ADVISORY PANEL ON CONSUMER PRICES – TECHNICAL

Improving price level data for different household groups

Expected publication: Alongside minutes

Purpose

This paper was commissioned by ONS to explore options for updating the Household Costs Indices (HCIs) to reflect different prices paid for the same or similar goods by different types of households. We focus primarily on goods prices, which account for 51% of the CPI basket; further methods of dealing with variation in prices paid for the same or similar services across household types are left for future research.

The paper explores existing approaches taken in other countries and in the academic literature, then reviews types of data available that may link household characteristics to information about prices paid for specific types of goods. The paper concludes by summarising potential methods for incorporating different prices paid for the same or similar goods into the HCIs.

Actions

Members of the Panel are invited to comment on the different options raised in the paper, in particular:

- Is there anything else not considered in the paper that should be taken into account?
- What are the relative merits of different methods? Are there any that seem most/least promising or practicable?
- What is the applicability of the methods considered in the paper to accounting for services?

Improving price level data for different household groups

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I. Executive summary

Households may experience different inflation rates because they buy different combinations of goods and services, substitute differently between goods and services, and pay different prices for the same or similar goods and services. Understanding which households are most affected by price changes is crucial for making informed decisions in monetary and social security policies, including the uprating of benefits.

Recently, the Household Costs Indices (HCIs) were introduced to measure rates of inflation experienced by different types of households. The approach used to estimate the HCIs takes into account different combinations of goods and services (called non-homotheticity) and assumes that prices change at the same rate in each goods category for all households.

However, research suggests that this assumption does not hold in practice, especially given the heterogeneous costs associated with different brands, stores, and qualities of similar goods and services. Estimates from other countries suggest that omitting this source of variation in experienced inflation underestimates the variation in inflation rates across households by as much as two-thirds (Kaplan and Schulhofer-Wohl 2017), although there is reason to believe that this variation is likely lower in the UK.

In this paper, we explore options for updating the HCIs to reflect different prices paid for the same or similar goods by different types of households. We focus primarily on goods prices, which account for 51% of the CPI basket; further methods of dealing with variation in prices paid for the same or similar services across household types are left for future research.

First, we evaluate existing approaches to heterogeneous inflation statistics taken by other countries. Our assessment indicates that while other countries generate estimates like the Household Cost Indices (HCIs), none consider the variations in prices paid within goods categories.

Second, we review the academic and grey literature to uncover potential methodologies for incorporating different prices paid for the same or similar goods. Most studies on this topic use commercial scanner data, which combines detailed household purchase data with household characteristic information (e.g. Kaplan and Schulhofer-Wohl 2017; Jaravel and O’Connell 2020b; Weber, Gorodnichenko, and Coibion 2023). One notable exception is a study using Japanese supermarket scanner and membership card data to link item-level expenditure data with household characteristics (Shoji 2023). Such studies emphasise the role of diverse prices in influencing household-level inflation rates.

Third, we review options for UK data sources that would yield information on both household characteristics and prices paid for specific goods. The options discussed include household and supermarket scanner data, household survey data, and banking data. Each option involves significant trade-offs between detailed information, coverage, and implementation costs.

We then explore different methods of incorporating different prices paid for the same or similar goods into the HCIs. These include:

- Linking supermarket scanner data to household characteristics through membership cards, a specialised app, or geographic information;
- Modifying the collection method of a household survey such as the Living Costs and Food Survey (LCFS) to collect more detailed expenditure information; and
- Linking banking data containing personal characteristics to other data.

We emphasise that none of these options would be inexpensive or quick to implement.

We also suggest that a universal solution may not be practical. For instance, household scanner data covers only 15-40% of CPI items; understanding the distribution of prices paid for less frequently purchased goods may require detailed household survey data.

Finally, we suggest that a one-time or periodic study estimating the relationship between household inflation rates and characteristics could be used to model the spread of inflation rates across households. These findings could help to incorporate different prices paid for the same or similar goods by different household groups into HCIs in a way that is aligned with current economic conditions and aggregate inflation rates.

II. Introduction

In October 2022, inflation peaked at 13.6% for low-income households, 2 percentage points above the rate of inflation experienced by high-income households (Office for National Statistics 2023d). These differences were measured by the Household Cost Indices (HCIs), a set of inflation statistics that measure rates of inflation experienced by different types of households.

Households may experience different rates of inflation because:

(1) they purchase different types and qualities of goods;

(2) they pay different prices for the same or similar goods; and

(3) they have different preferences and demand elasticities across available goods.

HCIs, the newest inflation measure produced by ONS, measure how inflation is experienced by different types of households. Both the HCIs and the (discontinued) CPIH-consistent inflation rate estimates for UK household groups account for different mixes of goods purchased by different household groups, but assume that all households face the same changes in price within categories of goods.

Research suggests that this assumption likely does not hold in practice. That is, households often pay different prices for the same or similar goods (Griffith, O'Connell, and Smith 2016; Jaravel and O'Connell 2020b). As much as two-thirds of the variation in individual households' experienced rates of inflation may be explained by these differences in prices paid for the same goods (Kaplan and Schulhofer-Wohl 2017).

Households are likely to purchase different specific items within a group of similar goods that may have different price points. For example, two households may both buy loaves of bread, but a lower-income household is more likely to buy a value brand while a higher-income household may buy a premium brand. If the price of store-brand bread goes up proportionally more than for luxury brands, then the lower-income household faces a larger cost-of-living increase than the higher-income household. This issue can also be framed as one of having much greater detail in household baskets of goods; for example, considering different brands or qualities of bread, or the same bread purchased from different types of shops, to be different goods.[1]

It is important to understand which types of households are most impacted by changes in price levels to better inform monetary and social security policy. For example, benefits are generally uprated using the Consumer Prices Index (CPI), which reflects an average rate of inflation across the UK economy. However, if lower-income households experience higher inflation on average in times of economic upheaval, then over time the real value of benefits will fall (Lyssiotou and Pashardes 2004; Jaravel 2021). Higher inflation rates lower on the income distribution may also lead to higher effective taxation of lower-income households (Baye and Black 1992). These considerations become even more important at times of macroeconomic instability, when the inflation rates experienced across households have greater variation (Adams-Prassl and Levell 2014; Braun and Lein 2020; Orchard 2020; Argente and Lee 2021; Weber, Gorodnichenko, and Coibion 2023).

[1] Throughout this paper, we refer to this type of heterogeneity as paying different prices for the same or similar goods. The exception is when discussing papers that analyse prices paid by different households for the exact same goods (for example, those that conduct their analysis at the barcode level), we sometimes refer to prices paid for the same goods.

Incorporating variation in prices paid for the same or similar goods into the HCIs is therefore worth consideration. This paper explores potential methods for achieving this goal. In particular, we address the following questions:

- How might more detailed baskets of goods for different households be understood and incorporated into the Household Costs Indices?
- What data sources can be used to measure the type of items purchased by different households and the price paid for each item? What approaches might work for different types of goods?
- What is the potential for these data sources or modelling to be incorporated into the current Household Costs Indices (HCIs)?

In this paper, we review the current status of household cost indices in the UK and approaches taken by other countries. We also review methods of incorporating different prices paid by different types of households into HCIs in the academic literature. We then summarise available data and the potential for better data collection to support the creation of more detailed HCIs. We conclude by summarising approaches for producing subgroup-specific price indices based on the methods and data sources reviewed in the paper.

The paper proceeds as follows: section III summarises the current ONS price indices and approaches in other countries. Sections IV and V explore the methods and data available to calculate household-level costs indices that account for differences in prices paid for the same or similar goods. Section VI reviews an alternative option to model dispersion of inflation rates, and section VII concludes with a summary of approaches to incorporating different prices paid for the same or similar goods into household-level price indices. An appendix contains a summary of approaches and data used in key academic papers.

III. Current statistical approaches in the UK and other countries

UK price indices

The ONS produces three main measures of price inflation: the consumer prices index (CPI), the consumer prices index including owner-occupiers' housing costs (CPIH), and the household costs indices (HCIs).[2]

[2] The retail prices index (RPI) is a legacy measure produced due to statutory obligation but is not recommended for most uses.

Main inflation measures

CPI is produced primarily as a macroeconomic indicator (Office for National Statistics 2017a). It is based on guidelines for the EU Harmonised Index of Consumer Prices (HICP), making it internationally comparable (Office for National Statistics 2017b), and is used as the UK Government's inflation target.

CPIH is the ONS's lead measure of inflation. It extends the CPI to include a measure of the costs associated with owning, maintaining, and living in one's own home, known as owner occupiers' housing costs (OOH – see box for more detail), along with Council Tax.

HCIs are the newest main measure of inflation currently produced by the ONS. They weight each component in the basket for each subgroup by the share of spending of the average household in that group, and thus provide insight into the inflationary experience of different household subgroups. Both the basket of goods considered and the methods used to calculate the HCIs differ from those used for CPI and CPIH.

CPI and CPIH methods

CPI is calculated by comparing the total cost of the basket in a given period with the cost of the same basket in the base period. The index is then expressed as a percentage change, indicating the overall inflation or deflation in consumer prices.

A representative basket of goods and services is selected that reflects the typical consumption patterns of all households. This basket is updated periodically to account for changes in consumer behaviour and preferences.

The basket of goods and the weights for categories of goods come from household final consumption expenditure (HFCE) and the Living Costs and Food Survey (LCF). Additionally, insights into trends are gathered from in-depth analyses conducted by market research companies, information found in trade journals, and reports in the press. Price collectors and auditors also contribute by providing updates on developments within the retail environment.

The goods and services in the basket are organised into categories, called strata, such as food, housing, clothing, transportation, healthcare, education, and recreation. Stratification allows for a detailed analysis of price changes within specific sectors.

Four main categories of weight exist within consumer price indices:

1. Central or regional shop weights
2. Stratum weights (region and shop type)
3. Item weights
4. Classification of Individual Consumption According to Purpose (COICOP) weights for the CPIH and CPI higher-level indices

Weights (1) and (2) help create item indices by combining individual price quotes for the items in the basket. Weight category (3) is used for making COICOP subclass-level indices, and weight category (4) is used to create indices for COICOP class, group, division, and all items together. Both COICOP subclass-level indices (3) and higher-level indices (4) are shared with the public, while (1) and (2) can theoretically be reproduced from publicly available data.

Weights are assigned to each stratum based on their share of the average household budget (expressed in base period prices) to reflect the relative importance of different items in the basket. Total expenditure on each stratum is used, so that households with higher spending implicitly have more influence in the weights (called *plutocratic weighting*). This ensures that items with a greater impact on overall spending have a higher weight in the index. For example, a 10% increase in the price of petrol has a much bigger impact on the CPI than a similar rise in the price of tea.

Prices for the items in the basket are collected regularly. Data is gathered from various sources, including retail stores, service providers, and online platforms.

CPIH is calculated similarly to CPI, but also includes housing-related costs, such as owner occupiers' housing costs (OOH). OOH cover expenses associated with owning, maintaining, and living in one's own home. This makes CPIH more reflective of the overall cost of living for homeowners. CPI is calculated by comparing the total cost of the basket in each period with the cost of the same basket in the base period. The index is then expressed as a percentage change, indicating the overall inflation or deflation in consumer prices.

Owner-occupiers' housing costs

Owner-occupiers' housing costs (OOH) are the expenses associated with owning, maintaining, and residing in one's own home. Currently, OOH make up 16.5% of the expenditure weight in CPIH.

OOH is measured using rental equivalence. This considers the rent paid for an equivalent house as a substitute for the costs faced by an owner occupier.

These costs are distinct from the cost of purchasing a house, which is made up of both the cost of housing services and an accumulation of wealth.

OOH excludes expenses like utility bills, minor repairs, and maintenance, as these are accounted for elsewhere in the CPIH.

The development of HCIs

HCIs are not the first attempt in the UK to address varying inflation rates for different households. In the 1970s, the Department of Employment and Treasury explored the idea with the Retail Price Index (RPI) for groups like pensioners and the low-paid (HM Treasury 1974). These were discontinued as recently as 2017 (Office for National Statistics 2016). Additionally, sub-group estimates that are consistent with CPIH were published between 2017 and December 2022.

In the mid-2010s, there was a growing recognition of the need for a more nuanced understanding of how inflation experiences differed across diverse households. Calls were made to enhance the accounting for costs such as mortgage interest and owner-occupied housing (Johnson 2015; Astin and Leyland 2015).

Following the consultation on the Johnson Review, a commitment was made in 2016 to develop HCIs, aiming to address user needs distinct from those met by the Consumer Price Index (CPI) and the CPI including owner occupiers' housing costs (CPIH). The development phase spanned from 2016 to 2023, with the official launch of HCIs occurring in December 2023 as quarterly official statistics in development.

In 2021, there were increasing concerns that rising inflation was having a disproportionate impact on people in poorer households in the UK. These concerns prompted the ONS to commit to do more to capture the impact of price increases on different income groups (Hardie 2022).

How HCIs differ from other measures

The HCIs represent a distinctive approach to measuring consumer price inflation that aims to reflect different UK household groups' experiences of changing prices and costs.

The weights for the HCIs are based on the average households' spending patterns *within specific subgroups of households.* Each household's budget shares are weighted equally within subgroups; this is called *democratic weighting*. The weights for different types of households are sourced from HFCE and the Living Cost and Food Survey (LCFS) (see section V).

The HCIs differentiate inflation measures for a range of population subgroups, defined by;

- Income decile;
- Expenditure decile (currently omitted from publication tables);
- Tenure type (whether a household is a private renter, a non-private renter, an outright-owner occupier, or a partial owner occupier);
- Retirement status; and
- Whether a household has children or not.

Strata are defined, and price measures are collected for each stratum, similar to the approach taken for CPI and CPIH.

The scope of the basket of goods and services in the HCIs differs slightly from that used in the CPIH and the CPI. Notably, the HCIs use a measure of direct OOH payments in place of rental equivalence. This includes items such as mortgage interest payments, dwelling insurance, ground rent, and Stamp Duty Land Tax. This adjustment allows HCIs to more closely align with the changes in housing costs experienced by different UK households.

Other notable differences include considerations for interest payments on debt (not covered by CPIH and CPI), university education (where HCIs factor in changes to student loan repayments), and unadjusted insurance weights.

By directly capturing different financial commitments of households, HCIs provide a more nuanced understanding of inflation's impact on different household types.

Household group price indices in other countries

Several countries' national statistics offices have implemented innovative approaches to understand the effect of price changes on specific household groups. These approaches are similar to those taken by the UK but use a number of different data sources and household groupings.

Both New Zealand and Australia regularly produce unique living cost indices which are designed to provide insights into the inflation experiences of specific sub-population groups. Conceptually, these indices are similar across countries in that they both focus on specific demographic subsets of the population. While these indices make use of granular price and expenditure information, currently these indexes do not account for brand level expenditure by household groups.

New Zealand: HLCPIs

New Zealand's Household Living-Costs Price Indexes (HLCPIs) date to 2016, reporting 13 unique indices for specific household groups on a quarterly basis. These groupings include income quantiles, expenditure quintiles, state beneficiaries, Māori, and state pension recipients (denoted as super-annuitants in NZ).

Information from the Household Economic Survey (HES) is used to gather group-specific expenditure patterns which inform item level weights. The HES gathers household expenditure information once every three years and includes detailed expenditure information on around 700 specific commodities. The HES is notably detailed; for instance, commodity-level information goes beyond whether the good was fruit, but also specifies the exact type of fruit. For specific goods, Stats NZ does not collect brand level information but calculates product type price averages. Additionally, the HES retains region and store-type information (i.e. discount store vs. flagship). This store and regional level information is then used to compute average prices, which are democratically weighted by expenditure shares for each household group. The HLCPI owner-occupied housing costs are calculated using the payments approach, which seeks to track housing costs and mortgage payments/ interest as they are incurred, interest rate changes are quality adjusted to maintain household purchasing power.

New Zealand uses several data sources to collect price data for inclusion in the HLCPIs. These include 100,000 commodity prices from various retail outlets along with around 1,700 surveys to firms in various sectors; scanner and web-scraped data (Krsinich 2011); and brand-level information from market research company GfK (Krsinich 2015; Bentley and Krsinich 2017). Stats NZ is also planning to incorporate web-scraped prices into their main CPI measures (Lynch, Stansfield, and Olivecrona 2018).

Australia: SLCIs

Australia's Selected Living Cost Indexes (SLCIs) are similar to the HCIs and HLCPIs and calculate price indices for specific subsets of the population. The SLCI is comprised of two distinct series of indexes, including the Pension & Beneficiary Living Cost Index (PBLCI) and the Analytical Living Cost Indexes (ALCIs).

The ALCIs are comprised of indices which focus on four specific household types based on their principal sources of income. These include employee households (where the principal source of income comes from wages and salaries), old-age pensioner households, other government transfer households, and self-funded retiree households. These indices are designed to measure how changes in prices and out-of-pocket expenses incurred by households might impact purchasing power and the cost-of-living for these unique subsets of the population. In many ways Australia's approach in calculating the ALCIs are like New Zealand's. The construction of the SLCIs is a three-stage process, where first plutocratic weights are calculated to be representative of the expenditure patterns of specific household types (Australian Bureau of Statistics 2023). Next, they identify the change in average prices in broad good categories, and finally the weights are matched with the price information so that aggregate indices can be calculated.

In keeping with the steps outlined above, Australia's expenditure weights are updated annually and are primarily based on Australia's Household Expenditure Survey (HES). The HES is Australia's most detailed survey which provides household characteristic and expenditure information by commodity groups (i.e. broad categories include clothing, food and housing). The expenditure component of this survey is taken relatively infrequently, once every 6 years. In non-HES years, ABS makes use of the Household Final Consumption Expenditure (HFCE) data from the National Accounts. As was the case for New Zealand, the infrequency of detailed household expenditure data marks a major limitation in the SLCIs. The SLCIs use the outlays approach for tracking expenditures related to dwellings, housing costs, financial services, and the use of credit. This approach includes changes in the amount of interest paid on mortgages and other costs, including maintenance costs and council rates for all owner-occupied housing.

Like New Zealand, Australia uses a number of data sources including supermarket scanner data and web-scraped prices for specific goods.

Other countries

Although the United States does not currently publish official CPI indices categorized by household subgroups, the Bureau of Labor Statistics (BLS) has developed additional sets of experimental price indices tailed for specific household demographics using existing CPI price information from the Consumer Expenditure survey.

Moulton and Stewart (1999) provide an instance of one such index, where the BLS computes CPI weights using the geometric mean or the Törnqvist Index instead of the Laspeyres index (arithmetic mean) to create price indices for elderly and low-income households. This adjusted index is said to be more representative of a true cost of living index. Klick and Stockburger (2021) provides a detailed analysis comparing modified Laspeyres and Törnqvist index approaches. Lastly, Cage et al. (2002) re-weight the CPI basket using the Consumer Expenditure Survey to analyse real welfare inequality in the U.S.

Most recently, the Panel on Improving Cost-of-Living Indexes and Consumer Inflation Statistics in the Digital Age (2022) recommended that BLS explore options to produce price indexes to measure inflation trends for subgroups of the population. Some of these approaches are detailed in section IV.

Some other countries do not produce inflation measures for different household groups, but use innovative methods of data collection to improve CPI. Where relevant, these are reviewed in section V.

IV. Theory and methods in academic and grey literature

Theoretical considerations

Consumer price indices approximate a cost-of-living index (COLI), defined as the change in nominal income required to maintain the same standard of living over time (Diewert 1990). Since it is impossible to make exact utility comparisons across households, or to observe what quantities of goods would have been purchased had another set of prices prevailed, COLIs cannot be directly calculated. Laspeyres and Paasche indices approximate an upper and a lower bound for a true COLI, and a Fisher index (the geometric mean of a Laspeyres and a Paasche index) is likely to approximate a COLI.[3]

The economic theory behind price indexes usually assumes that the preferences and utility function of a "representative consumer" can be aggregated to the national level (Triplett 2001) and that the law of one price holds (i.e., that the same good will cost the same everywhere) (United Nations 2004, 18). In practice prices for the same or similar goods vary by location, store type, and other factors, and changes in the price of different goods show significant heterogeneity (Bunn and Ellis 2012).

Interest in price indices that are specific to different household groups arises from the recognition that households buy different goods in different combinations (called non-homotheticity), pay different prices for the same or similar goods, and substitute differently between goods whose prices change at different rates.

In the following section, we review approaches taken in the academic literature to account for these differences across households.

Studies accounting for non-homotheticity

Many studies calculating household group-level price indices account for non-homotheticity but assume the same prices for the same or similar goods across households. Price indices are then compared across different household groups.

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[3] Some of the details of the theory behind these approximations, as well as a discussion of the theoretical issues in calculating household group price indices, are discussed in more detail in Jaravel (2021).

The majority of studies of this type use consumer surveys to produce different expenditure shares (weights) across types of households (Muellbauer 1974; Crawford and Smith 2002; Hobijn and Lagakos 2005; Adams-Prassl and Levell 2014).[4] They then assign the same prices within categories of goods for all households, usually obtained from CPI price data.

These studies often use very broad categories of goods, based on limitations introduced either by categorisations in the survey data or available price data. For example, Muellbauer (1974) studies nine categories of goods for which Blue Book price indices have already been calculated: food, clothing, housing, fuel and light, drink and tobacco, travel, miscellaneous goods and services, and durables. Later studies typically aggregate to narrower categories of goods as available data grow more granular. For example, Crawford and Smith (2002) use UK Family Expenditure Survey data and aggregate to 69 goods categories to match price data from the RPI.

Other studies of this type use large-scale consumer panels like the Nielsen HomeScan data (Jaravel and O’Connell 2020b). These data have much more specific (i.e. barcode-level) information about the quantity of separate goods purchased and the average price paid per unit.

Household groupings depend on the context, available data, and what is considered of most interest. Common groupings include by income quantile, age (e.g. pensioner and non-pensioner households), and by region or rural and urban status.

Another approach is to use statistical methods to determine household groups. Chelli, Gigliarano, and Mattioli (2009) use non-parametric discriminant analysis to determine which household characteristics create household groups with the largest differences in shopping and consumption behaviour. They find that household consumption behaviour is most different when households are defined by the presence of someone under 18 and the gender of the main householder. There is also evidence that there is more variation in household group price indices calculated on the basis of composition or age than for those defined by household income groupings (Hobijn et al. 2009).

In the UK, studies estimating household group price indices that account for non-homotheticity typically find that lower-income households experience higher inflation (Muellbauer 1974; Adams-Prassl and Levell 2014; Gürer and Weichenrieder 2020). Crawford and Smith (2002) calculate plutocractic Laspeyres indices across the income distribution from 1976 to 1999 and find that lower-income households more often have higher inflation rates, but that when higher-income households see higher inflation, the difference in rates is larger. However, using a similar approach and the same data, Levell and Oldfield (2011) find that lower-income

[4] The most comprehensive household expenditure survey in the UK is the Living Costs and Food Survey (LCFS). The LCFS, formerly called the Expenditure and Food Survey (EFS), replaced both the Family Expenditure Survey (FES) and the National Food Survey (NFS) after 2001. The Institute for Fiscal Studies has created a consistent time series of expenditure and household demographic data derived from the FES, EFS, and LCFS that covers 1968-2017, which was last updated in 2020.

households had higher inflation rates than higher-income households for much of 2000-2009, due mainly to higher budget shares going towards goods with higher inflation rates.

The exceptions to this finding are two studies focusing on economic crises: Jaravel and O'Connell's (2020b) study of the pandemic and Stempel's (2022) estimate for inflation by quintile in 2010.The first calculates a fixed base Fisher index with expenditure weights defined at the household level and a common set of prices across households to compare the first five months of 2020 to the same period in previous years. Using the Kantar FMCG Purchase Panel data until May 2020, they find that those in lower-income households and households with younger household heads experienced lower inflation during the first lockdown in 2020, but contrast this to the opposite finding in 2018 and 2019. Stempel also find higher inflation rates among lower-income households for all years except 2010, which may be attributable to lingering effects from the Great Recession.

The findings on lower-income households also hold in the US for 1987-2001 (Hobijn and Lagakos 2005), 2003-2018 (Klick and Stockburger 2021) and during the Covid-19 lockdown (Cavallo 2023), Italy from 1997-2007 (Cepparulo et al. 2012), Australia for 2011-2018 (van Kints and Breunig 2021), Türkiye for 2006-2021 (Dasdemir 2022), and Bangladesh from 1970-2012 (Hossain and Mujeri 2020). In contrast, Cage, Garner, and Ruiz-Castillo (2002) find pro-poor relative changes in price levels in the US during the 1980s, but higher relative inflation in urban areas compared to rural.

Some international findings differ in conclusions about older households. Whereas most studies on the US, UK, and other Western countries find lower inflation rates among older households, Abe and Shiotani (2014) find that older Japanese households pay higher prices using a relative price index approach. They conclude that although some of the price differential is accounted for by shopping at different types of stores, the residual differences are unexplained by their data. Lieu et al. (2013) come to a similar overall conclusion for Taiwan using data from 1981-2001. Additionally, in the US, higher inflation rates may be calculated for older households when medical costs are accounted for (Hobijn et al. 2009).

Studies of inflation rates across regions within the UK find higher rates of inflation in London and the South East from 1997-2008 (Rienzo 2017) and in 2016 (Hearne 2021).

An alternative approach to calculating price indices within household groups is to regress estimated household-level inflation rates on household characteristics to determine which factors are most related to higher inflation. The procedure for calculating household-level inflation rates is generally similar to those above, albeit at the household rather than household group level. That is, the same vector of changes in prices is weighted by individual household expenditure shares obtained from survey data.

This approach yields similar conclusions for the UK (Fry and Pashardes 1985) and the US (Michael 1979; Hagemann 1982) to studies that calculate household-level inflation and aggregate into measures for different types of households; that is, they find that income is negatively related to experienced inflation. In contrast, estimates for Greece using this method show higher inflation for higher-income households, childless couples, single households, and households with older or less educated heads (Livada 1990).

There is also some divergence in findings regarding the persistence of different inflation rates between household types. Where Muellbauer (1974) concludes that consumer prices rose more for low-income households between the 1940s and 1970s in the UK, US studies covering the 1940s to 1970s and 1987-2001 find little persistence in relative inflation rates for given household groups over a similar period (Hollister and Palmer 1969; Michael 1979; Hagemann 1982; Hobijn and Lagakos 2005).

Studies accounting for non-homotheticity and different prices

A smaller body of work accounts for both non-homotheticity and different prices paid for the same or similar goods. Further details of key papers of this type are summarised in Appendix Table A1.

Early studies in this area focus on comparing prices paid for the same goods cross-sectionally across groups of households. Evidence from the Nielsen HomeScan data for the US shows that retired households pay less for the same goods (identified via barcode) because they shop more frequently (Aguiar and Hurst 2007) and across a greater number of stores (Kaplan and Menzio 2015); Japanese data shows a similar pattern (Abe and Shiotani 2014). Using a telephone consumer survey combined with CPI store and price data, Kurtzon and McClelland (2010) compare prices paid for the same goods across different stores and found that lower-income households do not systematically pay more or less for the same goods than higher-income households.

However, comparisons of prices paid for the exact same goods ignore non-homotheticity of the bundles households buy. Using Nielsen HomeScan data for the US from 1994-2005, Broda and Romalis (2009) allow bundles to vary across household income groups and the introduction of new goods with differing effects across households. They calculate exact price indices for non-durable goods at the barcode level, and then apply weights averaged within income groups. They find that lower-income households experienced lower inflation rates for non-durable goods over this period. When a component accounting for households' willingness-to-pay for new goods is incorporated and the calculation is repeated for a larger set of goods, higher inflation for lower-income households persists (Kaplan et al. 2019).

Like Broda and Romalis, Kaplan and Schulhofer-Wohl (2017) apply Nielsen HomeScan data for the US to the question of heterogeneous inflation rates. However, rather than calculate bundles within income groups, they calculate annual inflation rates for each household individually, then aggregate up to democratic household group-level indices. Their study is limited by the restriction of goods in each household's basket to those that were purchased in both the start and end period, thus covering mainly frequently-purchased goods. They estimate that their sample covers about 30% of the goods in CPI.

In contrast to Broda and Romalis, but more in line with previous literature on non-homotheticity, Kaplan and Schulhofer-Wohl find a wide dispersion of inflation rates at the household level. Nearly two-thirds of the dispersion in this context comes from paying different prices for similar goods and one-third from differences in the mix of goods purchased within broad categories. Consistent with previous studies differentiating between households only by consumption patterns across broad categories of goods and services (strata), they find greater inflation for lower-income households, larger households, and households with older heads. These differences are small on an annual basis, but persist and accumulate over time. They conclude that only about 7% of the variation in inflation across households arises from differences in consumption across strata. This indicates that previous estimates of household-specific inflation for the US significantly under-estimate the variation in household-level price indices.

An alternative approach with household scanner data is to average prices paid for specific continuing goods (defined at the barcode level) within household groups at each time period, then calculate the change in prices paid for each good by each group (Jaravel and O'Connell 2020a; 2020b; Argente and Lee 2021). This has the advantage of not limiting the sample of goods to only those purchased twice by a given household. A third approach is to aggregate goods to modules within barcode-level scanner data (similar goods, e.g. different brands of milk) and calculate price indices at the household level (Weber, Gorodnichenko, and Coibion 2023).

Two additional studies stand out for their contributions to this literature.

First, Braun and Lein (2020) use Nielsen HomeScan data for Switzerland and calculate Redding-Weinstein indices, which account for differences in household preferences in addition to different bundles of goods and prices paid for similar goods. Preferences include different demand elasticities across goods in response to changes in relative price. They conclude that differences in preferences across households account for two-thirds of the variation in inflation rates in their data, where prices paid for the same goods accounted for about one-fourth and different goods bundles the remainder. In contrast to other studies, they find that households with higher demand elasticities (i.e. that substitute more readily between goods when relative prices change) experience lower inflation, including lower-income households and larger households.

Braun and Lein's results stand in contrast to a body of work that tends to find higher inflation rates for these groups. Further, their findings suggest that even if inflation measures can account for different prices paid for the same or similar goods, they may not give an accurate picture of different inflations across groups when variation in preferences is not also taken into account.

Second, Shoji (2023) employs a novel data source to link household characteristics to scanner data in Japan. He uses supermarket scanner data linked to household characteristics through store membership cards. He averages prices paid by each household in each period at the module level (one level of aggregation up from barcode-level, e.g., all brands of milk), and then weights the household-level inflation rate for each module by the average share of expenditure over the current and past periods. This approach has the benefit of including more goods through the module-level aggregation (where it is more likely that households purchase something from a given module in more than one period), but also avoids averaging prices paid across a large group of households.

Price variation in the UK

Studies accounting for homotheticity and different prices paid for the same or similar goods focus on non-UK contexts, particularly the US. They suggest that, in these contexts, a large amount of the variation in the inflation rates experienced by individual households can be explained by paying different prices for the same or similar goods.

However, there are reasons to believe that variation in prices paid for the same or similar goods would account for a smaller proportion of the difference in household-level inflation rates in the UK than elsewhere. First, most supermarket chains in the UK apply standard pricing for the same goods across their locations, reducing differences paid by region. Second, regulations reduce differences in energy prices. Third, there is less market segmentation in retail goods in the UK than in the US, so that a smaller number of firms account for a large proportion of the market in many types of goods.

The amount of variation in measures of goods price changes also depends on the level of measurement. Several of the studies above calculate household-level inflation measures, which have a greater degree of variation. Household group-level measures would likely have less dispersion.

V. Data and applications

As is clear from the work of statistical agencies, academics, and others, there is a wide range of data that can be leveraged to yield information about changes in prices. These data sources include household and supermarket scanner data, banking data, and consumer surveys. In some methods, creative or theoretical ways of linking different types of data also offer options for accounting for the prices different households pay for the same or similar goods.

Table 1 describes some of these key data sources and presents some of the strong points and limitations of each.

Table 1: Description of key data sources

Characteristic	Household Scanner Data	Supermarket Scanner Data	Receipt Scanning	Banking data	Living Cost and Food Survey
Data Type	Barcode-level dataset of purchases with household characteristics	Record of purchases from supermarkets	Information from scanned receipts	Financial transactions	Household expenditure data
Collection Method	Provided scanners to households for purchases	Supermarket records	Scanned manually or via mobile apps	Anonymised individual account data	Voluntary sample survey - interviews, diaries, measurements

Granularity	Includes prices and quantities at the barcode level	Includes prices and quantities	Basic, quantity and total cost information	Limited – only total transactions	Total spent on goods by type; includes irregularly purchased goods
Household Characteristics	Yes, including: Age/retirement status and number of household members Region Income Sometimes race, gender, education	Broad geographic information may be assumed (e.g. region)	Limited; if collected by mobile app, may collect some information on household composition and characteristics, age, gender, etc.	Limited, and generally aggregated to geographic area (e.g. postal sector) May also have: Gender Age band Estimated income, some benefits	Yes, including: Age, number, and gender of household members Region Income, including benefits Ethnicity Employment
Limitations	Retail purchases only; excludes some categories, especially infrequently-purchased goods (housing, healthcare, fresh fruit) High cost	Need data linkage or imputation from external sources to supplement missing characteristics Captures only frequently purchased goods	Lacks granularity; less detailed May be biased depending on how sample is recruited	Single bank or card focus Aggregate figures; Integration challenges	Declining response rates Potential underreporting
Sources/ONS usage	Examples - Nielsen HomeScan data, and FMCG Purchase Panel. Not currently used by ONS.	ONS plans to introduce use of grocery scanner data across inflation measures in 2025	Collected by statistical agencies or market research companies. Not currently used by ONS.	ONS partnership with Visa for card payments data (usage in development) Smart Data Foundry (NatWest Group)	ONS produces LCFS and uses it to create weights for production of CPI, CPIH, and HCIs

Scanner data

Scanner data collected from households and retailers can be a source of very detailed information on consumer spending but is often costly to collect or buy and may cover only a subset of goods. An overview of the past uses and potential applications of scanner data in economic research can be found in Dubois, Griffith, and O'Connell (2022).

Household scanner data

Household scanner data is usually obtained by giving households a scanner and asking them to scan all their purchases. The result is a barcode-level dataset of purchases, including prices and quantities, that can then be linked to household demographic and economic information.

Examples of this type of data include the Kilts-Nielsen Consumer Panel (KNCP) data, Nielsen HomeScan data, the Kantar Fast-Moving Consumer Goods (FMCG) Purchase Panel, and data collected by the market research firm GfK. While the KNCP is a modified version of the Nielsen HomeScan data that applies only to the US, the other datasets cover a number of countries including the UK.

The primary strength of these data is their ability to tie unit prices and quantities purchased to household characteristics. Characteristics typically collected include household composition and respondent age, education, annual income, employment, and marital status. The inclusion of these variables is a key consideration for incorporating different prices paid for the same or similar goods into the HCIs.

One concern in the past has been whether or not household characteristics are updated (Abe and Shiotani 2014); currently, Nielsen update survey households' characteristics annually. It is not clear if Kantar and GfK similarly update characteristics.

Another strength is the level of disaggregation of product types available in these data. All of the datasets listed above identify items using a 12-digit universal product code (UPC), allowing purchases of very specific goods to be tracked over time. Households typically stay in these panels across several quarters or years, allowing the calculation of inflation rates that follow the same households. Barcodes are also sorted into modules, which are formed of similar goods (e.g. different brands of the same type of good). As discussed in the previous section, module-level analysis may be preferred to increase the likelihood that households purchase a good from the module over successive periods.

These data also have significant limitations. Kaplan and Schulhofer-Wohl (2017) highlight that household scanner data captures only retail purchases. This is emphasised by the Kantar data, which promises only to track purchases of fast-moving consumer goods. Categories like housing, healthcare, and education are not well-accounted for by these data, although unit prices may vary widely across households. Additionally, these data typically do not include information on the purchase of goods that do not have barcodes, such as fresh food (Abe and Shiotani 2014). Typical coverage reported by studies using household scanner data is between 15-40% of the goods included in CPI.

It is also unclear how quality changes are controlled for in these data for changes that do not result in a new barcode. Even when new barcodes are assigned, researchers may want to make a quality or quantity adjustment and treat the two barcodes as the same good. Quality controls introduced by the user, like those currently used by ONS, may be possible, although doing so at the barcode level would be labour-intensive.

Furthermore, commercial datasets of this type are typically expensive to access, such that the cost may be prohibitive to national statistics agencies.

PRISMA

In 2018, the European System of Central Banks (ESCB) set up the Price-setting Microdata Analysis Network (PRISMA), which aims to better understand price-setting behaviour and inflation rates within EU countries.

PRISMA uses various sources of data in their research, including supermarket and household scanner data (the latter from GfK/Kantar). They have published work on inflation heterogeneity across household groups estimated for 16 European countries, including the UK, between 2005 and 2018 (Strasser et al. 2023).

Broadly, they find that the dispersion of inflation rates across households tends to be lower in Europe than in the US. In their estimates, more of the variation in household-level inflation rates comes from purchasing different goods within broad categories and regional variations in price rather than from paying different prices for the same goods. Like other studies, they find that lower-income households in the UK experience higher inflation rates than higher-income households.

Supermarket scanner data

Supermarket scanner data consists of a record of purchases from supermarket records, usually including the unit price, quantity, and classification of the good at the barcode level. It differs from transaction data in that it also includes quantity and unit price, rather than simply the overall amount spent on a particular good. It is therefore very useful for tracking changes in the price of specific goods over time.

Examples of this type of scanner data include the Nielsen Retail Panel and GfK data collected from supermarkets. These are used by a number of national statistics bodies to feed into their household group inflation statistics.

However, supermarket scanner data is of more limited usefulness for improving the HCIs than household scanner data because it does not directly include information about household characteristics. Furthermore, it has similar limitations to household scanner data, such as only including frequently purchased goods and capturing only a part of the goods usually included in the CPI. However, it may have a slight advantage over household scanner data on purchase frequency, since there are likely more goods that are purchased more than once in a given period at the same store than would be true within the same household. It can also account for differences in prices paid for the same or similar goods at the same store.

Using supermarket scanner data to calculate HCIs that account for different prices paid for the same or similar goods would require data linkage and/or imputation of some household characteristics from other data that accompany the scanner data.

The ONS are currently developing supermarket scanner data for use in their calculation of CPI and CPIH starting in 2025. Thus, an approach that makes use of supermarket scanner data would likely be less costly than purchasing expensive household scanner data and possibly quicker to implement than other approaches.

Scanned receipts

Information obtained from scanned receipts provides basic information regarding the quantity and cost of newly purchased goods and services but lacks the granularity inherent in point-of-sale scanner data. Traditionally, scanned receipt data have been collected through posted paper receipts, to be scanned manually, or through emailed scanned images. Participation in samples collecting scanned receipts may be voluntary, which may introduce participation bias, or may be conducted through sampling as with representative surveys.

Some notable examples of countries that have used receipt scanning for household budget survey purposes include Sweden, Finland, Ireland, and the Netherlands. Pre- 2020, all of these countries scanned receipts in-house, including manual coding and editing, with varying levels of accuracy (Benedikt et al. 2020). Austria is also notable as they require virtual cashier integration, where QR codes representing each product on receipts are required.

More recently, the collection of receipt data has evolved, with mobile scanner apps enabling on-site automatic transcription of receipt information, making the collection of this type of data more feasible. Recent literature discussing receipt scanning has focused on integrating machine learning models and artificial intelligence in order to automate receipt scanning and product classification (Benedikt et al. 2020; Lin, Liu, and Lee 2022). Efforts in the UK with a sample from the Understanding Society panel show that scanned receipts plus direct entry for non-receipted purchases track closely with expenditures as measured in the Living Costs and Food Survey (Wenz et al. 2023).

Banking data

Banking data consists of comprehensive information related to financial transactions, account balances, income, and expenditures, offering a detailed overview of an individual's account.

An example of this is the Smart Data Foundry, which has access to NatWest Group (NWG) bank account data. This consists of anonymised personal data from approximately 5 million UK-based customers' current accounts (up from 1.2 million in 2019).

This dataset includes weekly summaries of account balances, estimated income, and expenditures categorised for each customer, along with demographic details such as age, gender, and postcode district. In cases where a customer holds multiple current accounts within NWG, the balances, incomes, and expenditures from all accounts are combined.

The ONS also possesses some banking data already, making it a promising route for future work (Office for National Statistics 2023c). Through a partnership with Visa, the ONS receives aggregated and anonymized data on card payments in the UK.

Strengths of these data include the timeliness of Visa card spending data, offering near-real-time data on consumer behaviour. The ONS receives monthly data refreshed every quarter, providing granular spending details at a postal area level, offering a distinct dataset with high geographical granularity.

While banking data is potentially useful, it has significant limitations for the calculation of household-level inflation rates. Banking data captures only part of a consumer's purchases if they have multiple accounts, and it is difficult to link consumers into household units. Additionally, the dataset only includes aggregate figures such as the total amount spent on transactions, as opposed to information on specific goods purchased or unit prices paid. This lack of specific information is a problem when trying to figure out how prices are changing for different things, which is crucial for understanding inflation rates. Finally, unless the ONS partners with all credit card providers or banks, the data will only capture a subset of bank users, and it may be difficult to tell if the sample is representative of the wider population even when the proportion of the market captured is known.

In an ideal scenario, merging banking and supermarket data could facilitate the creation of nuanced inflation rates for different demographic groups. However, practical implementation of this poses significant challenges.

Living Costs and Food Survey

The Living Costs and Food Survey (LCFS) is the main source of weights assigned to categories of goods in the calculation of CPI, CPIH, and the HCIs. Adjustments to the way the survey is collected may provide an avenue for improving the HCIs to include different prices paid for the same or similar goods.

The LCFS provides the most detailed household expenditure data currently available for the UK. In addition to capturing details of spending, the survey also collects valuable information about the income and characteristics of household members (Office for National Statistics 2023b).

Method of collection and content

The LCFS is a voluntary sample survey of private households, drawing from an achieved sample of approximately 6,000 households annually. However, declining response rates in social surveys have led to a reduction in the achieved sample over time, impacting the precision of estimates (Office for National Statistics 2023a).

The LCFS chooses its sample from the Royal Mail's Postcode Address File (PAF) of small users. Recognised as the largest address database in the UK, the PAF is regularly updated every day, covering approximately 30 million addresses. The survey is calibrated with survey weights to be nationally representative.

The survey has several components, including a household questionnaire, an income questionnaire answered by all household adults, and a spending diary. Additional household characteristics like region, composition, and income are also included.[5]

In the household questionnaire, participating households are surveyed on their characteristics, including size, members' age and gender, ethnicity, and employment status. This part of the survey also collects retrospective information on regular spending, such as mortgages and insurance policies, and infrequently purchased items like vehicles.

Respondents, including children, keep a detailed diary of expenditure for two weeks. Respondents also record the weights and measures of food and drink items bought.

Potential for use to improve HCIs

One notable advantage of the LCFS is its provision of household-level expenditure data, allowing for a comprehensive analysis of spending patterns and demographics.

However, despite its strengths, the LCFS has notable limitations. The level of detail on specific goods purchased currently is not nearly as detailed as in scanner data. The survey is also suspected of underreporting expenditures for certain items, such as alcohol and tobacco. Moreover, its exclusive focus on private households excludes specific segments of the population like those residing in student halls or communal establishments such as nursing homes, potentially leading to incomplete demographic representations.

One possibility is that the collection method of the LCFS could be updated to offer some of the same characteristics as commercial household scanner datasets. For example, if households were given scanners or a receipt scanner app, their demographic characteristics would be linked to barcode-level records of units purchased and average prices paid. However, this would require significant investments of money and time on the part of ONS, including the creation of a new system to produce household-level estimates before aggregation.[6]

There are also several issues that might affect the utility of the LCFS for informing HCI estimates. One is non-response bias, which might affect the accuracy of estimates for particular groups more than others. As with other data sources, it may also be difficult to accurately capture less frequently purchased goods, since they will appear in relatively few observations within each household group. In the case of a receipt scanner app, the additional processing required would be resource-intensive (either manual or through an algorithmic approach).

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[5] More specific geographic variables are available in the secure version of the data.

[6] Current subgroup estimates are aggregated at the Class level.

APPLIED EXAMPLE: The @HBS project app

In response to Eurostat's call to modernize household budget surveys, the @HBS project has created a smartphone app designed to streamline the collection of household budget data by integrating various forms of data.

On the front end, the app acts as a household budgeting app, where users can track their spending habits over time on broad categories such as food, housing, recreation, and alcohol/ cigarette purchases. It collects scanned receipts, geographic data, and connects to supermarket scanner data and banking data through big data linkage. This app is currently active in the Netherlands but the extent to which these data are currently used in inflation statistics is unclear.

The first component of the data is receipt scanning, which is integrated into the @HBS app. Users scan their receipts directly into the app using their phone cameras and specify at which store the purchases were made. The app then processes the information to gather basic quantity and price information on brand-specific products. This method improves on both the respondent experience and the ease of processing. Receipt scanning can reduce respondent burden, and app-based receipt scanning had similar accuracy to traditional flatbed scanner receipts (Schouten 2022).

Information from scanned receipts is then linked to two other forms of data. First, the app asks respondents for consent to link to data which is already in the possession of the specific country's national statistics institute. These data include barcode product descriptions and price data as well as supermarket scanner data. Second, respondents are asked to self-request data from external data holders, includingbank transaction data and loyalty card data. For example, the @HBS app can send requests to the API of a user's bank to share their data. Loyalty card data linkages work in a similar way, where app users input into the @HBS up the store names and loyalty card numbers and loyalty card data are requested on their behalf. Finally, geo-locations are collected when app users enter "geographic fences" in the vicinity of storefronts.

One considerable limitation is that respondents are sometimes hesitant to consent to bank transaction data linkages. Similarly, respondents questioned what added value statistics offices get from transaction data over aggregate expenditure measures. Furthermore, while the app allows for the collection of detailed household expenditure data, it is not clear whether this data can be linked to household income and employment information (along with other household demographic characteristics). While use of the app can be targeted to a representative sample, there may also be issues with non-response bias if some groups are less likely to use the app (or allow data linkage) when asked than others.

There are a few other examples of countries that collect data through apps, but none are as comprehensive as @HBS. Examples include Finland's Household Budget Survey App and the most recent iteration of the Norwegian Household Budget Survey (2022) both of which solely focus on receipt scanning. Belgium and Eurostat spent time developing a Household Budget and time-use survey app (Sabbe, Kelly et al. 2018) which would collect expenditure data by broad categories of goods.

VI. Other options

Beyond approaches like those used in the academic literature, there are a few methods using data linkage or modelling that might offer insights into price level changes experienced by different household groups.

Store scanner data linkage

One possibility is that supermarket or other store scanner data combined with other data on household characteristics could be used to create measures of changes in goods prices experienced by different types of households.

This could be achieved in several ways. For example, suppose that store membership card data can be linked to supermarket scanner data. Household characteristics can then be derived either through information provided by consumers when they registered for the card, as in Shoji (2023). Alternatively, purchase patterns could be linked to household characteristics like average income, demographics, and indices for multiple deprivation via the postcode associated with the membership card.

Another possibility is that the location of each supermarket could be used to impute the characteristics of people likely to shop there, with the recognition that most people shop locally for certain types of goods like food. Store-level inflation rates could then be related to these characteristics across the UK. Similarly, it may be possible to relate broad household characteristics like income to certain store chains to estimate rough measures of price changes for certain types of goods to household groups.

Both of these approaches would likely offer information on only a subset of goods, but could still provide insight into differential price changes across different types of households.

Modelling variation in inflation rates

As highlighted in the previous two sections, the direct calculation of inflation rates for different household groups is difficult and costly. Therefore, it may be desirable to take a modelling approach that can be implemented more quickly and at a lower cost. However, a modelling approach is more likely to be experimental, and would require proof of concept before being widely implemented.

One potential approach for modelling would be to use a one-off or periodic study that calculates household-level inflation rates for the UK to characterise the relative inflation experienced by different household groups at different times.

Such a study could:

- Calculate household-level inflation rates over time using UK data, following methods described in section IV;
- Relate the relative inflation rate of particular groups to the all-household HCI inflation rate; for example, estimate the difference between the all-household HCI and the inflation rate experienced by low-income households as a function of the HCI rate;

- On a quarterly or annual basis, use the estimates above and the current all-household HCI rate estimate to model a likely relative inflation rate for each household group.

The process takes into account that differences in inflation rates between household groups seem to be larger when aggregate inflation is high by estimating dispersion as a function of aggregate inflation (Adams-Prassl and Levell 2014; Braun and Lein 2020; Orchard 2020; Argente and Lee 2021; Weber, Gorodnichenko, and Coibion 2023).

Alternatively, an element of direct construction could be incorporated by modelling household group adjustment factors for Class-level price indices from data that links consumer behaviour to household characteristics. The adjusted indices could then be aggregated using democratic weights to obtain overall price index estimates for each group.

These approaches would be less accurate than direct construction of inflation statistics for each household type as described in section V, but would also be less costly and labour-intensive. The underlying study could be updated periodically to maintain the applicability of estimates. However, given that the estimates would be based on only 10-20 years of data, it is not clear how well they would reflect future dispersion of household group inflation rates, particularly in periods of high inflation. Furthermore, these data are unlikely to reflect the full range of supply and demand shocks that may drive inflation in any given period, which may impact the generalisability of observed past relationships between the all-household HCI rate and the inflation rate for a given household group.

Current work by the Institute for Fiscal Studies (IFS) may be suited for such an exercise. The IFS purchases access to the Kantar At-Home Purchase Panel for fast-moving consumer goods, which extends back to 2004 (Jaravel and O'Connell 2020a; Fox, Levell, and O'Connell 2023). It is possible that a study like the one described above could be conducted as an extension of the IFS's ongoing work to explore differences in goods baskets, prices, preferences, and experienced inflation across households.

VII. Conclusion

This paper has approached the question of how to reflect different prices paid for the same or similar goods by different types of households in household costs indices. We focus on goods prices, and leave consideration of prices paid for services for future research.

First, we review the current approaches taken in the UK and other countries to this question. We conclude that, although other countries produce estimates similar to the HCIs, none currently incorporate differences in prices paid for the same or similar goods.

Second, we review the academic and grey literature to see if there are approaches that could be adapted by the ONS. Studies accounting for non-homotheticity use methods and data sources similar to those in the HCIs, and come to similar conclusions that lower-income households in the UK tend to experience higher inflation rates. Studies that account for both non-homotheticity and different prices almost exclusively draw on commercial household scanner data, and emphasise that differences in prices paid by different households are an important source of variation in inflation rates across households. The exception is a paper on Japan that uses supermarket scanner data combined with store membership card data, which includes basic demographic information (Shoji 2023). Different levels of aggregation may be used to calculate household-group price indices, each with benefits and limitations.

Third, we summarise types of data that may offer insights into household-level inflation rates. While household scanner data is expensive and covers only a subset of goods included in CPI, it also offers the most detailed information on purchases and average prices paid linked to household characteristics. Supermarket scanner data offers a similar level of specificity on goods purchased and average unit prices paid, but does not include demographics unless linked to other data. Banking data has the opposite problem: information on personal characteristics and estimates of income, but no specific quantities or average unit prices. Finally, household survey data has more aggregated data on goods and prices, but contains the most detailed household characteristics.

Overall, while there are several viable approaches to improving the UK HCIs, none will be quick to implement or inexpensive.

The crucial issue is that of linking household characteristics to spending behaviour. Viable options for data sources include:

- Purchasing commercial household scanner data;
- Linking supermarket scanner data to household characteristics either through store membership cards or information about a consumer's postcode; and
- Updating the LCFS collection method to collect more specific goods and price information.

Each of these approaches is costly either in terms of data purchase or investment in data collection and maintenance. Furthermore, all of these types of data would require significant processing before they could be used, even in cases where the ONS is already using the same data for another purpose, requiring large time and resource investments before they could be used in the HCIs.

It is also apparent that the optimal data and approach may not be the same across all categories of goods. While household scanner data is very detailed, household-level inflation rates calculated from this type of data typically account for only 15-40% of the goods included in CPI. Goods purchased less frequently, such as vehicles, or goods without barcodes like fresh fruit may be better covered by a detailed household survey.

Finally, we consider two further options for modelling these differences across household groups. One is to use supermarket scanner data linkage to store membership card data or local characteristics to gain insights into price changes experienced by different household group. The second is to implement a one-off or periodic study for the UK that estimates the relationship between household inflation rates and characteristics conditional on aggregate inflation. These estimates could then be used to model estimated HCIs based on current inflation rates and other economic conditions. While likely less precise than methods of direct calculation, a modelling approach would likely require fewer resources while still offering insights into household group inflation rates. However, there is not an established approach to this problem; modelling dispersion of inflation rates in this way would require further research and proof of concept before it could be reliably implemented.

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A. Details on key papers

Table A1: Summarised details of studies accounting for non-homotheticity and different prices

Paper	**Country and period**	**Data and sample size**	**Estimated coverage of goods in CPI**	**Household groupings**	**Types of index(es)**	**Level of aggregation**	**Methods**	**Improvements over previous literature**	**Findings**
Aguiar and Hurst (2007)	United States (Denver) 1993 – March 1995	Nielsen HomeScan (2.1k hhs) American Time Use Survey (17k hhs)	Not specified	Age	Similar to Laspeyres/ Paasche (constant basket)	Household	Average price paid for each good in a given month among all households; measure cost of month's purchases for each household relative to the cost of the same bundle at average prices; then normalise the resulting index by average for all households	--	Older shoppers/households pay less for the same goods due to their shopping behaviour (higher frequency)
*Broda and Romalis (2009)	United States 1994 – 2005	Nielsen HomeScan (40k hhs)	Non-durables and food	Income	Exact price indexes	Income group	Define strata at the UPC level, then calculate weights by income group and apply these to the inflation rate of each UPC-defined good	Calculates inflation rates for different household groups, not just relative price indices at a given point in time	Non-durable inflation over this period was lower for lower-income households than for higher-income households
Kaplan and Schulhofer-Wohl (2017)	United States 2004 – 2013	KNCP (50k hhs)	30%	Income Age Size Region	Laspeyres Paasche Fisher	Household	Average (volume-weighted) price paid for each good (defined by UPC) by each household in each quarter; restrict sample of goods for each household to those purchased in both start and end period; calculate price indexes for each household on an annual basis;	Calculates household-specific price indices rather than group level indices; incorporates actual prices paid rather than average prices for each good	• 2/3 of the variation in the household-level price index comes from variation in the prices paid for the same goods • Assuming that all households buy the same mix of goods within strata also underestimates variation in inflation rates by about ½

							constructs indexes for aggregate inflation rates and for different household groups accounting only for non-homotheticity for the covered goods as a comparison; synthetic cohort approach to calculate cumulative inflation across income groups over 9 years; regresses household inflation rates on demographic factors to explore associations		• Variation in household-level inflation rates is larger when aggregate inflation is higher • Cumulative inflation rates over 9 years and median annual inflation rates were higher for (1) lower-income households; (2) larger households; and (3) households with older heads • Most (91%) of the variation in each household's annual rate of inflation is due to heterogeneity and only 9% from variation in aggregate inflation
Jaravel (2019)	United States 2004 – 2015	Nielsen HomeScan (50k hhs) Nielsen Retail Scanner data (45k stores)	40%	Income Age	Törnqvist	Price deciles within each goods module (prices) Income quintile/decile (weights)	Divides each product module (next level of aggregation to barcode) into price deciles and calculates inflation among each module x price decile; calculates module x price decile expenditure weights for each income quintile/decile and applies to vector of inflation rates for each module x price decile	Uses a similar approach to Broda and Romalis (2009), but includes a component accounting for household WTP to pay for products not available in first period; covers greater proportion of CPI goods than Kaplan and Schulhofer-Wohl (2017), and is able to take into account the role of product variety	• Lower-income households had higher inflation rates for full period of study • Shopping behaviour does not explain a large proportion of inflation inequality
*Braun and Lein (2020)	Switzerland 2010 – 2016	Nielsen HomeScan (4k	<15%	Income Age/retireme nt status	Redding-Weinstein (CES exact	Household	Calculate average price paid per good (defined at barcode	Accounts for differences in preferences across	• Variation in inflation rates across households

		households)		Size	price index) Fisher		level) by each household on a quarterly basis; calculate price indices for each household that correspond to economic and statistical approaches; regress average inflation rate per household on household characteristics	households in addition to different mixes of goods and different prices paid for the same goods	increases when aggregate inflation is higher • Differences in preferences across households account for a larger share (2/3) of variation in inflation rates than either prices paid (1/4) or mixes of goods (remainder) • Households with higher demand elasticities (i.e. that substitute more readily when relative prices change) experience lower inflation rates; these include lower-income households, households with at least one retired member, and larger households
Jaravel and O'Connell (2020a)	United Kingdom 2019 – May 2020	Kantar FMCG Purchase Panel (30k households)	Not specified	Income/expe nditure	Laspeyres Fisher	Expenditure quartile	Split transactions by shopping format, retailer type, promotion status; compute fixed-base and chained indexes on a monthly basis	Estimates inflation rates accounting for different prices paid for different household groups in the UK	• Over the first five months of the pandemic, lower-income households experienced slightly lower rates of monthly inflation than higher-income households • This was because lower-income households use fewer promotions, which fell during the first lockdown
Jaravel and O'Connell (2020b)	United Kingdom 2018 – May 2020	Kantar FMCG Purchase Panel (23k households)	Not specified	Income/expe nditure Region Age/retireme nt status	Laspeyres Paasche Fisher	Household (expenditure weights) Barcode (prices)	Averages prices for each good (defined at barcode level) in a given period across households, then calculates a	Similar to Jaravel and O'Connell (2020a), but calculates household-specific expenditure weights	• In 2020, households in the South East, in the highest expenditure quartile, and with older members had

							good-specific inflation rate; uses household-specific expenditure weights to calculate fixed-base household-level inflation; accounts for product entry-exit using assumptions about household utility functions; regresses household inflation rates on demographic characteristics	rather than averaging across expenditure quartiles; averaging prices paid for the same specific good relaxes requirement that individual households have to purchase the same good in multiple periods for experienced inflation of that good to be observed	higher inflation • The patterns for region and expenditure quartile were the reverse in 2018 and 2019
Argente and Lee (2021)	United States 2004 – 2006	Kilts-Nielsen Consumer Panel Nielsen Retail Scanner data	40%	Income	Exact price indexes	Income groups	Follows Broda and Romalis (2009), but observes average prices paid for each good in each period for individual household groups defined by income categories	Similar to Jaravel and O'Connell (2020b) in that averaging prices within household groups relaxes requirement that individual households have to purchase the same good in multiple periods to be included in measured inflation; improves on Broda and Romalis (2009) by averaging prices paid within income groups rather than using an overall average	• Inflation rates across household income groups diverged from 2008-2013, when inflation rates were on average 0.85 percentage points higher for those on the lowest incomes than those on the highest incomes • This was because higher-income households can more easily adjust shopping behaviour and quality of goods purchased in response to changing prices
Shoji (2023)	Japan Jan 2012 – Dec 2013	Magee Co. store scanner data linked to store member cards (1.7m people)	20%	Gender Age	Laspeyres Fisher Paasche Törnqvist	Household (expenditure weights) Barcode and store (prices)	Follows Aguiar and Hurst's (2007) calculation for a household price index, but calculates good-specific inflation by averaging the price paid for a given	Much larger sample than previous studies; improves on Aguiar and Hurst (2007) by calculating inflation rates at the household level, and on Kaplan and	• Retired consumers pay higher prices, but have lower inflation rates overall • Relative price levels and experienced inflation rates do not change together

							good (defined at barcode level) at each store in each period; applies household-level expenditure weights; follows Feenstra (1994) to calculate cost-of-living inflation while allowing for changes in the basket of goods	Schulhofer-Wohl (2017) by allowing intertemporal changes in the goods basket for each consumer	over the lifecycle
*Strasser et al. (2023)	16 European countries 2005 – 2018	GfK/Kantar FMCG Purchase Panel (sample size not stated)	Not specified	Income Residence	Plutocratic Laspeyres index	Group	Plutocratic index calculated within each household group; exact method unclear	Extends literature to 16 EU countries	• Differences in prices paid contribute only a small proportion of variation in inflation rates; the majority comes from purchasing different goods within product categories and regional differences • Generally speaking, inflation rates are most different for the highest and second-lowest income households, with lower-earning households generally experiencing higher inflation • In the UK, low-income households have the highest inflation rates and middle-high income households have the lowest

Weber, Gorodnichenko, and Coibion (2023)	United States 2018Q1 – 2021Q2	Nielsen HomeScan (43k households)	Not specified	Income Race Education Region	Unclear - approximates a Fisher index	Household by goods module	Averages prices for each household at the goods module level (multiple barcodes grouped together), then weights by average quantity purchased of that module over current and previous quarters	Uses household-specific bundles and prices, just at a higher level of aggregation to avoid both (1) excluding goods because they are not purchased across periods by the same household or (2) averaging prices across a large group of households	• Black, lower-income, and less-educated households experienced higher inflation than others during the Covid-19 lockdown • These differences were driven by the prices of frequently-purchased foods like cereal, pasta, and eggs; variation in prices of goods within categories does not seem to contribute

Notes: Table summarises only selected key papers in publication order. Non-peer-reviewed working or occasional papers are indicated by a * in the first column.
Abbreviations: KNCP = Kilts-Nielsen Consumer Panel; FMCG = Fast-Moving Consumer Goods