013. This compares with the unadjusted data, which were much more stable over this period.

Figure 3: The mean of the richest 10% across the five adjustments

Mean equivalized household disposable income of the richest 10% of people, with varying thresholds, 0.5% granularity, UK, financial year ending 2002 to financial year ending 2018



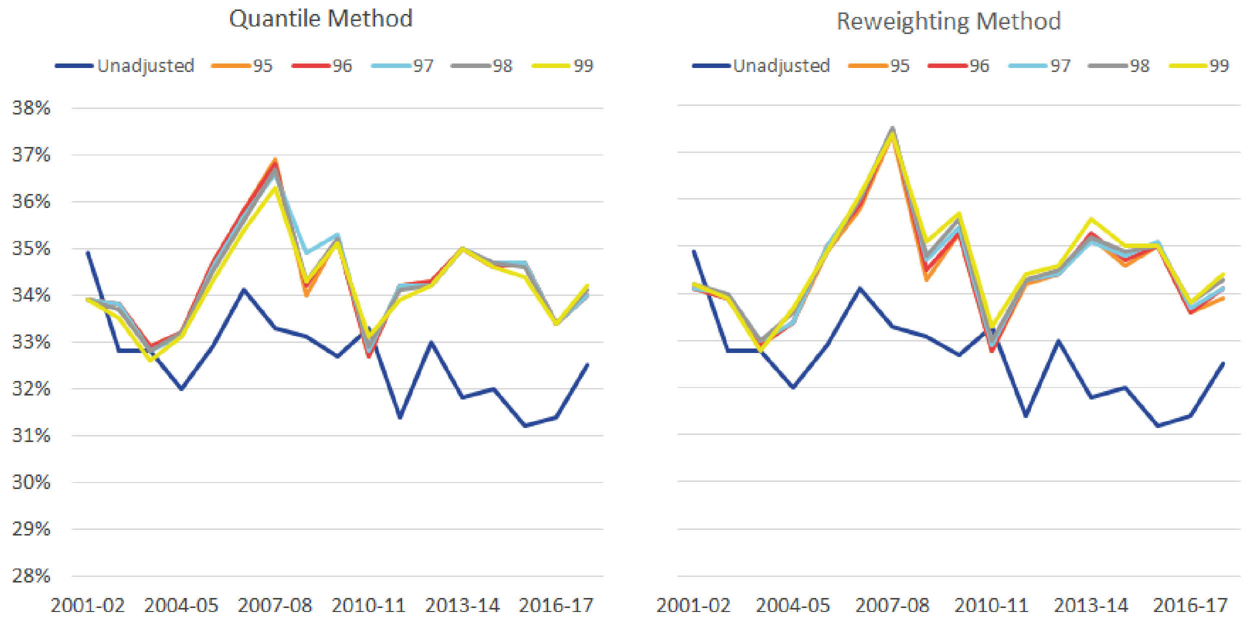
Source: Office for National Statistics – Living Costs and Food Survey; HM Revenue and Customs – Survey of Personal Incomes

The trends of adjusted data compared with unadjusted data over time are broadly similar. The most notable exception is during the four years from the financial year ending 2006, where income inequality increases sharply as measured using adjusted data, before falling back to similar levels observed in the unadjusted data. Also, between the financial year ending 2013 and the financial year ending 2016, there is a larger rise in inequality in the adjusted data compared with the unadjusted data. However, the gap between adjusted and unadjusted data narrows between the financial year ending 2016 and the financial year ending 2018 because of a larger rise in the inequality in the unadjusted data.

In the financial year ending 2011, there is little difference between the Gini coefficients for the adjusted and unadjusted data. This most likely reflects the introduction of a 50% top tax rate in the financial year ending 2011, with evidence to suggest that this led to people forestalling their income (HM Revenue and Customs (HMRC), 2012), which has resulted in the tax data for top earners being not as different to the survey data in the financial year ending 2011 as they are in other years.

Figure 4: The Gini coefficient at varying thresholds

Gini coefficient of disposable income, with varying thresholds, 0.5% granularity, UK, financial year ending 2002 to financial year ending 2018



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

Looking across the time series, the threshold that is the furthest away from the average of the adjustments is the 99th percentile threshold. Suggesting that the 99th percentile threshold may not fully address the survey under-coverage (though, these differences are very small in comparison to the difference between having an adjustment and not).

Recommended quantile band size

Another consideration when applying a methodology for adjusting top incomes is the width of quantile bands. While smaller quantile groups may provide more granularity to the adjusted data - potentially allowing for a closer representation of the upper tail of the income distribution - we risk finding ourselves with very few, maybe zero, cases within bands in the survey data. However, this can only be found under the reweighting approach. By construction, there will always be cases on the survey data when bands are formed on the basis of quantiles, as is the case under the quantile approach, rather than the income thresholds used for the reweighting approach.

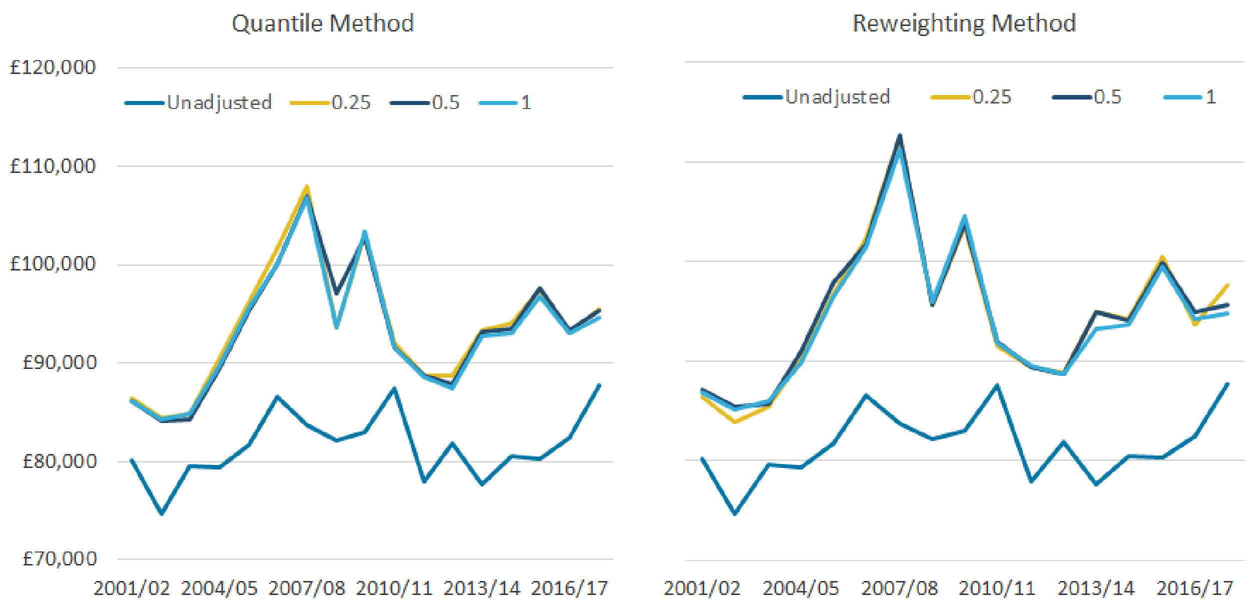
Whichever quantile group size is used, the top-income adjustment has a similar effect on both the average income of the richest 10% (Figure 5) and the Gini coefficient (Figure 6). In both cases, the differences between adjustments are much smaller than any differences between adjusted and unadjusted data (excluding the financial year ending 2011, as discussed earlier).

Across all years, the average change in income of the richest 10%, compared with the unadjusted data, is 14.5% for the quantile method and 15.9% for the reweighting method (Figure 5). The different trends in the adjusted and unadjusted data, in the income of the richest 10% over time, are broadly similar to those discussed in the recommended income threshold for adjustments.

While the differences between adjustments based on different quantile bands are small under the quantile method, they are slightly more pronounced under the reweighting method. For example, while the average absolute difference between adjustments based on 0.25% and 1.0% quantile bands is 0.6% under the quantile method, it is 0.8% using the reweighting approach.

Figure 5: Whichever quantile group size is used, the top-income adjustment has a similar effect on the average income of the richest 10%

Mean equivalised household disposable income of the richest 10%, with varying granularities, 97th threshold, UK, financial year ending 2002 to financial year ending 2018

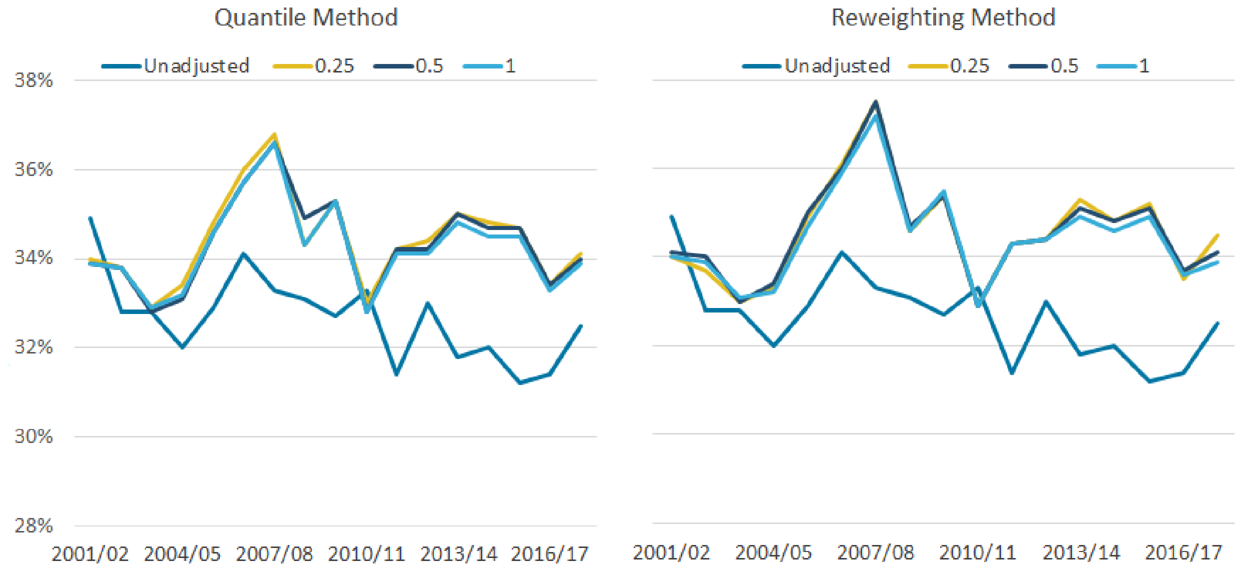


Source: Office for National Statistics – Living Costs and Food Survey; HM Revenue and Customs – Survey of Personal Incomes

Looking at the Gini coefficient, over the period analysed, the average difference between the unadjusted and adjusted data is 1.7 and 1.9 percentage points for the quantile and reweighting methods respectively. The differences between the different quantile sizes is considerably smaller. The difference between the 1.0% and 0.25% quantile bands in the reweighting approach is not so pronounced when measuring the Gini coefficient, compared with measures for the average income of the top 10%.

Figure 6: Whichever quantile group size is used, the top-income adjustment has a similar effect on the Gini coefficient

Gini coefficient of disposable income with varying granularities, 97th percentile threshold, UK, financial year ending 2002 to financial year ending 2018



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

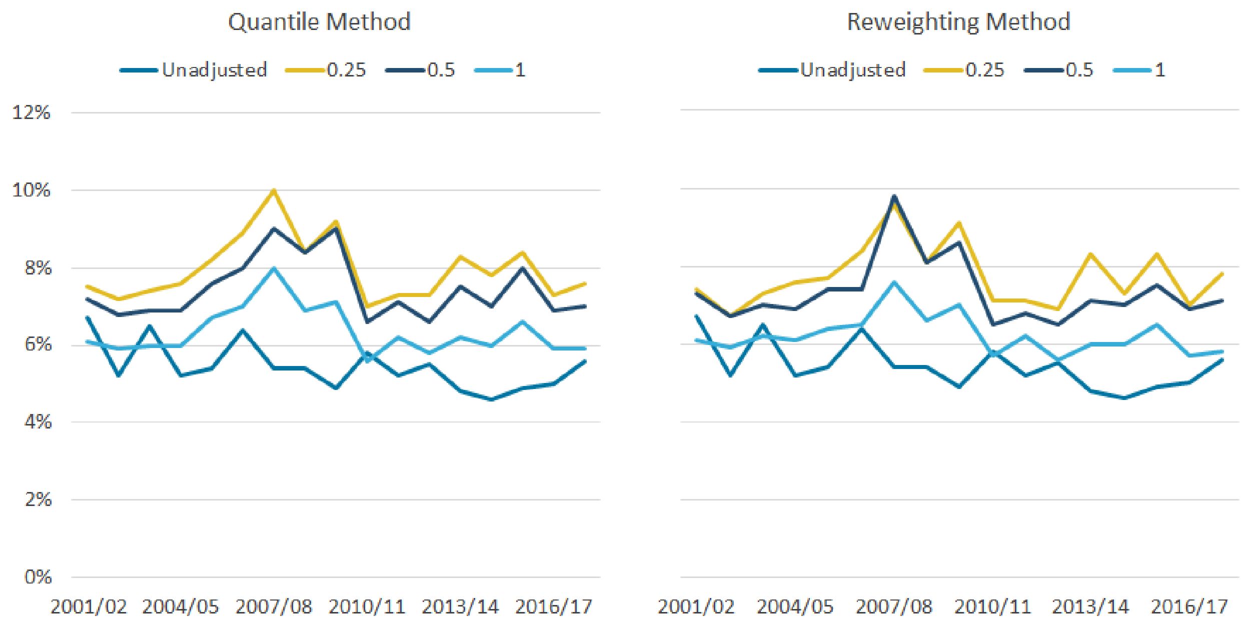
Income share of the top 1%

While the impact of changing the granularity is modest on estimates of income of the richest 10% and the Gini coefficient, there are much more substantial differences between quantile band sizes when examining the top 1% of individuals.

Figure 7 highlights that estimates for the income share of the top 1% are slightly higher with a 0.25% quantile band size, compared with 0.5%, which in turn gives considerably higher estimates in most years than 1.0%. For example when using the reweighting method, the average share of income for the top 1% is 6.1% between the financial year ending 2011 and the financial year ending 2018, based on quantile band sizes of 1.0%, compared with 5.1% when the data are unadjusted. This average increases to 7.1% and 7.7% for 0.5% and 0.25% quantile band sizes respectively.

Figure 7: Estimates for the income share of the top 1% are slightly higher with a 0.25% quantile band size, compared with 0.5%

Share of household equivalised disposable income received by the richest 1% of individuals, with varying granularities, 97th threshold, UK, financial year ending 2002 to financial year ending 2018



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

These differences arise as a result of the composition of households at the top of the distribution. This reflects that most households have multiple occupants, but typically only one person will have a personal income high enough to warrant being adjusted. For instance, in the 2017 to 2018 dataset, just under half of the people in the top 1% of people based on personal income are in the top 1% based on household income. This means that most of those in the top 1% of household income, using a 0.25% quantile band size adjustment, will contain those whose incomes have been replaced with an average of the 0.5% richest people as reported in the SPI. Whereas, people in the top 1% of household income, adjusted using 1.0% quantile band sizes, will include people who have had their income replaced with the lower mean derived from the top 1% of the SPI data, and hence they have a lower estimated income share.

Given the increasing focus on measures such as the income share of the top 1%, these findings suggest that 1.0% quantile bands are too broad. However, the trade-off when applying the reweighting method is the increasing likelihood of empty bands on the survey data for smaller quantile band sizes, resulting in adjusted survey data that are not as representative of the tax data. For example, in the hypothetical situation where the richest three 0.25% bands of pensioners are empty, adjusted data will not reflect the average income of the richest 0.75% of pensioners, resulting in less precise measures of income inequality and greater volatility at the top of the distribution.

From the financial year ending 2002 to the financial year ending 2018, only 7 out of 340 bands were empty. This highlights that while the issue of empty bands can occur, it is not at a scale considered large enough to be considered a major issue. Therefore, adjustments based on 0.25% quantile bands are most likely to be optimal, with the greater granularity offered ensuring a more realistic approximation of the upper tail of the income distribution.

Recommendations on quantile and reweighting methods

The analysis presented so far highlights that while estimates of the Gini coefficient (using a 97 percentile threshold and quantile band sizes of 0.25%) were broadly similar since the financial year ending 2012, the Gini coefficient under the reweighting approach has been marginally higher than for the quantile approach.

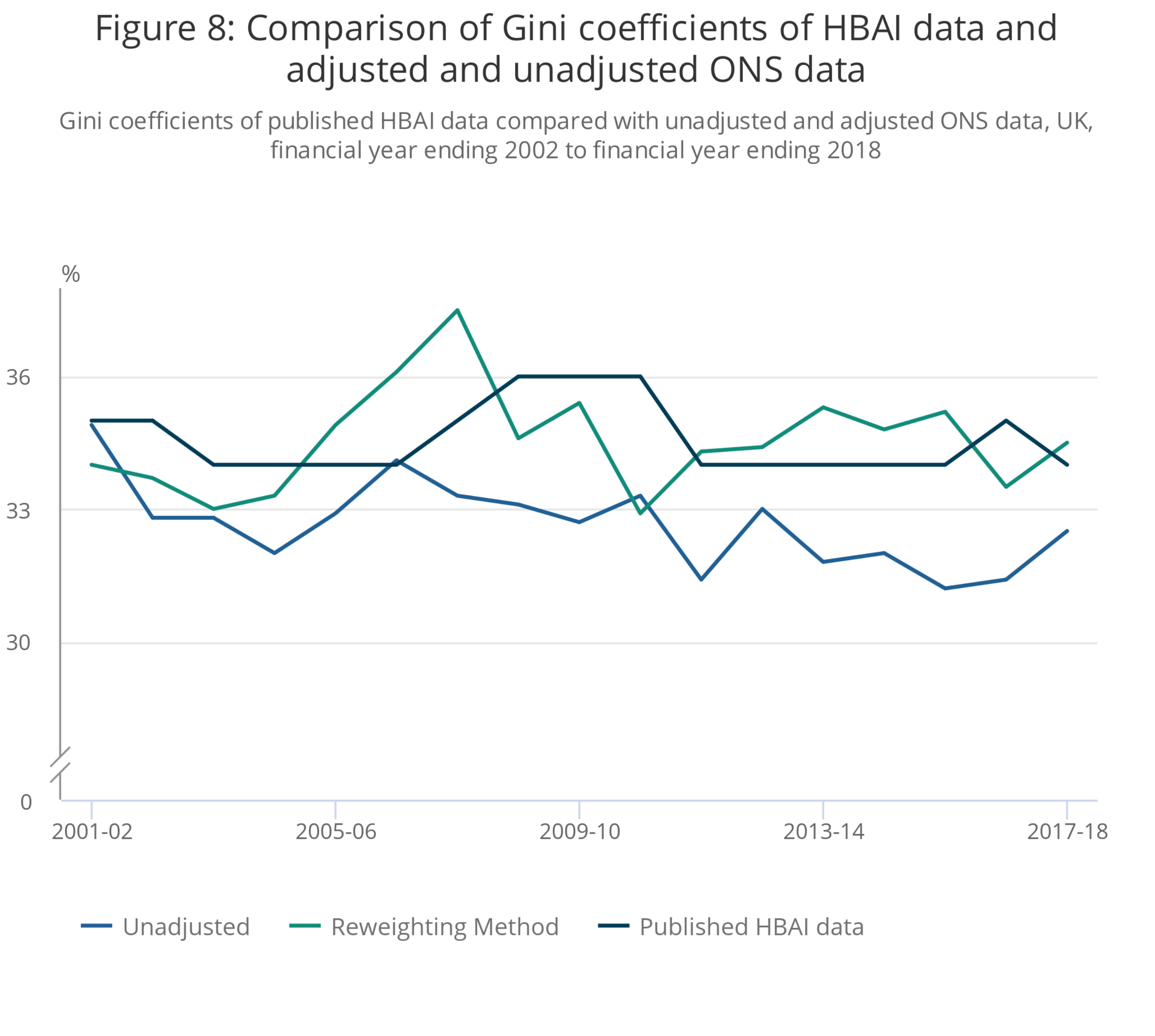
Figure 1 suggested that the primary reason for the under-coverage of top incomes in the LCF was under-reporting rather than unit non-response. However, if that were entirely the case, it might be expected that the quantile and re-weighting approaches would be almost identical. That the Gini coefficient is marginally higher under the reweighting approach suggests that non-response at the top of the distribution does play some role. This indicates that although more complex, the reweighting approach is preferred.

Another reason for adopting the reweighting approach comes from Figure 2, which highlighted that, although non-response may be a lesser concern for the overall income distribution (mirroring the findings of Burkhauser et al.), there is evidence to suggest it may be more noticeable in the distribution of pensioners' incomes.

A further important consideration is coherence. The reweighting approach is closest in methodological terms to the SPI adjustment currently used by the DWP's HBAI statistics. Adopting this approach therefore ensures coherence in terms of methods across the UK Government Statistical Service (GSS).

Figure 8: Comparison of Gini coefficients of HBAI data and adjusted and unadjusted ONS data

Gini coefficients of published HBAI data compared with unadjusted and adjusted ONS data, UK, financial year ending 2002 to financial year ending 2018



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

Recommendation on whether estimates should be revised once final outturn data are available

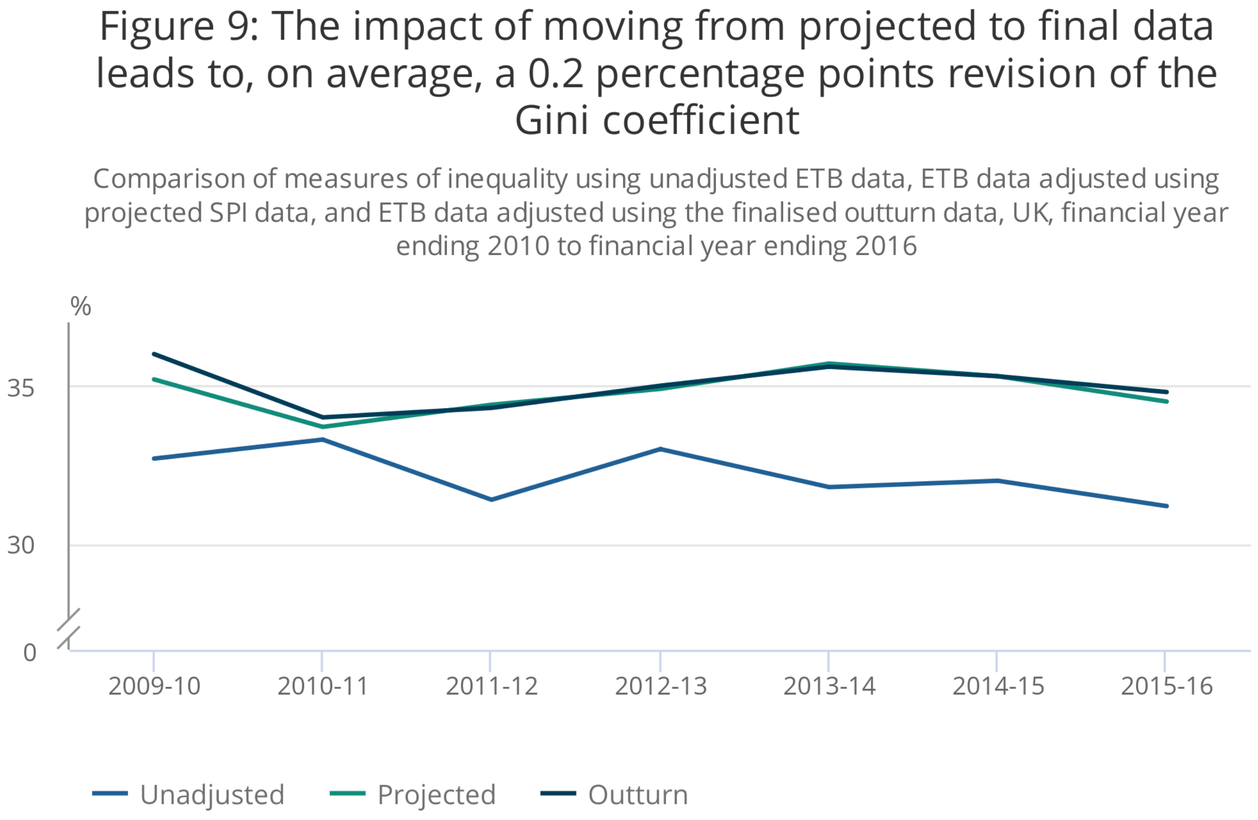
One of the challenges in implementing the approaches discussed in this paper is their reliance on SPI data, which are not typically made available to researchers until at least two years after the end of the income reference period. Therefore, it is necessary to use estimates provided by HMRC, which are based on projections from historical SPI datasets. This raises the question of whether to revise the measures of Gini coefficients once the final SPI data become available.

To address these questions, we compare estimates of inequality based on projected and outturn data. In this analysis, we used projected SPI estimates that were originally supplied to the DWP in the production of their HBAI statistics to adjust ETB statistics. These results were then compared to estimates using the same adjustment but using final outturn data that had since been published.

The analysis in Figure 9 demonstrates that the impact of moving from projected to final data leads to, on average, a 0.2 percentage points revision of the Gini coefficient. Given that the 95% confidence intervals of published Gini coefficients are usually wider than even the largest observed revision, these results do not provide a compelling case for revising measures of Gini coefficients once final SPI data are made available at this stage. Therefore, we do not propose a policy of regular revision to our household income statistics, following the adoption of the new top-income adjustment, to take account of the outturn SPI data when they become available. However, this will need to be closely monitored, initially once the financial year ending 2018 SPI data are released later in 2020 and for a few years thereafter to determine whether this revision policy needs re-evaluating.

Figure 9: The impact of moving from projected to final data leads to, on average, a 0.2 percentage points revision of the Gini coefficient

Comparison of measures of inequality using unadjusted ETB data, ETB data adjusted using projected SPI data, and ETB data adjusted using the finalised outturn data, UK, financial year ending 2010 to financial year ending 2016



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

6 . Conclusion

The analysis presented in this article confirms that survey under-coverage of top incomes in effects of taxes and benefits (ETB) data is an issue, but it is one that is addressed by employing methods that adjust the income of the highest earners with information provided by administrative tax records. We have demonstrated that the optimum approach to use is the reweighting approach, which stratifies by pensioners and non-pensioners at the 97th percentile threshold and in 0.25% quantile groups.

We plan to introduce this adjustment in income distritbutions statistics covering 2018 onwards, to be published in March 2020. At this stage, the adjusted ETB time series will go back to the financial year ending 2002, reflecting the availability of Survey of Personal Incomes (SPI) data from the UK Data Service (UKDS). However, we intend to explore options for extending the time series back further, ideally to 1977, reflecting the start of the ETB data currently available. We will also make the top income-adjusted ETB statistics available to researchers via the UKDS.

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8 . Authors and Acknowledgements

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