Office for National Statistics

Compendium

Economic review: July 2019

Analysis of price statistics is presented to raise understanding of the UK's main inflation measures – mainly, the CPI and CPIH. The economic review compendium is published quarterly, usually in January, April, July and October.

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Chapters in this compendium

Compendium

Volatile components and their role in the Consumer Prices Index

Investigates whether the most volatile components of the Consumer Prices Index (CPI) basket make a larger contribution to the change in the 12-month growth rate of CPI in periods of relatively stable headline CPI growth.

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1 . Main points

- This article investigates whether the most volatile components of the Consumer Prices Index (CPI) basket make a disproportionately large contribution to the change in the 12-month growth rate of CPI; while these movements may offer limited insights into the underlying inflationary picture, they can play an important role in how we communicate headline movements in inflation to the wider public.

- These volatile components of CPI include transport insurance, sea and air fares, and also gas and fuels, and have a combined weight of 6.4% of the total basket in 2019; but on average account for around 10% of the monthly change in the headline 12-month CPI rate, although these components were not found to have a more pronounced effect in periods of relatively "non-volatile" headline CPI growth.

- The prices of these components exhibit volatility for a variety of different reasons, such as their pricing mechanisms as well as their exposure to the wider economy.

2 . Introduction

The Consumer Prices Index (CPI) is one of the leading measures of the overall change in the price of consumption goods and services in the UK. It aims to represent price movements for a basket or a sample of items that are purchased by the average household in the UK.

Overall, prices for over 700 items are collected around the middle of every month, with price collectors visiting outlets across the UK to record 100,000 prices for around 520 items. Price quotes for remaining items have national pricing so are collected centrally by our office-based collection teams. Prices for each item in this representative basket are used to calculate an average price, with each item's price weighted using the composition of that month's national expenditure.

Every month we report on price movements for the entire basket, to explain what has been driving changes in the headline Consumer Prices Index including owner occupiers' housing costs (CPIH) inflation rate. The CPIH has the same coverage as CPI with the addition of owner occupiers' housing costs (OOH) and Council Tax, which together account for 19.1% of the CPIH basket in 2019.

As the inclusion of additional components - such as OOH - in CPIH reduces the weighting of the other CPI basket items, potentially masking some of the volatility in these components, we have focused on CPI for the purposes of this analysis.

Each month we highlight particular drivers that explain movements in the headline 12-month inflation rate, so that users are able to identify which components of the basket are the largest drivers of change in that period. This analysis provides additional context around such movements, which at times can be volatile in nature.

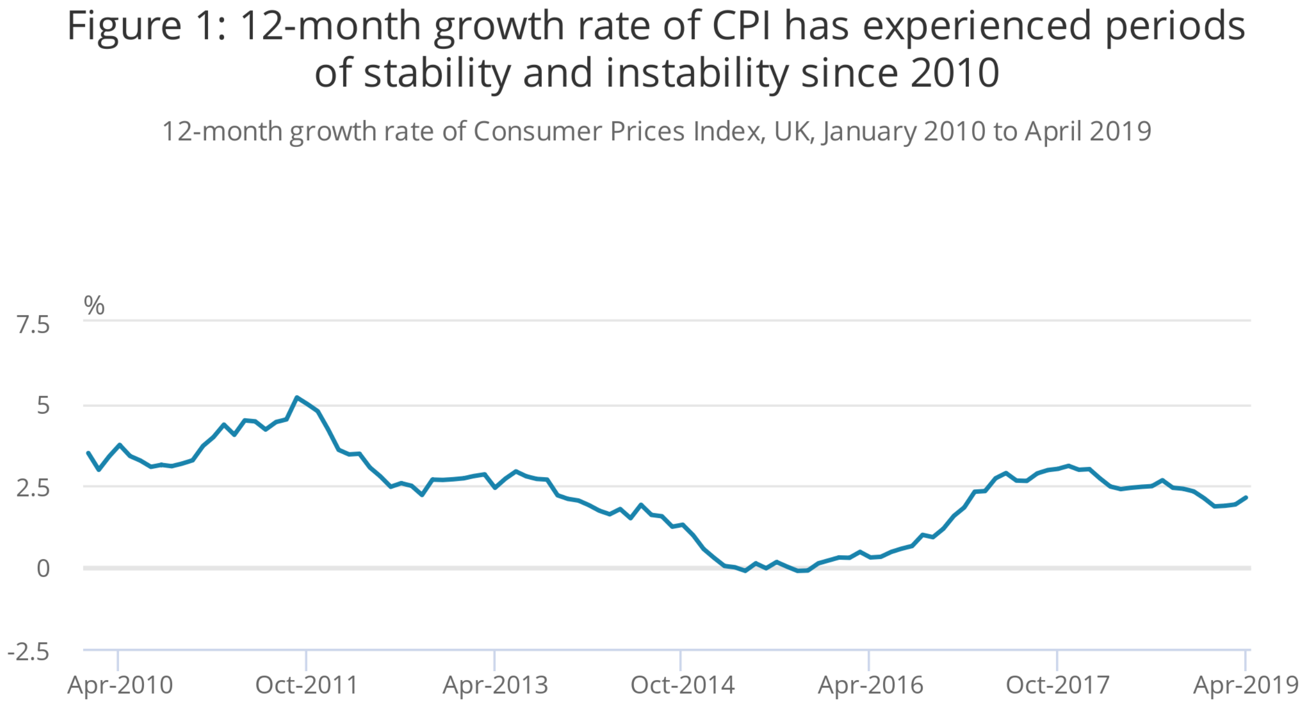
This article will focus on movements within the CPI and will provide further insight into the monthly changes in the 12-month CPI inflation rate. In particular, we will examine the most volatile components of the CPI basket to see if these components play a disproportionate role in explaining such changes.

In assessing the drivers of these movements, we typically highlight the components of the basket that have made the largest contribution to the change in CPI. While there is often some focus on the underlying inflation rate to examine the extent to which there are inflationary pressures in the economy, volatility can also play a large role in explaining how the headline CPI inflation rate moves from month to month.

Figure 1 shows the 12-month growth rate of CPI for every month between January 2010 and April 2019. Over this period, the average rate of CPI inflation has been 2.6%.

Figure 1: 12-month growth rate of CPI has experienced periods of stability and instability since 2010

12-month growth rate of Consumer Prices Index, UK, January 2010 to April 2019



Source: Office for National Statistics – Consumer Prices Index

The components that have caused some of the short-term fluctuations in headline CPI may have a relatively small weight in the basket but can have a disproportionate impact on the monthly changes in the 12-month CPI rate. While these movements may offer limited insights into the underlying inflationary picture, they can play an important role in how we communicate changes in the annual rate of CPI.

3 . Methodology

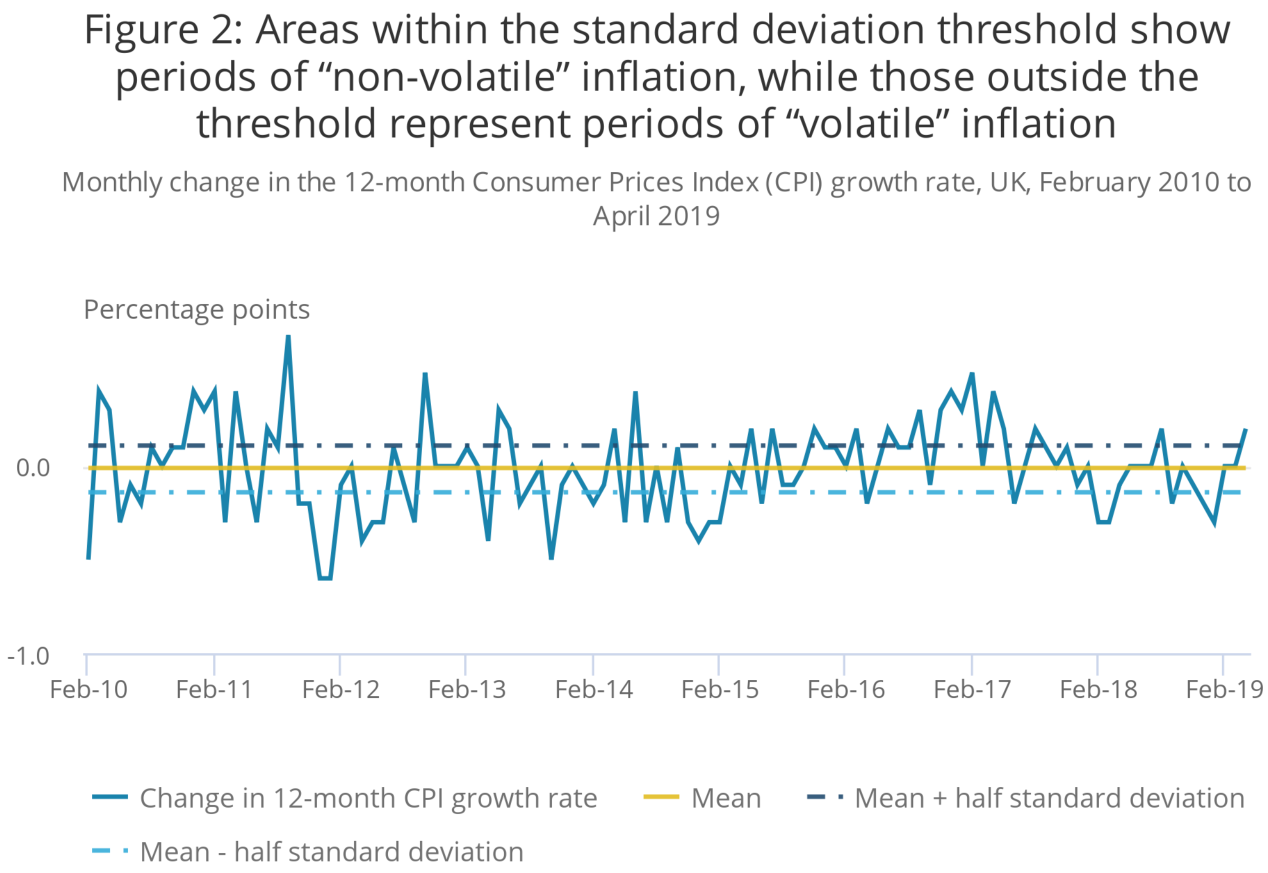
Figure 2 shows the monthly percentage point [change in the 12-month Consumer Prices Index (CPI) inflation rate]. Between January 2010 and April 2019, given the periods of downward movement in the CPI annual rate, the mean change was negative 0.012 percentage points. These movements can be particularly pronounced in certain months, showing up to 0.7 percentage point changes. These movements can be particularly pronounced in certain months, showing up to 0.7 percentage point changes. Over the period, it is apparent that contribution to change in CPI rate has become less variable in the more recent months (mid-2015 onwards).

To provide more context around these monthly changes, we look to capture whether the contributions to these are related to the underlying volatility in the change in the headline CPI inflation rate. For the purpose of this analysis, monthly changes above or below 0.5 standard deviations from the mean change have been identified as “volatile” and all those within half a standard deviation of the mean have been identified as “non-volatile”. In other words, more extreme movements are those that fall outside these thresholds, while steady movements are those which are within the threshold.

Across the entire period of 111 months, 47 months have been classified as “non-volatile”, while the remaining 64 months have been classified as “volatile.

Figure 2: Areas within the standard deviation threshold show periods of “non-volatile” inflation, while those outside the threshold represent periods of “volatile” inflation

Monthly change in the 12-month Consumer Prices Index (CPI) growth rate, UK, February 2010 to April 2019



Source: Office for National Statistics – Consumer Prices Index

To investigate the role of volatile components, we have identified the top 10% most volatile of the 85 class components in the CPI basket – which equates to eight classes of the CPI basket - based on the standard deviation in their 12-month growth rate. This does not account for variability in month on month changes. Economic commentary of CPI usually focuses on class-level components that have driven changes in the 12-month CPI rate, therefore, our analysis was carried out at this level. However, it should be noted that volatility at the item level may offset by opposing movements of other items when aggregated to class level.

Table 1 shows the most volatile 10%, alongside their respective 2019 CPI basket of goods and services weight. These volatile components of CPI comprise a relatively small proportion of CPI, with a combined contribution of just 6.4% of the total CPI basket in 2019. Other components, falling just outside of this top 10%, include oils and fats, equipment for the reception and reproduction of sound and pictures (for example, televisions, portable speakers, DAB radios, and so on), and second-hand cars.

Table 1: Top eight volatile Consumer Prices Index (CPI) components in order of volatility
UK, 2019

Volatile items	2019 weight
Liquid fuels e.g. kerosene	0.1%
Photographic, cinematographic and optical equipment e.g. cameras – digital, action, etc.	0.2%
Fuels and lubricants – mainly petrol and diesel	3.0%
Insurance connected with transport – car and travel insurance	0.3%
Data processing equipment – personal and laptop computers along with their associated software and peripherals	0.8%
Passenger transport by air	0.5%
Gas	1.2%
Passenger transport by sea and inland waterway	0.3%
Combined total	6.4%

Source: Office for National Statistics – Consumer Prices Index

4 . Results and analysis

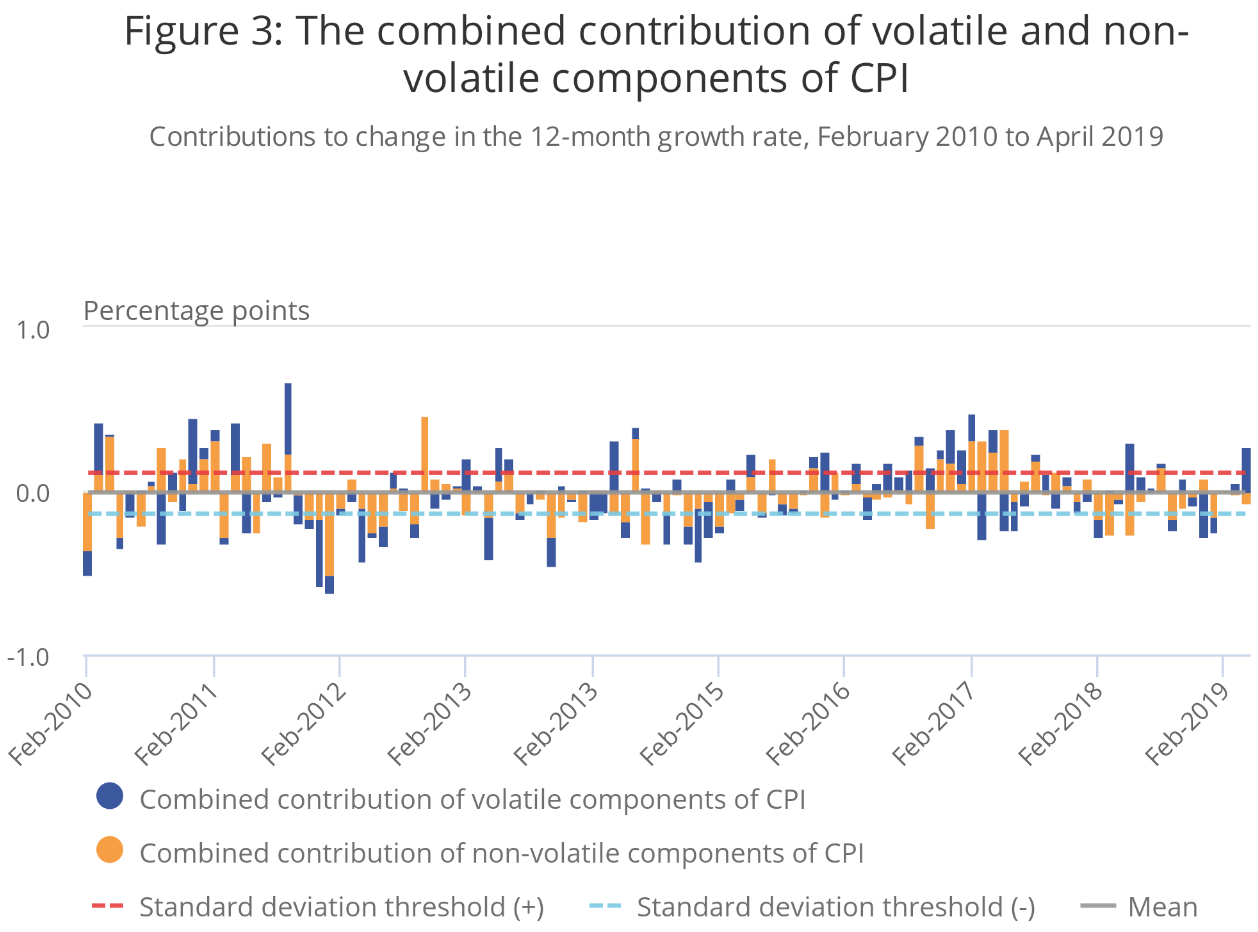
This section analyses the contribution of the top 10% most volatile Consumer Prices Index (CPI) components to the change in the 12-month rate of CPI inflation from 2010 onwards. In addition, we explore whether the contribution of these volatile components differs during “non-volatile” and “volatile” periods.

Top 10% most volatile CPI components

The top 10% most volatile CPI components – despite only representing 6.4% of the CPI basket – on average account for 10% of the change in the headline 12-month CPI rate (Figure 6, Annex A) . As outlined in the conclusion, further work is planned to look at the composition of these volatile components to see the extent of these contributions vary over time.

Figure 3: The combined contribution of volatile and non-volatile components of CPI

Contributions to change in the 12-month growth rate, February 2010 to April 2019



Source: Office for National Statistics – Consumer Prices Index

Some of the top 10% of volatile CPI components that have been identified are volatile in their nature but also sometimes in their pricing strategy. For example, products such as air and sea fares – which accounted for a combined 0.8% of the CPI basket in 2019 – are priced using dynamic pricing strategies. Retailers of tickets for air and sea travel often attempt to segment the market and aim to price discriminate by grouping consumers according to their willingness to pay, dependent on various factors including demographics, peak-time travel and time of purchase.

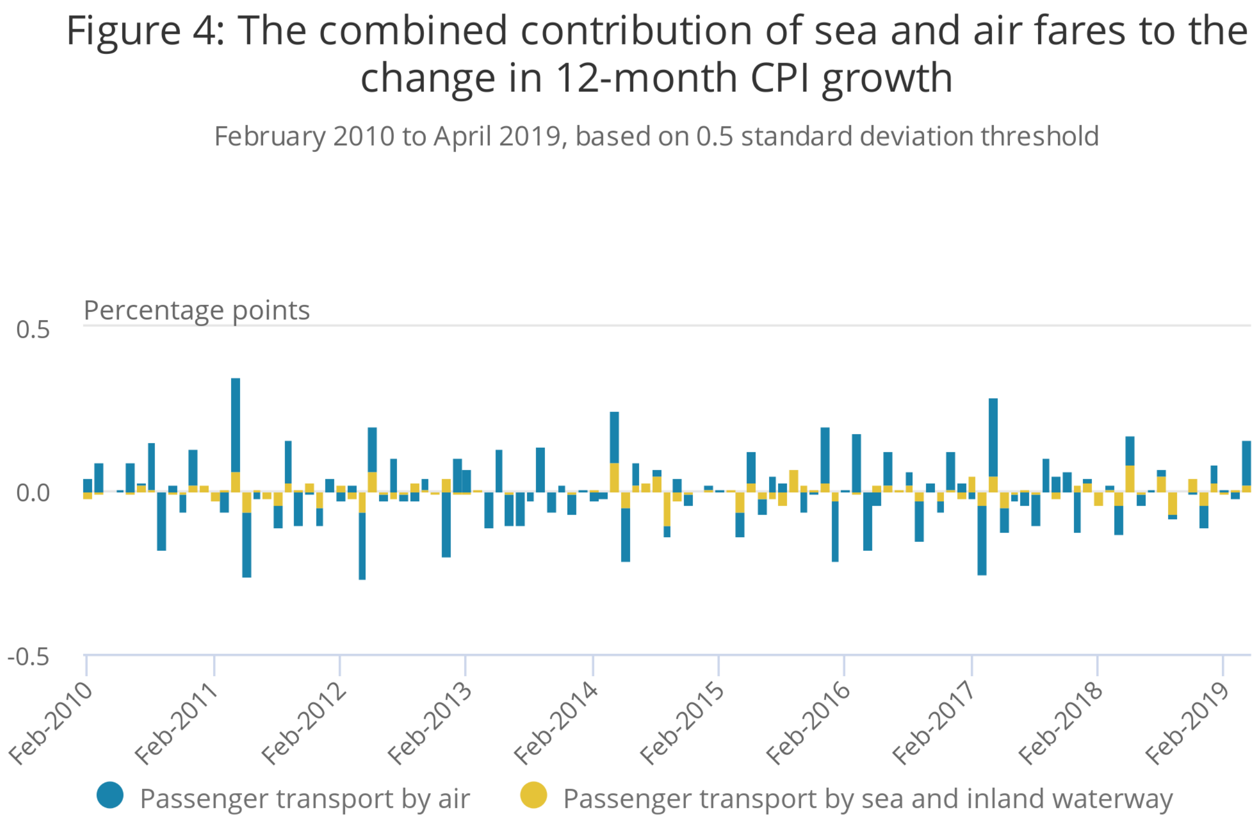
Dynamic pricing is often used to maximise revenue as well as to gain a competitive edge. This flexible approach to pricing may account for some of the volatility of products such as air and sea fares, which have had such a pronounced effect on the change in the 12-month growth rate of CPI at specific and consistent periods of each year throughout the sampled period.

For holiday and travel items, we observe large price rises during peak holiday periods (August and December). Factors such as the timing of Easter - as seen in 2011 in Figure 4 when Easter was later in the year - have caused notable upwards movements in the contributions of air fares to the change in 12-month CPI growth, as retailers have increased their prices during peak travel times.

Similar patterns are also evident in the contributions of sea fares, albeit to a lesser extent than air fares, with retailers in both sectors appearing to use similar pricing strategies.

Figure 4: The combined contribution of sea and air fares to the change in 12-month CPI growth

February 2010 to April 2019, based on 0.5 standard deviation threshold



Source: Office for National Statistics – Consumer Prices Index

In addition to sea and air fares, the pricing mechanisms of some of the other volatile CPI components may also offer some explanation as to why they are among the most prominent causes of the change in the 12-month growth rate of CPI.

The pricing of products such as transport insurance for cars and motorbikes are heavily dependent on factors including age, location, experience and the previous history of each individual driver. Insurance premiums are often dependent on factors including age, location, experience and the previous history of each individual driver. However, some of the short-term volatility in this series caused by these factors is mitigated by our methodology used in compiling these statistics, as price quotes are compared for the same person in successive months.

The price movements of components such as gas, liquid fuels, and fuels and lubricants – which account for a combined 4.3% of the CPI basket respectively – are heavily reliant on a number of factors, including both supply and demand side factors.

On the supply side, the price of products such as gas are dependent on factors such as natural gas production, net imports (which are heavily dependent on variations in exchange rates) and storage inventory levels. Increases in supply tend to pull prices down, while decreases in supply tend to push prices up. Increases in prices tend to encourage natural gas production and imports, and sales from natural gas storage inventories. On the demand side, factors include weather (temperatures), economic conditions and petroleum prices.

In addition to the top 10% most volatile components, which have been identified using this methodology, certain other items of the CPI basket have been highlighted in more recent months as having a prominent impact on the change in the 12-month CPI growth. For example, computer games from the top 20 chart and theatre admissions items have featured regularly in recent months as driving the change in the 12-month growth rate of CPI, despite only representing 0.26% and 0.21% of the CPI basket respectively in 2019. This may also be down to the unconventional pricing strategies from the firms that sell them.

The retail price of computer games has broadly risen over time, partially because of the increased quality of the product. However, this is not always the case as each individual game is priced using a unique pricing strategy. For example, some computer games are priced using a high one-off payment, while an ever-increasing amount of games are priced at a lower level (or in some cases completely free for games available to purchase online), dependent on multiple in-play payments for additional content required once purchased for downloadable content. It should be noted that the index does not include free games nor in-play payments in games.

This unique pricing strategy, combined with the fairly high turnover and wide-ranging price of games in the computer games component, offers some explanation as to why they have been having a particularly notable impact on the change in the 12-month CPI growth rate.

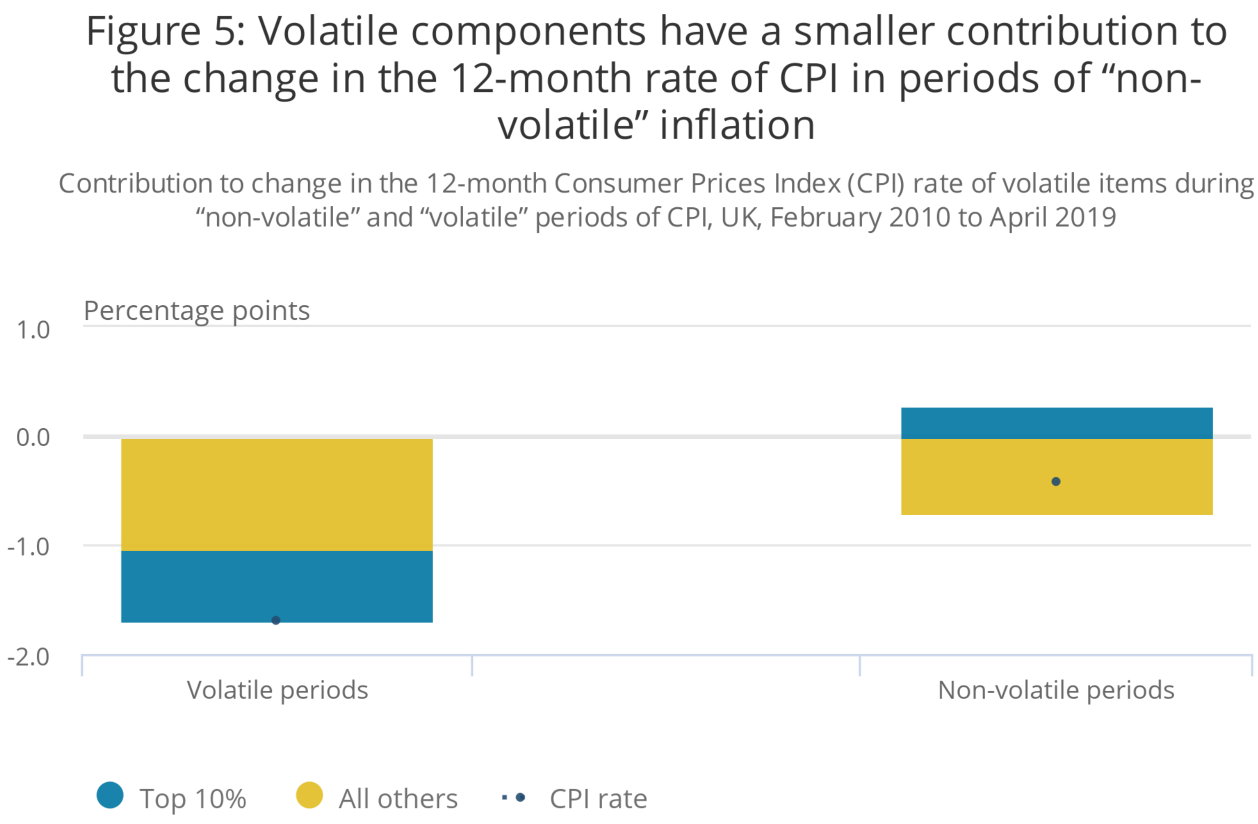
Relationship between volatile and non-volatile components

The relationship between the contributions of volatile and non-volatile CPI components differs over time, as the headline 12-month CPI growth rate experiences periods of relative stability and instability. Figure 5 shows the combined contributions that the top 10% most volatile and remaining 90% of components make in non-volatile and volatile periods. The net contribution to the change in the 12-month growth of the volatile components of CPI during periods of non-volatile CPI growth is substantially smaller in absolute size than the contributions of the volatile components during volatile periods of CPI growth, across the period of February 2010 onwards.

The volatile components of CPI form 39% of the absolute contributions to change in the 12-month growth rate of CPI (total lengths of bars in Figure 5) during volatile months, while they comprise only 29% during non-volatile months of growth, across the period from February 2010 onwards. The value for non-volatile months is not a percentage of the total change in the 12-month growth rate of CPI, as this measure does not account for direction of the contributions.

Figure 5: Volatile components have a smaller contribution to the change in the 12-month rate of CPI in periods of “non-volatile” inflation

Contribution to change in the 12-month Consumer Prices Index (CPI) rate of volatile items during “non-volatile” and “volatile” periods of CPI, UK, February 2010 to April 2019



Source: Office for National Statistics

Notes:

1. Based on 0.5 of a standard deviation threshold.

To investigate this further, the net annual contributions in volatile periods and in non-volatile periods have also been calculated using the same standard deviation threshold (0.5). CPI has endured several periods of volatility since 2010, where these volatile periods have been identified using the approach outlined in the Methodology section.

The number of years in which the top 10% of volatile classes have made a larger contribution to the overall change in the CPI rate compared with the remaining 90% of the basket is relatively even. However, the relative size of the contributions of the non-volatile components of CPI considerably outweighs the contributions of volatile components.

5 . Conclusions

Our analysis finds that the top 10% volatile Consumer Prices Index (CPI) components – which have a combined CPI basket weight of only 6.4% in 2019 – do have a disproportionately large impact on the change in the 12-month growth rate of CPI.

These volatile classes include transport insurance, sea and air fares, and also gas and fuels. These classes exhibit price volatility for different reasons such as their pricing mechanisms and exposure to the wider economy. Despite these volatile components having a disproportionate effect on the change in the 12-month rate, these components do not have a larger impact on the change in the CPI rate in non-volatile periods of growth.

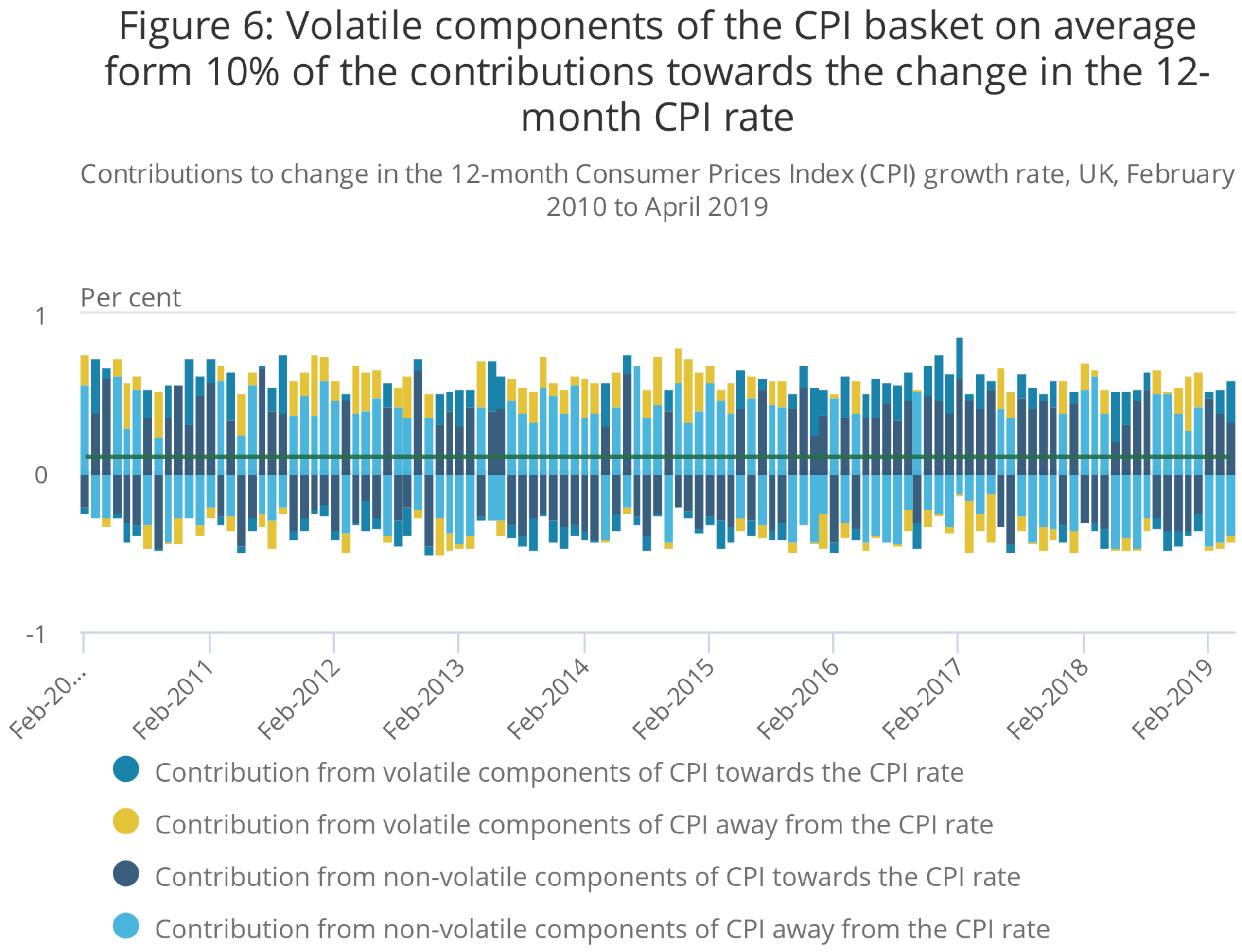
The analysis in this article should provide stakeholders with a more in-depth understanding of the role of some of the lower-weighted, more volatile components of the CPI basket, and the part they play in the change in CPI from one month to the next. This in turn should also allow data users in general to better understand some of the short-term fluctuations within the CPI basket from the drivers of the longer-term underlying inflationary picture, allowing for more informed decisions to be made.

Further work will be carried out to look at the composition of these volatile components to see the extent of these contributions vary over time, while also looking at the properties of these movements to understand how persistent this volatility is and how it changes from one month to the next.

6 . Annex

Figure 6: Volatile components of the CPI basket on average form 10% of the contributions towards the change in the 12-month CPI rate

Contributions to change in the 12-month Consumer Prices Index (CPI) growth rate, UK, February 2010 to April 2019



Source: Office for National Statistics

Percentage of contributions towards and away from the 12-month Consumer Price Index (CPI) growth rate from volatile and non-volatile components of the CPI basket. Percentages are calculated as the fraction of total absolute contributions of all classes to the CPI rate from either volatile or non-volatile classes. The sign of the percentage represents whether the contribution is towards (positive) or away from (negative) the total change in 12-month CPI rate.

Compendium

Household Costs Indices: the intersections of tenure type, retirement status and the presence of children

Analysis of changing household costs between 2005-2018 for retired and non-retired households and households with and without children grouped by tenure type.

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1 . Main points

- We extend the analysis presented in Household Costs Indices (HCIs), second preliminary estimates, UK: 2015 to 2018 to examine the effect of the intersection of household tenure type with retirement status and presence of children in the household.

- The extent to which households experience different rates of change of household costs is predominantly driven by their exposure to mortgage interest payments during the period 2008 to 2010.

- Childless households in subsidised rented accommodation have on average seen their costs rise 33% faster than owner occupied households with children (2.8% compared with 2.1%).

- Among non-retired households, the proportion of household expenditure spent on housing is nearly twice as large for private renters as for owner-occupiers.

- Other factors driving differences between the groups are food and energy bills for households with children and retired households, while transport costs are influential for households without children.

2 . Introduction

On 25 April 2019 we published the Household Costs Indices (HCIs), second preliminary estimates, UK: 2015 to 2018. The HCIs are a new set of measures designed to complement our lead measure - the Consumer Prices Index including owner occupiers' housing costs[1] (CPIH). The HCIs reflect changing prices and costs as experienced by different household groups. In other words, they reflect the month-on month impact of changing prices on household budgets. The publication focussed on a range of subgroups: retired and non-retired households, households with and without children, income deciles, and different tenure types.

This article will explore these findings further by focussing on different types of households, within groups. We examine the effect of tenure type on retired and non-retired households, as well as households with and without children.

For each grouping we present an all-items Household Costs Index and its annual growth rate, alongside an analysis of the divisional expenditure breakdown, contributions to the annual growth rate and the drivers of the differences within groups.

Notes: Introduction

1. The most comprehensive measure of inflation as it includes owner-occupiers' housing costs and Council Tax, which are excluded from the CPI

3 . The Households Costs Indices – purposes and design

The Household Costs Indices (HCIs) have been designed to complement our other measures of price change:

- the Consumer Prices Index including owner occupiers' housing costs (CPIH), which is our most comprehensive measure of inflation

- the Consumer Prices Index (CPI), which omits certain housing costs; it is an internationally comparable measure

- the Retail Prices Index (RPI) – a legacy measure that only continues to be produced for ongoing use in pre-existing gilts and long-term contracts

The focus of the HCIs on the impact of price changes on household budgets leads to several key differences in their design. Like our other indices, the HCIs capture expenditure data from the Living Costs and Food survey (LCF), however they weight this data differently. CPI and CPIH weight a household's expenditure contribution according to its share of the total. This so-called "plutocratic" approach to weighting most closely captures the value of money across the whole economy, at the expense of emphasising contributions from higher-spending households. In contrast the HCIs weight expenditure contributions according to how representative the specific household is of the population. In this way, the "democratic" weighting approach of the HCIs more closely captures the experience of a typical household.

Another difference in the design of the HCIs brought about by the focus on household budgets is that expenditure on goods and services is, in principle, counted at the point in time that they are paid for, which is not necessarily the point in time at which they are acquired. For many goods the distinction between the payments approach of the HCIs and the acquisition approach, which largely underpins CPI and CPIH, is inconsequential. For larger items however, this can be significant. Items such as owner-occupied housing, cars, tertiary education and household appliances are acquired at a point in time but paid for over many years through finance agreements. The HCIs aim to reflect this reality in their design.

The adoption of a payments approach leads to differences in the scope of items included in the HCIs. If goods are paid for via finance arrangements that attract interest then it is logical to include a measure of this interest in the index as this is a monthly cost that households incur, while CPIH deems this out of scope. The last release of the HCIs included a measure of credit card interest, and treated student loan repayments rather than headline tuition fees as the measure of higher education costs. The HCIs also consider insurance premia on a gross basis rather than net of claims, as this more closely reflects the experiences of households.

More detailed description of the HCIs and our other price change measures can be found in our previous publications:

- Measuring changing prices and costs for consumers and households: March 2018

- Household Costs Indices: methodology

4 . HCIs for retired and non-retired households, separated by tenure type

In the publication Household Costs Indices, UK: second preliminary estimates, 2005 to 2018 , we introduced a new population subgroup for analysis – that of housing tenure type. Households were grouped according to whether they were subsidised rented, privately rented or owner-occupied. As housing costs make up the largest share of household expenditure across all households they proved to be a significant driver of differences between groups.

Analysis of the Household Costs Indices (HCIs) for retired and non-retired households showed that retired households overall spend a smaller share of their expenditure on owner-occupied housing payments, but more on other housing related costs (for example energy). This is expected as many retired households own their homes outright and no longer make mortgage payments. Their proportionally larger expenditure on energy may be explained by spending more time at home, which would align with the observation that they also spend proportionally less on transport. Retired households tend to spend more on food and healthcare, and less on restaurants and accommodation, and clothing.

Examining the household characteristics of the Living Costs and Food (LCF) data shows the sample sizes available to us for analysis. This reveals firstly that there are very few retired households living in privately rented accommodation, meaning we are unable to provide a robust analysis of their expenditure trends. It also shows that proportionally more retired households are owner-occupied (75% compared with 67% for non-retired).

Table 1: Mean annual LCF sample sizes broken down by retirement status and tenure type, UK, 2005 to 2018

	Non-retired households			**Retired households**		
Tenure type	Count	% of group	% of total	Count	% of group	% of total
Subsidised rented	726	18%	13%	333	21%	6%
Privately rented	595	15%	11%	55	3%	1%
Owner-occupied	2726	67%	49%	1175	75%	21%

Source: Office for National Statistics

Table 2 shows the year-on-year average annual growth rates in the HCI, alongside the cumulative costs increase between 2005 and 2018 for each type of household. It bears out the observations from the second preliminary release of the HCIs that cost increases have been lower for non-retired households and lower for those in owner occupied housing. The combination of these effects has been more pronounced amongst non-retired households.

Table 2: Summary annual growth rates and cumulative costs increases for retired and non-retired households by tenure type, UK, 2006 to 2018

	Non-retired households		**Retired households**		**All Retirement Statuses**	
Tenure Type	Annual Growth Rate	Cumulative % costs increase, 2005-2018	Annual Growth Rate	Cumulative % costs increase, 2005-2018	Annual Growth Rate	Cumulative % costs increase, 2005-2018
Subsidised rented	2.6	40.80%	2.9	45.70%	2.7	42.40%
Privately rented	2.5	38.20%	N/A	N/A	2.5	38.50%
Owner occupied	2.2	34.20%	2.7	43.10%	2.3	36.60%
All tenure types	2.3	35.90%	2.7	43.70%	2.4	38.00%

Source: Office for National Statistics

Notes

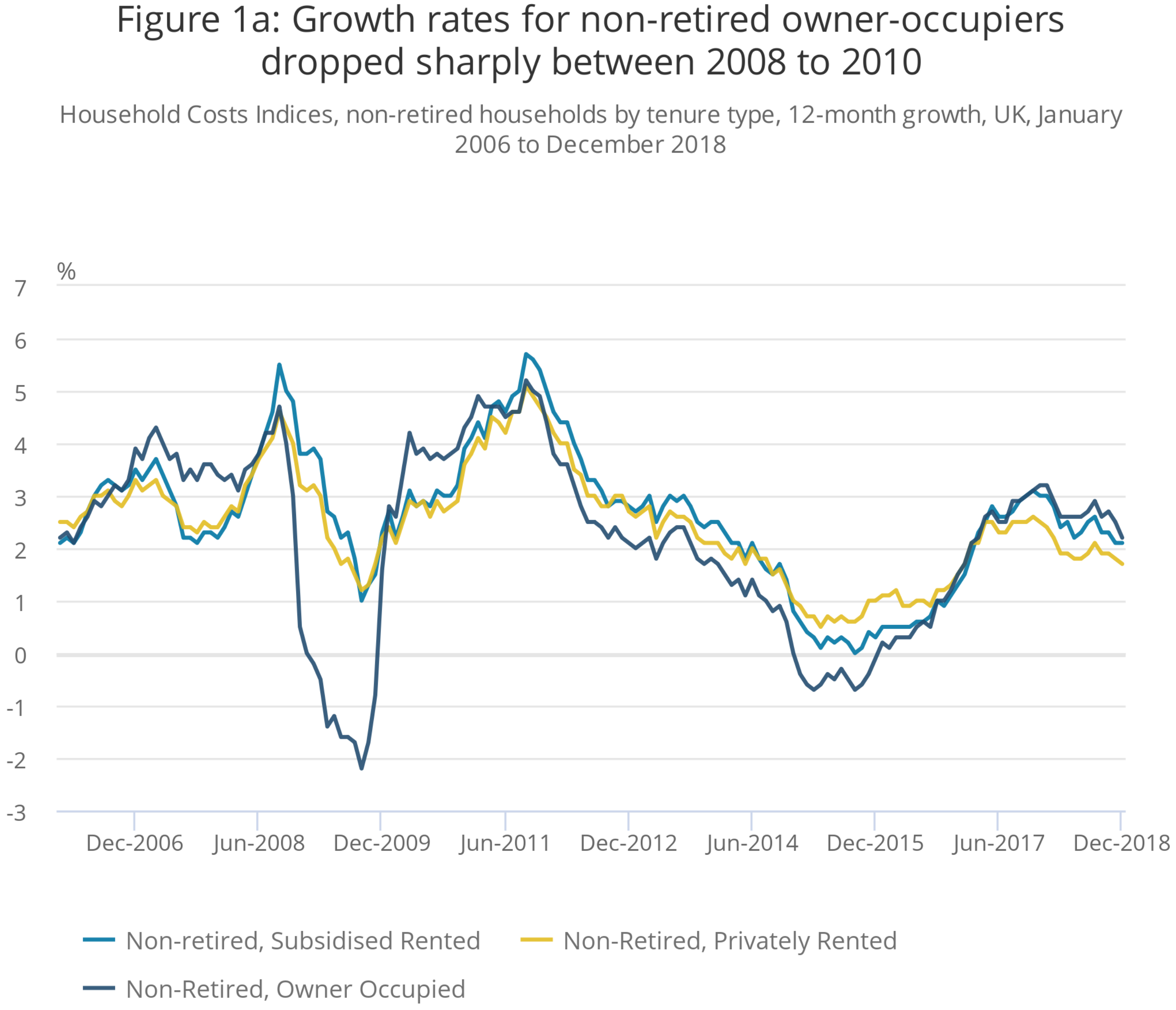
1. The average presented is the compound average 12-month growth rate of the unrounded indices. Consequently it may differ from the arithmetic average of the 12-month growth rates presented in this article. Back to table

2. All figures presented in this table are rounded to 1 decimal place (dp). Back to table

Examining the progress of household costs over time gives an indication of the drivers of this difference between groups. Figure 1 shows the year-on-year growth rate of the HCIs for each of the subgroups. While the HCIs for retired households of all tenure types track each other relatively closely, for non-retired households there is a pronounced decline for owner-occupiers between 2008 and 2010 coinciding with the financial downturn and related interest rate cuts. This had the effect of reducing mortgage payments for those households that were making them, and these households were predominantly non-retired. Elsewhere on the chart the growth rates are much closer to each other, suggesting that most of the difference between non-retired owner-occupied households and other non-retired households at the end of 2018 can be accounted for by this event.

Figure 1a: Growth rates for non-retired owner-occupiers dropped sharply between 2008 to 2010

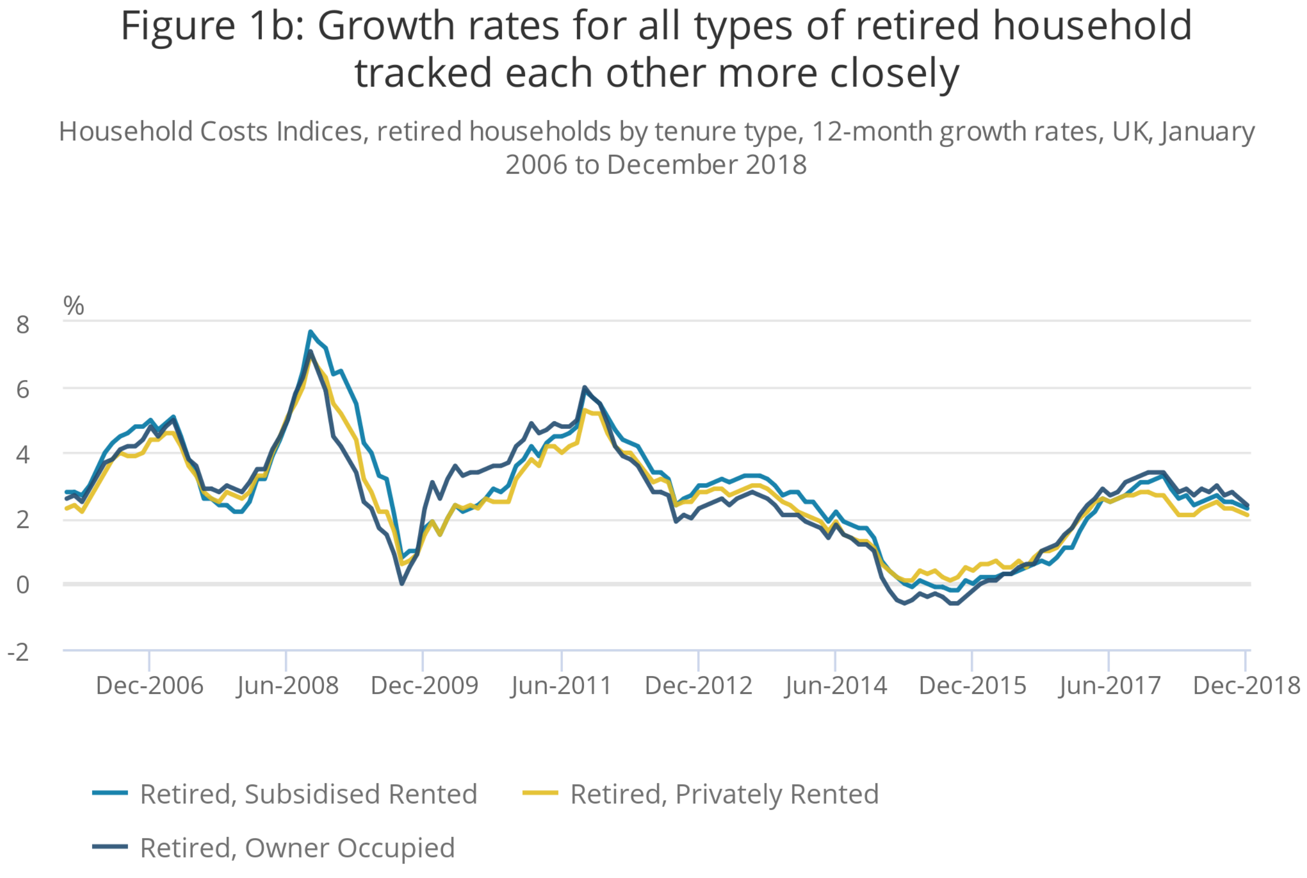
Household Costs Indices, non-retired households by tenure type, 12-month growth, UK, January 2006 to December 2018



Source: Office for National Statistics

Figure 1b: Growth rates for all types of retired household tracked each other more closely

Household Costs Indices, retired households by tenure type, 12-month growth rates, UK, January 2006 to December 2018

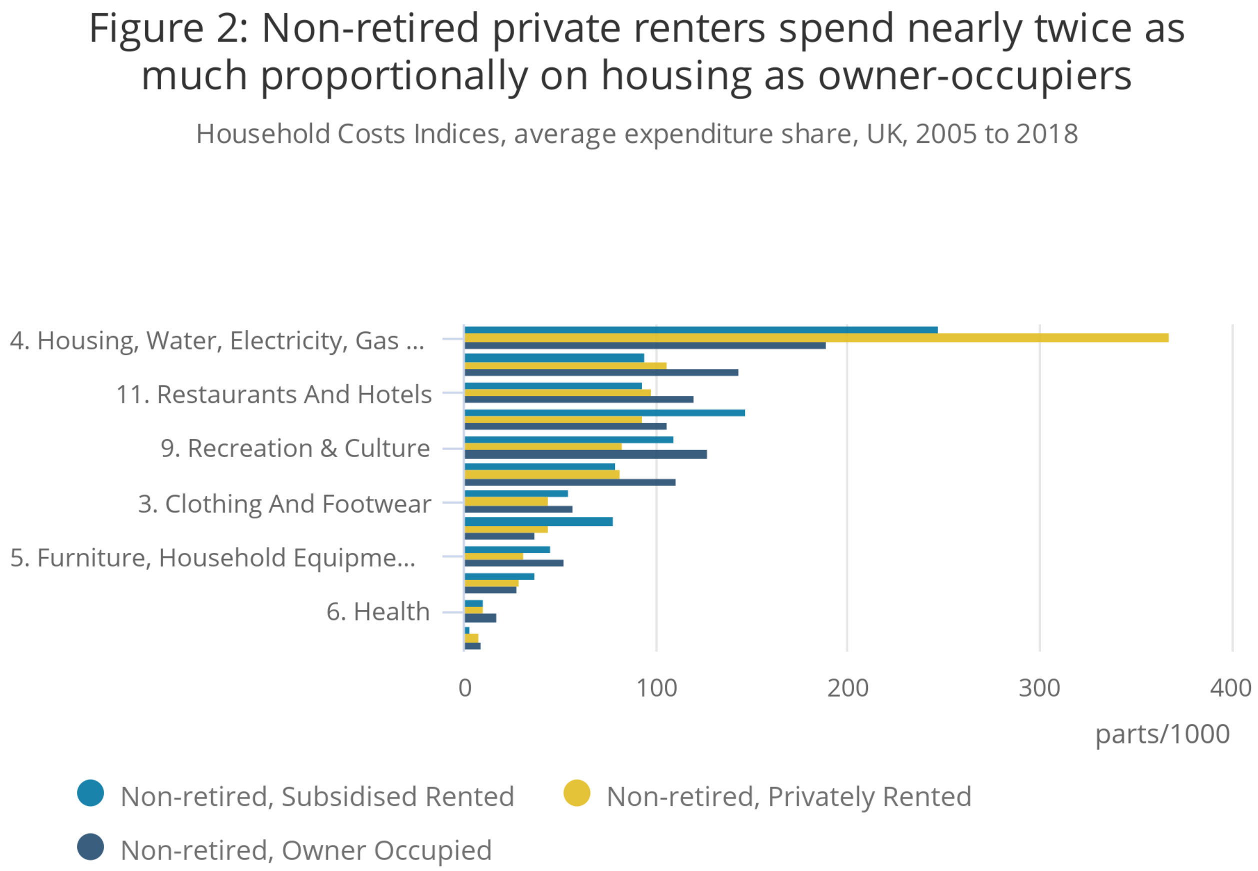


Source: Office for National Statistics

Examining the breakdown of expenditure shares between subgroups illustrates the increased proportion of expenditure that subsidised, and especially private renters devote to housing. For non-retired households the proportion of expenditure spent on housing is 95% larger for private renters than owner-occupiers (368 parts per thousand compared with 189). When we look at where owner-occupiers distribute their displaced expenditure there is no single category that dominates, suggesting that owner-occupiers have wide discretion over how they spend their budgets outside of housing.

Figure 2: Non-retired private renters spend nearly twice as much proportionally on housing as owner-occupiers

Household Costs Indices, average expenditure share, UK, 2005 to 2018



Source: Office for National Statistics

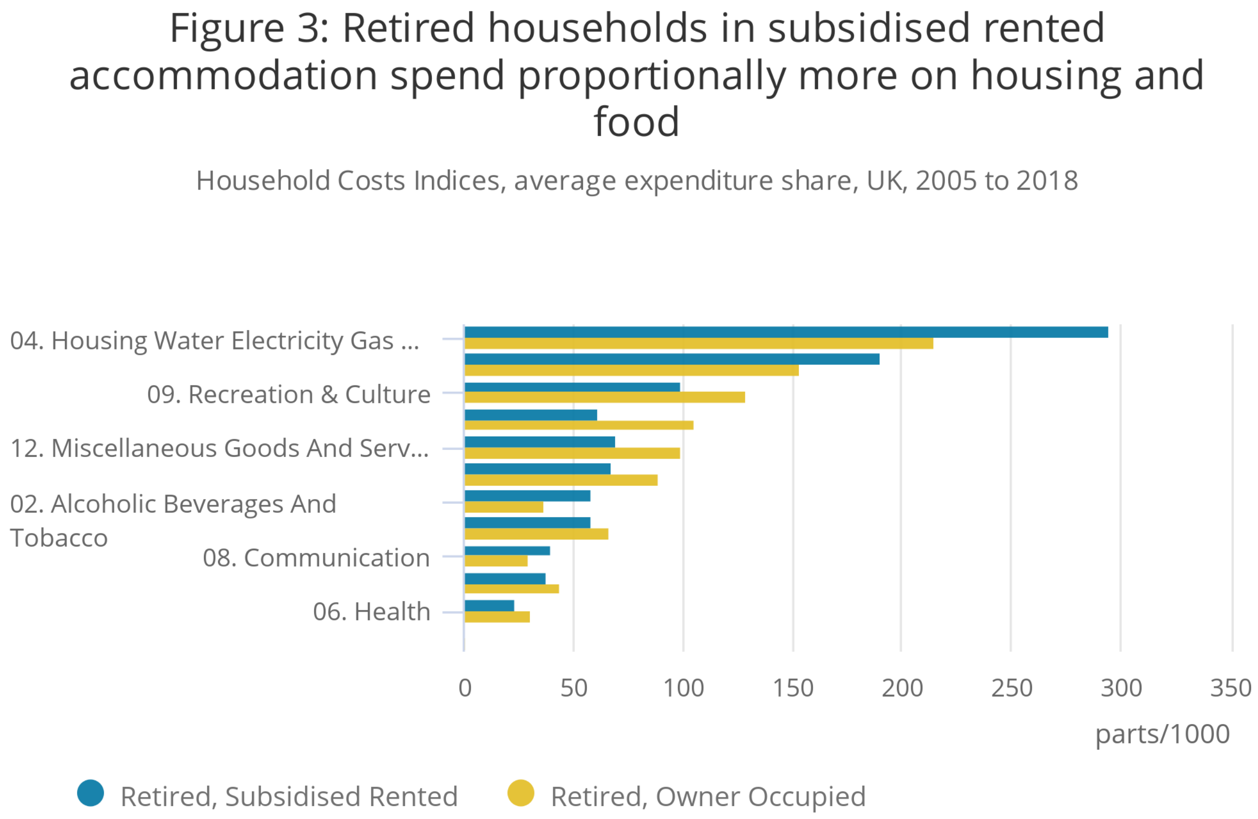
Notes:

1. Expenditure shares may not sum to 1,000 due to rounding.
2. Weights for each category of spending are averaged across the period of 2005 to 2018.

When considering retired households, the small sample size of private renters means it is more appropriate to compare subsidised renters and owner-occupiers. It is notable that subsidised renters still spend a greater proportion of their expenditure on housing than owner-occupiers (296 parts per thousand compared with 219).

Figure 3: Retired households in subsidised rented accommodation spend proportionally more on housing and food

Household Costs Indices, average expenditure share, UK, 2005 to 2018



Source: Office for National Statistics

Notes:

1. Expenditure shares may not sum to 1,000 due to rounding.

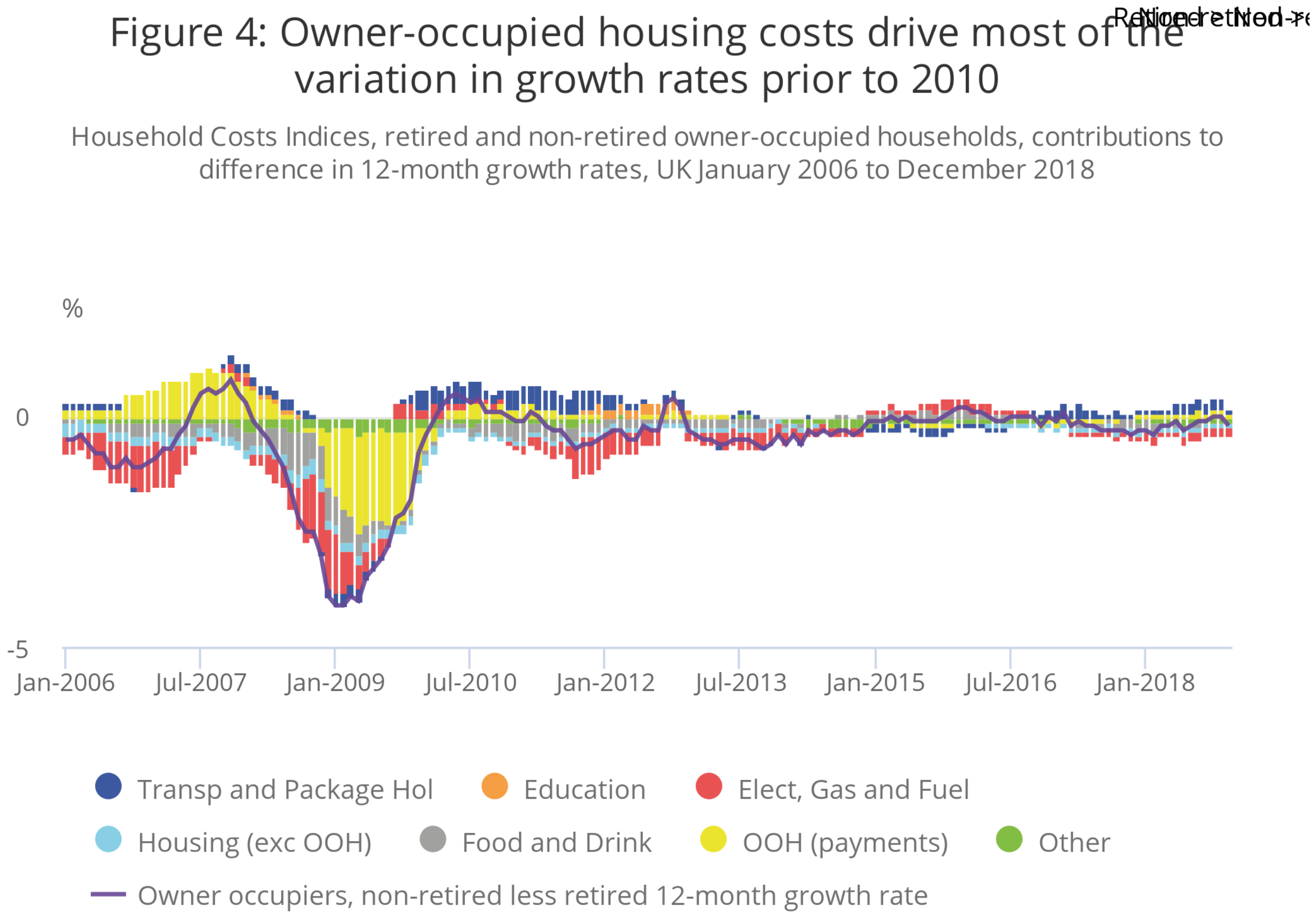
2. Weights for each category of spending are averaged across the period of 2005 to 2018.

Understanding how households distribute their expenditure between categories helps to explain drivers of differences in their annual growth rates. For example, households that spend a greater proportion of their outgoings on food will be more exposed to price changes in that category. Analysing contributions to the annual growth rate can display how this plays out over time, and studying the differences between groups in these contributions can show how and where experiences of costs growth diverge the most.

As Figure 1 demonstrated, growth rates for retired households track each other closely, and a contributions analysis shows that the underlying expenditure shares are also consistent. However, some interesting observations can be made if tenure type is held fixed and we compare between retirement statuses. A chart of the differences in contributions between non-retired and retired owner-occupied households clearly shows the effect of owner-occupied housing payments early in the series, as well as the increased exposure to energy costs faced by retired households.

Figure 4: Owner-occupied housing costs drive most of the variation in growth rates prior to 2010

Household Costs Indices, retired and non-retired owner-occupied households, contributions to difference in 12-month growth rates, UK January 2006 to December 2018



Source: Office for National Statistics

Notes:

1. Stacked bars reflect the percentage point contributions of each of the 87 class-level items to the 12-month growth rate, or the difference in 12-month growth rates. The contribution of each of the 87 class-level items is estimated separately, before being aggregated to seven distinct categories.

2. A reduction in the contribution of series to the annual rate of change need not imply falling prices, but could also reflect a lower rate of increase than the previous year.

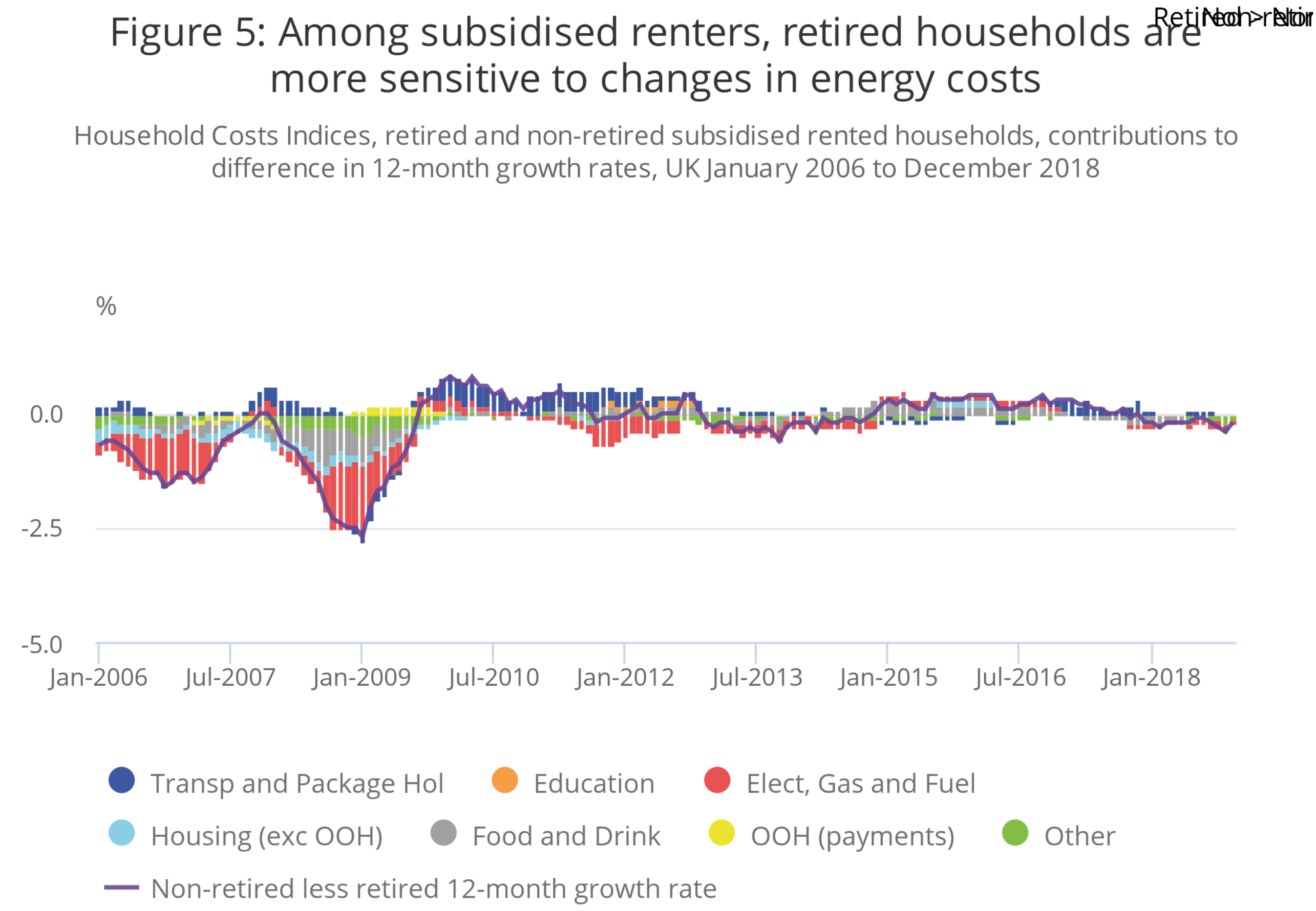
3. "Food and drink" comprises food, non-alcoholic and alcoholic beverages and tobacco. "Housing (exc. OOH)" comprises actual rents, Council Tax, and products and services for the repair of dwellings. Owner occupiers' housing costs (payments) is a separate category. "Elect., gas and fuel" comprises electricity, gas and other household fuels as well as fuels and lubricants for motor vehicles. "Transport and package holidays" includes passenger transport by road, rail, air and sea, as well as package holidays. "Education" reflects the division-level contribution. The "other" category reflects the combined contributions of the remaining class-level items, bringing the sum of contributions to the inflation rate.

4. Contributions may not sum due to rounding.

A similar chart for subsidised renters further emphasises the impact of energy bills on retired households and highlights the increased exposure to transport costs faced by non-retired households.

Figure 5: Among subsidised renters, retired households are more sensitive to changes in energy costs

Household Costs Indices, retired and non-retired subsidised rented households, contributions to difference in 12-month growth rates, UK January 2006 to December 2018



Source: Office for National Statistics

Notes:

1. Stacked bars reflect the percentage point contributions of each of the 87 class-level items to the 12-month growth rate, or the difference in 12-month growth rates. The contribution of each of the 87 class-level items is estimated separately, before being aggregated to seven distinct categories.

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4. Contributions may not sum due to rounding.

5 . HCIs for households with and without children, separated by tenure type

As the Living Costs and Food survey (LCF) captures details of the number of children living in households it is also possible to construct Household Costs Indices (HCIs) for households with and without children. Extra care is required when interpreting these results however, as almost all (99.1%) of retired households are also childless. This means that a proportion of what we observe in this analysis can be associated with retirement status rather than the presence or absence of children. The picture is complicated further when we are reminded that the distribution of tenure types across retired households is markedly different from the wider population.

We find that for households without children, 47% of subsidised rented households and 42% of owner-occupied households are also retired, while the figure for privately rented households is only 13%. For consistency with the second preliminary release of the HCIs, the following analysis includes retired households in the without children group.

The annual growth rates and cumulative costs increase between 2005 and 2018 for households with and without children are shown in Table 3:

Table 3: Summary annual growth rates and cumulative costs increases for households with and without children by tenure type, UK, 2006 to 201

	Households without children		**Households with children**		**All households**	
Tenure type	Annual Growth Rate	Cumulative % costs increase, 2005-2018	Annual Growth Rate	Cumulative % costs increase, 2005-2018	Annual Growth Rate	Cumulative % costs increase, 2005-2018
Subsidised rented	2.8	44.5%	2.4	38.0%	2.7	42.4%
Privately rented	2.5	39.1%	2.4	37.1%	2.5	38.5%
Owner occupied	2.5	38.4%	2.1	32.1%	2.3	36.6%
All tenure types	2.5	39.7%	2.2	33.9%	2.4	38.0%

Source: Office for National Statistics

Notes

1. The average presented is the compound average 12-month growth rate of the unrounded indices. Consequently it may differ from the arithmetic average of the 12-month growth rates presented in this article. Back to table

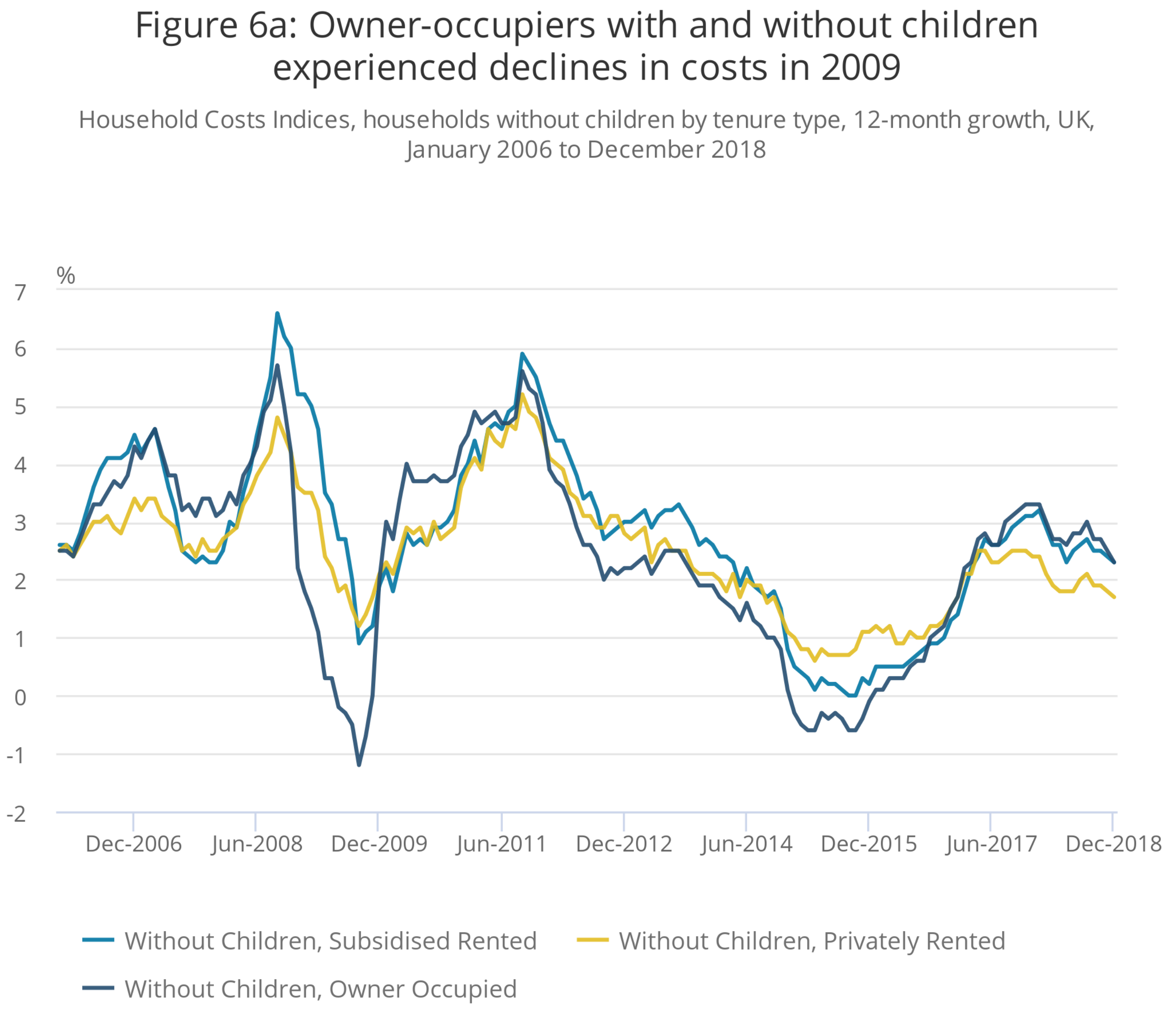
2. All figures presented in this table are rounded to 1 decimal place (dp). Back to table

Households without children have experienced larger increases in costs than households with children. Some of this will be explained by the composition effect already described, as retired households have also encountered larger costs increases and almost all retired households are childless. Excluding retired households from the without children group would be expected to lower their growth rates, especially in the case of owner-occupiers. The difference between childless subsidised renters and owner-occupiers with children is striking: 2.8% compared with 2.1%.

Figure 10 shows where growth rates have diverged over the period 2005-2018. As already seen with the retired /non-retired analysis, owner occupiers saw a significant drop in their costs during the financial downturn. This effect is far more pronounced for households with children, an effect partly caused by the absence of retired households (who are largely free of mortgage payments) from this group. Compared with owner occupiers, the series for private and subsidised renters follow each other closely and are less volatile overall

Figure 6a: Owner-occupiers with and without children experienced declines in costs in 2009

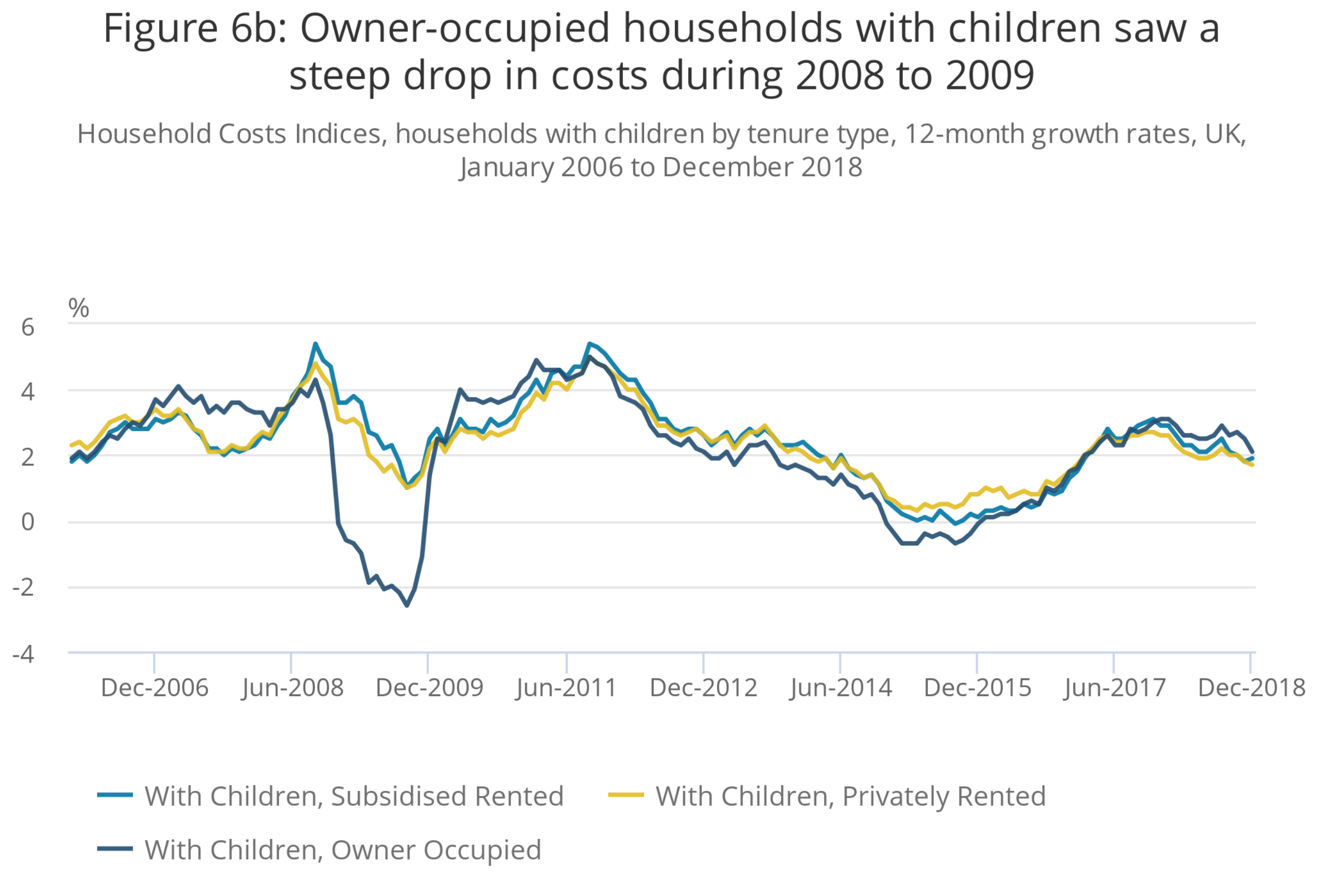
Household Costs Indices, households without children by tenure type, 12-month growth, UK, January 2006 to December 2018



Source: Office for National Statistics

Figure 6b: Owner-occupied households with children saw a steep drop in costs during 2008 to 2009

Household Costs Indices, households with children by tenure type, 12-month growth rates, UK, January 2006 to December 2018

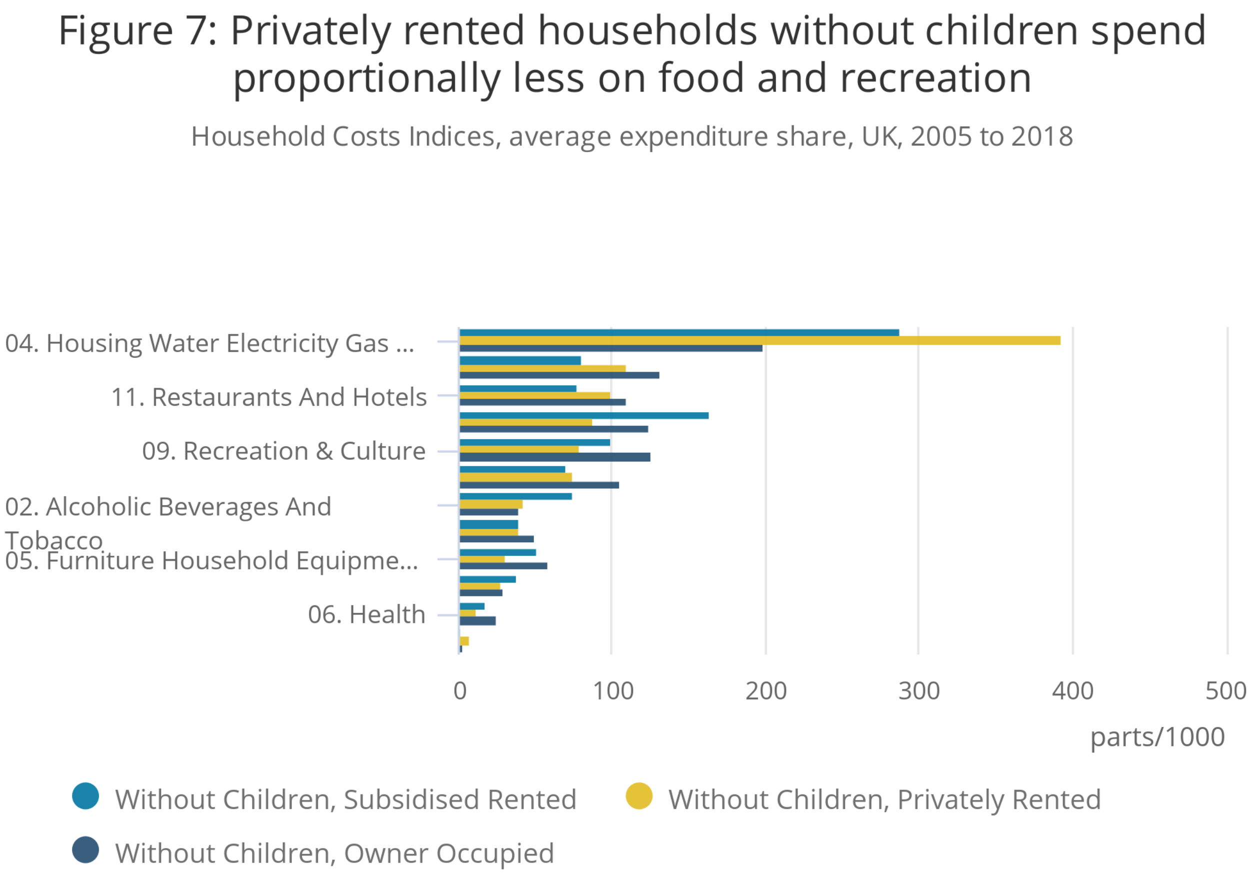


Source: Office for National Statistics

A breakdown of expenditure into classification of individual consumption by purpose (COICOP) divisions shows that housing dominates. This is especially true for private renters, and of those it is households without children who have spent the greatest proportion of their outgoings on housing (390 parts per thousand).

Figure 7: Privately rented households without children spend proportionally less on food and recreation

Household Costs Indices, average expenditure share, UK, 2005 to 2018



Source: Office for National Statistics

Notes:

1. Expenditure shares may not sum to 1,000 due to rounding.

2. Weights for each category of spending are averaged across the period of 2005 to 2018.

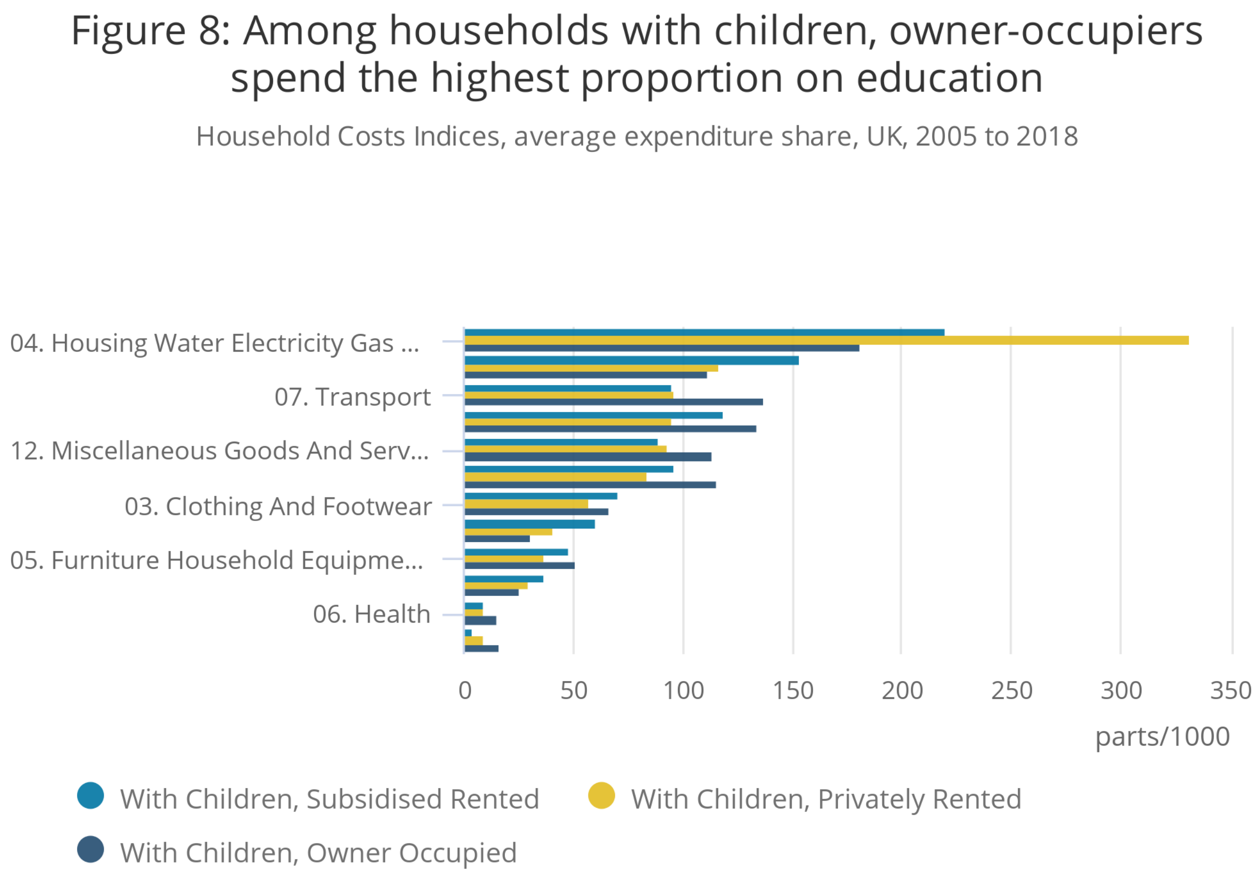
Examining the differences in expenditure breakdown, we can see that for households without children there are some clear patterns. Privately rented households have spent a far greater proportion of their outgoings on education than either subsidised renters or owner-occupiers. It might be expected that private renters are as a group younger than the other tenure types (recall Table 1, and the lack of retired households in privately rented accommodation) and therefore feature a greater proportion of recent graduates.

Owner-occupiers have spent a far smaller proportion of their outgoings on housing than either category of renter. Compared to subsidised renters, owner-occupiers spend more on education, transport, financial services and health. However, when comparing with private renters a different set of expenditure categories emerges. After health, furniture, recreation and food are the next largest differences in percentage terms. This resonates with the analysis for retired and non-retired households, because as there are relatively few retired households in privately rented accommodation the expenditure patterns for private renters are more likely to track those of the non-retired population.

Turning to households with children, owner-occupiers spend a far larger proportion of their outgoings on education services than private renters, who in turn spend a larger proportion of their outgoings on education than subsidised renters. Housing costs make up a much greater proportion of expenditure for private renters than either subsidised renters or owner-occupiers.

Figure 8: Among households with children, owner-occupiers spend the highest proportion on education

Household Costs Indices, average expenditure share, UK, 2005 to 2018



Source: Office for National Statistics

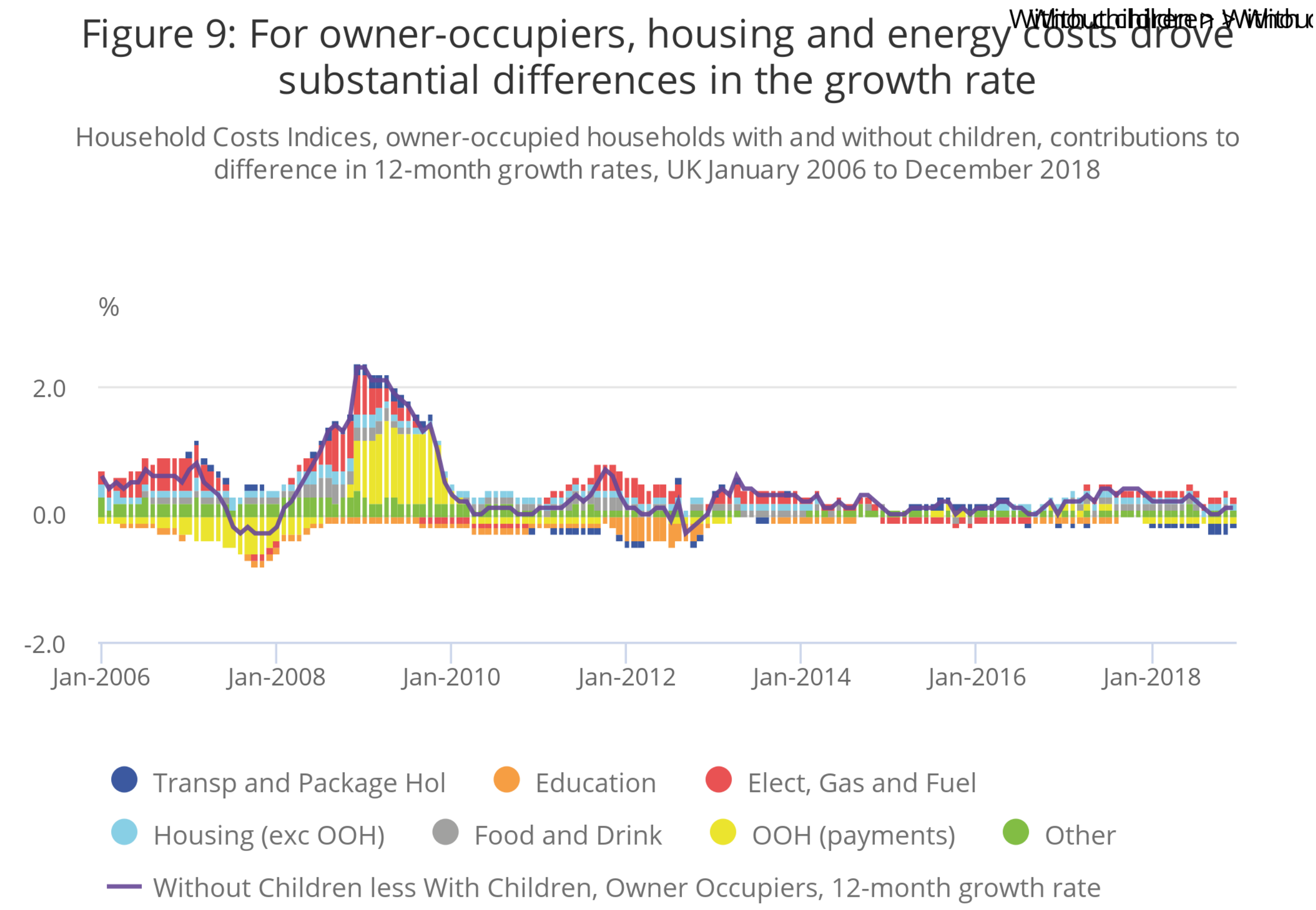
Notes:

1. Expenditure shares may not sum to 1,000 due to rounding.
2. Weights for each category of spending are averaged across the period of 2005 to 2018.

Examining the differences in contributions for households with and without children shows that the sharp difference in annual growth rate for owner-occupied households between 2008 and 2010 was caused mainly by owner-occupied housing and energy. Only education costs have consistently worked to increase the growth rate for households with children.

Figure 9: For owner-occupiers, housing and energy costs drove substantial differences in the growth rate

Household Costs Indices, owner-occupied households with and without children, contributions to difference in 12-month growth rates, UK January 2006 to December 2018



Source: Office for National Statistics

Notes:

1. Stacked bars reflect the percentage point contributions of each of the 87 class-level items to the 12-month growth rate, or the difference in 12-month growth rates. The contribution of each of the 87 class-level items is estimated separately, before being aggregated to seven distinct categories.

2. A reduction in the contribution of series to the annual rate of change need not imply falling prices, but could also reflect a lower rate of increase than the previous year.

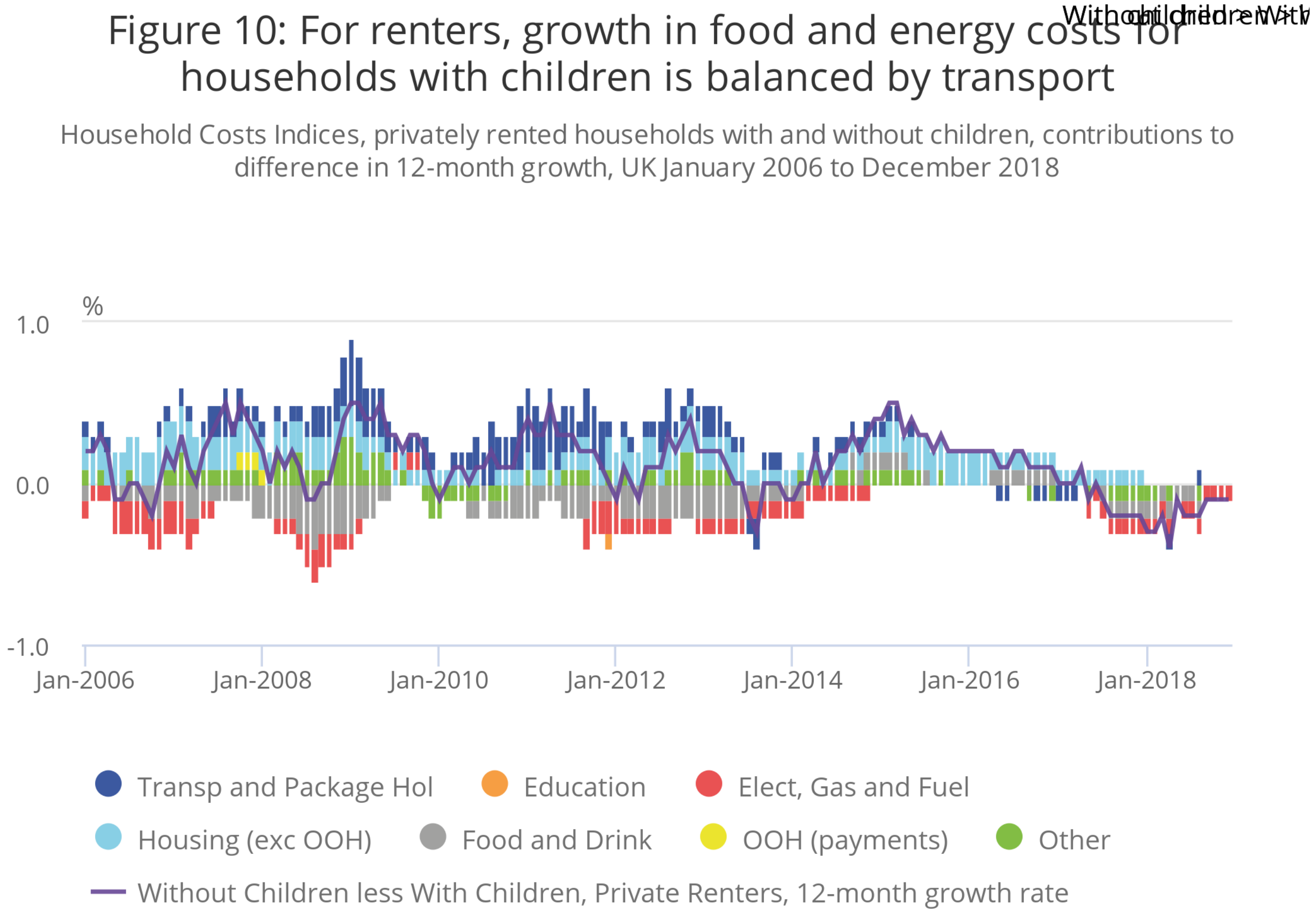
3. “Food and drink” comprises food, non-alcoholic and alcoholic beverages and tobacco. “Housing (exc. OOH)” comprises actual rents, Council Tax, and products and services for the repair of dwellings. Owner occupiers’ housing costs (payments) is a separate category. “Elect., gas and fuel” comprises electricity, gas and other household fuels as well as fuels and lubricants for motor vehicles. “Transport and package holidays” includes passenger transport by road, rail, air and sea, as well as package holidays. “Education” reflects the division-level contribution. The “other” category reflects the combined contributions of the remaining class-level items, bringing the sum of contributions to the inflation rate.

4. Contributions may not sum due to rounding.

Turning to the privately rented sector, the overall difference in growth rate between households with and without children does not show the dramatic divergence between 2008 and 2010 seen among owner-occupiers. Food and energy costs are the most prominent categories for households with children, reflecting a tendency firstly for this group to spend more time at home, and secondly for them to be larger households generally. Transport and housing (excluding owner-occupied housing costs) are the main drivers for households without children. The influence of transport on households without children is notable as the analysis of retired and non-retired households revealed that transport is a driver of growth for non-retired households. The presence of transport as a growth driver for households without children suggests that it is strong enough to override the influence of retired households within this group.

Figure 10: For renters, growth in food and energy costs for households with children is balanced by transport

Household Costs Indices, privately rented households with and without children, contributions to difference in 12-month growth, UK January 2006 to December 2018



Source: Office for National Statistics

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4. Contributions may not sum due to rounding.

6 . Conclusions

The main conclusion from this analysis is that greatest driver of differences between groups is exposure to interest rates between 2008 and 2010. Households repaying mortgages at that time benefitted from sharp cuts in interest rates, and ongoing low rates have meant that this difference has carried through to the present day amounting to about 6% between subsidised renters and owner-occupiers.

Elsewhere, we can see where particular circumstances lead to households facing greater or lesser exposure to price and expenditure movements in certain categories of goods. Households with children and retired households are both sensitive to price changes in food and energy. Households without children are more sensitive to price changes in transport, even allowing for the inclusion of retired households who tend to spend less in this category.

It is reasonable to argue that tenure type may be taken as a proxy for income level, and therefore the case could be made that some of the effects we see in this analysis are really driven by income. One avenue for further analysis in the future could be to use income data to separate out these effects.

As the Household Costs Indices (HCIs) continue to develop it is hoped that they will be used to inform public debate and other social analysis. The differential experiences of household groups with regards to changing costs is a recurring public concern and the HCIs can help to ground the discussions that arise as a result. Examining the variation in how changing prices and costs impact on the baskets of different household groups can tell us about the choices and challenges with which they are confronted. In so doing, the HCIs can help to analyse potential responses to economic changes as they occur.

7 . Author

Huw Pierce

Compendium

Exchange rate pass through and transmission to consumer prices following the 2015 to 2016 depreciation of sterling

Comparison of the exchange rate movements with price movements looking at the path of exchange movements and CPI inflation.

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Table of contents

1 . Main points

- The 2016 exchange rate changes had more impact on high import intensity products than low import intensity products. Half of the subsequent increase in Consumer Prices Index (CPI) inflation was driven by the elements of the basket with more than 25% import intensity.

- The impact of exchange rate changes on high import intensity products was particularly pronounced in the initial months following the 2016 change.

- Following the 2016 exchange rate changes, the growth rate for the Consumer Prices Index for durable goods was more responsive than that for non-durable goods. This is in line with what prior empirical literature has shown regarding how the observed relationship between exchange rate and prices depends on sector and product characteristics.

2 . Introduction

The degree to which exchange rate changes are transmitted to import prices and consumer prices is commonly referred to as the exchange rate pass-through. Understanding the role of exchange rates in shaping economic outcomes is important from a monetary policy perspective. In particular, assessing the degree of pass-through of exchange rate movements is essential for monitoring and forecasting inflation.

Exchange rate changes are transmitted to import prices and then to final consumer prices via a number of channels, both direct and indirect. Inflation may be influenced directly – by higher prices of goods imported for direct consumption, as well as indirectly – through changes in the costs of imported goods which are subsequently used as inputs into domestic production. Following an exchange rate depreciation, imported final consumer goods become more expensive, pushing up overall consumer inflation. The cost of direct imports [1] makes up about 13% of overall final household consumption expenditure, with indirect imports at 8%, hence direct imports are the channel with the larger impact.

The indirect effect, which works via production costs and takes longer to trickle through the economy, is a two-stage process. In the first stage, the sterling depreciation translates into higher production costs due to more expensive imported inputs and these feed through the domestic intermediate and final goods production. In the second stage an inflationary impact is passed on to domestic consumer prices. We therefore examine both the direct effect, which works via impact of depreciation on higher prices for direct consumption, and the indirect effect, which operates via pass-through at different stages along the distribution chain (import prices, producer prices and subsequently consumer prices)[2].

However, changes in import prices are likely to translate into changes in the producer and consumer prices of an economy only if producers raise their prices in line with the increase in import prices. Firms may pass on the increase in costs resulting from the sterling depreciation to sustain mark-ups and profits, or they may keep prices constant and accept lower profits, thus dampening the pass-through to final consumer prices, or somewhere in-between.

It should be emphasised that additional factors determine the extent and speed of exchange rate pass-through. Some of these relate to the macroeconomic factors such as the degree of openness to trade, the structure of imports, the expected persistence of the exchange rate change, and the degree of slack in the economy. Other factors relate to the microeconomic structure and behaviour of firms, for example their pricing power, the degree of market concentration, and firms' hedging against exchange rate movements [3] . In addition, the share of imported final goods and services in the price index, and the importance of imported inputs (for example commodities) in domestic production all influence the magnitude and timing of pass-through (Hahn and O'Brien, 2018).

All mentioned factors can lead to variation in the magnitude and timing of transmission across components of the Consumer Prices Index (CPI), but these may also depend on the underlying drivers of the exchange rate movements (Forbes and others, 2018). We should emphasise that the change in the exchange rate can affect consumer prices with considerable delays. For these reasons this article has not attempted to compare the recent episode of exchange rate depreciation with previous episodes.

This article examines the experience of the sterling depreciation from the end of 2015 to the second half of 2016 to analyse the subsequent movement of prices, looking at:

- the transmission of exchange rate changes to consumer prices for high import intensity and low import intensity goods; goods versus services and durables versus non-durables
- the relationship between exchange rate changes and import prices, producer prices and consumer prices

Notes: Introduction

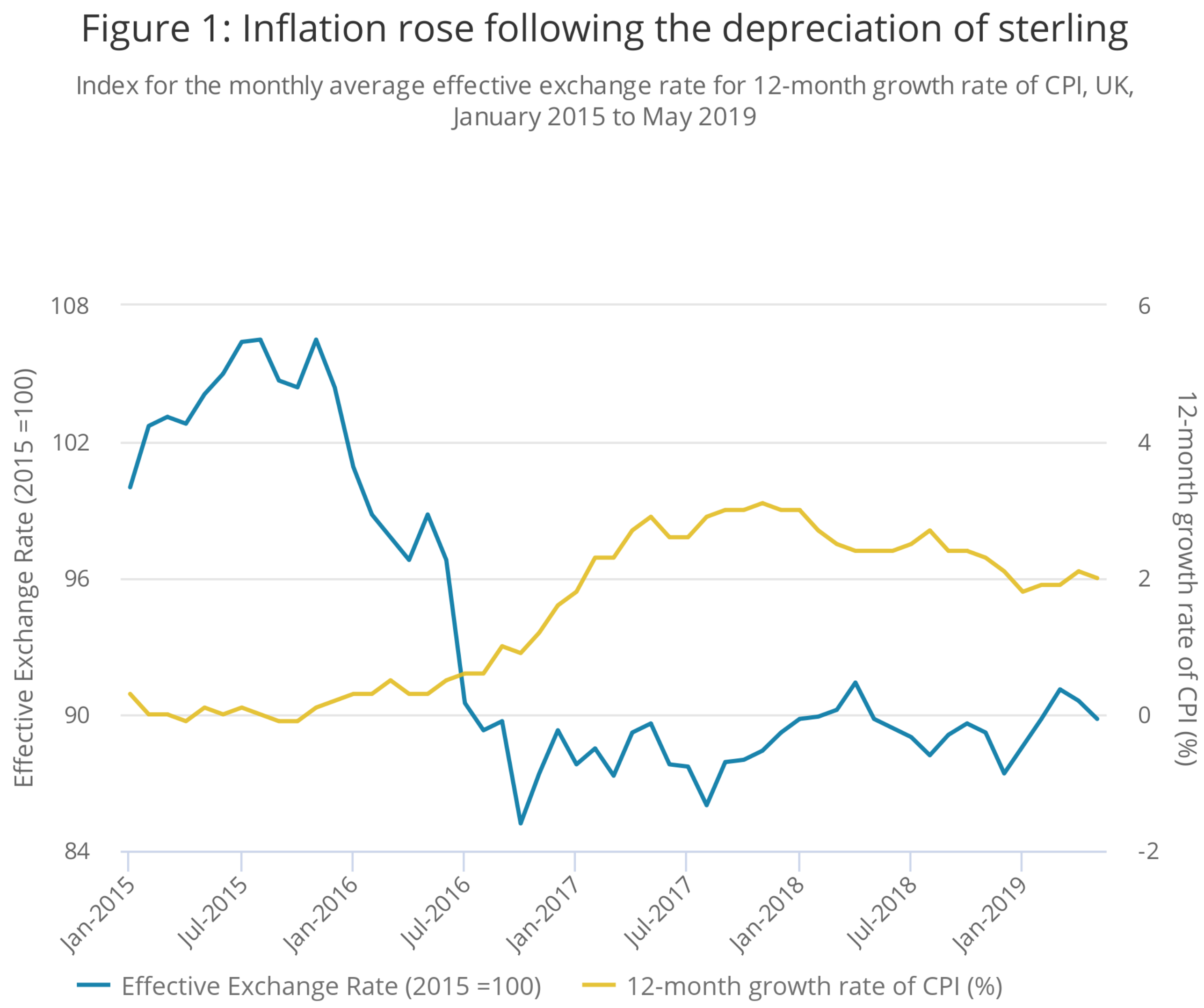
1. This excludes margins, taxes and subsidies to reflect their impact on prices.
2. Another type of indirect effect may be observed if the depreciation pushes up demand for cheaper domestically produced goods which can lead to higher prices. This effect may be relevant especially for food, but it is outside the scope of this article.
3. Firms may reduce their exposure to exchange rate risk by investing in financial instruments or holding reserves of foreign currency.

3 . The path of exchange rate movements and Consumer Prices Index (CPI) inflation

Figure 1 shows the sterling effective exchange rate from 2015 onwards. From December 2015 there was a fall in the sterling effective exchange rate which mostly reflects the market participants pricing the probability of different outcomes in relation to the referendum on the UK's membership of the EU [1]. After the outcome of the referendum on the UK's membership of the EU in June 2016, sterling fell sharply by 7% in one month. This reflected both higher uncertainty surrounding the future relationship with the EU and related change in policy, but also a decline in the expected future openness of the UK to trade, investment and immigration with the EU (Breinlich and others, 2017). In other words, the observed depreciation of sterling reflected market participants' revised expectations of the UK economy. By October 2016 sterling's effective exchange rate was 20% below where it had been at the previous peak.

Figure 1: Inflation rose following the depreciation of sterling

Index for the monthly average effective exchange rate for 12-month growth rate of CPI, UK, January 2015 to May 2019



Source: Bank of England - Bank of England Database, Office for National Statistics - Consumer Prices Index

The lower exchange rate raises the cost of importing both consumption goods and intermediate inputs, leading to the observed rise in the of the UK Consumer Prices Index (CPI) 12-month inflation rate. Figure 1 shows that during 2015 CPI inflation stayed close to zero, but then reached a peak of 3.1% in November 2017.

Stylised fact 1: The depreciation of sterling from 2015 to 2016 was followed by a rise in consumer price inflation from 2016 to 2017

However, we should note that higher inflation may also be driven by global events such as rise of the price of oil and inflationary pressures due to growth in the EU and the US (Breinlich and others, 2017). Hence, to more closely capture the effect of the referendum on the UK's membership of the EU on inflation, we investigate whether products that are likely to be more exposed to changes in the value of sterling, such as high import intensity products, experienced higher increase in prices compared to low import intensity products.

Notes:The path of exchange rate movements and Consumer Prices Index (CPI) inflation

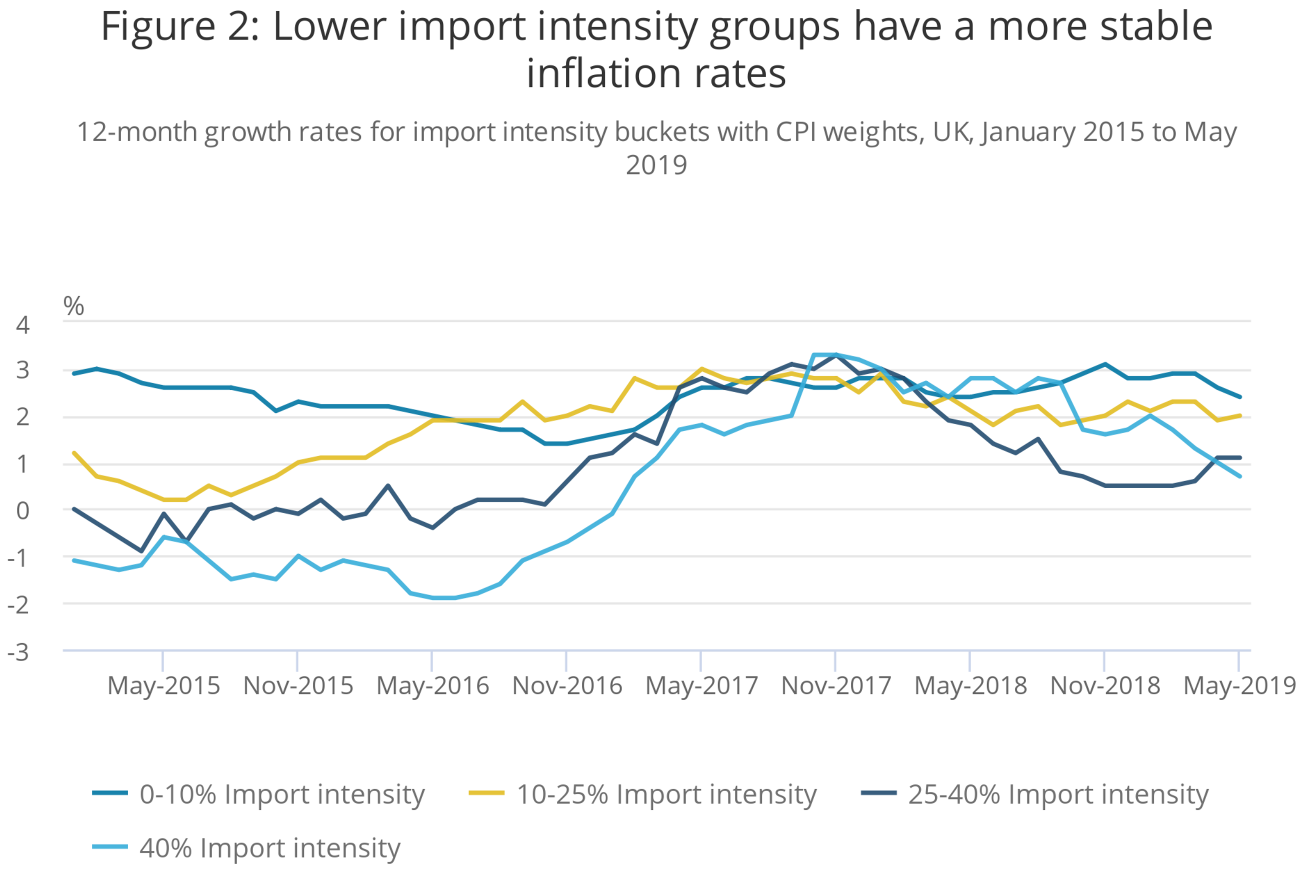
1. We should note that betting markets implied around 85% probability that the UK would choose to remain in the UK (The Economist, 2016).

4 . Import intensity and inflation

Import intensity, also known as import penetration, refers to the percentage of final household consumption which is due to imports. Once the estimation for the import intensity has been made, we are able to group the products into import intensity buckets. We exclude energy products and divide the remainder into four buckets of import intensity 0 to 10%, 10% to 25%, 25% to 40% and 40% plus. The lowest intensity bucket includes services such as hairdressing services, and the highest import intensity bucket includes goods such as new cars. It is worth noting that the categories are defined to reflect impact on consumer price so goods that face heavy domestic taxation, such as wine, have an import intensity figure much lower than would be implied by looking at only at the volume of imports. Figure 2 shows the 12-month growth rate of the Consumer Price Index (CPI) for each of the import intensity buckets[1] . We expect that products with a higher import expenditure share (high import intensity products) will experience larger price rises when the costs of imported goods increase.

Figure 2: Lower import intensity groups have a more stable inflation rates

12-month growth rates for import intensity buckets with CPI weights, UK, January 2015 to May 2019



Source: Office for National Statistics - Consumer Prices Index

In line with our expectations, Figure 2 points to the strong contrast between the rise in inflation following the depreciation for the high import intensity group compared with the low import intensity group. The higher import intensity groups switched from negative to positive inflation. In contrast the lowest two import intensity groups had more stable levels of inflation. The caveat is that the impact of exchange rate movements on inflation are likely to be spread out over time so we cannot draw simple conclusions about the length of lags, but the observed pattern is notable.

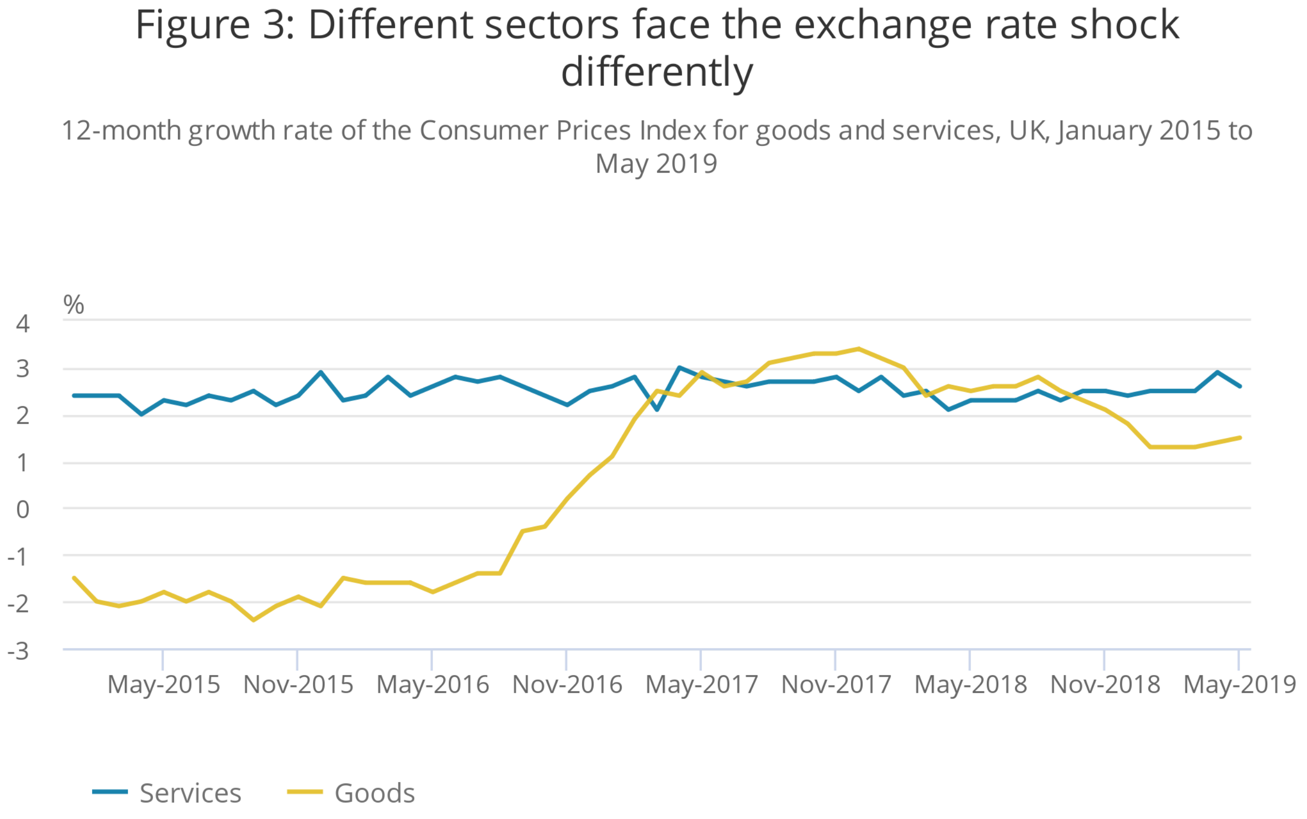
Stylised fact 2: High import intensity goods generally experienced a higher increase in inflation compared with low import intensity goods. Along with energy, they were the main drivers of the rise in the overall consumer price inflation rate following the depreciation

We also check the reliability of our initial results in relation to high and low import intensity products by comparing the price movements of goods and services separately. At the broadest level for services, which tend to be domestically produced, hence less import intensive and relatively more labour intensive, we might observe less impact on their price than manufactured goods.

Figure 3 shows the marked difference between the path of inflation for goods and services following the depreciation of sterling. The inflation rate for services was remarkably stable, staying between 2% and 3% for the whole period from 2015 to the present. Goods price inflation, in contrast, changed from negative 2% before the depreciation to over 3% after it. The chart is not adjusted for labour cost growth, nor does it exclude the impact of energy prices; both are potentially significant additional drivers.

Figure 3: Different sectors face the exchange rate shock differently

12-month growth rate of the Consumer Prices Index for goods and services, UK, January 2015 to May 2019



Source: Office for National Statistics - Consumer Prices Index

Notes: Import intensity and inflation

1. Consumer prices that are highly dependent on imports relate mainly to particular manufacturing products such as footwear and cars and some food products. Low import intensity tends to apply to services such as repair services or to products where distribution or taxation drives a high proportion of the final price to consumers, such as alcoholic beverages which are also heavily taxed.

2. The one percentage point contribution to change in inflation is the largest such swing for the highest import intensity group since at least January 2006.

5 . The size and the speed of transmission mechanism over the pricing chain (via import prices, producer prices (PPI) and consumer prices (CPI))

Exchange rate movements also affect domestic prices through the production process where changes in the cost of imported inputs to production feed through to changes in the price of firms' outputs. We would expect changes in the exchange rate to be reflected more quickly and more sizeably in movements in import price inflation than in producer and consumer price inflation, in part reflecting that the latter are more indirect in nature.

Indirect effects, which take longer to trickle through the economy, work via production costs which connect import prices with producer prices and then consumer prices, and depends on the pricing behaviour of domestic firms. The firms may pass on the increase in costs, depending on their market power, resulting from the sterling depreciation to maintain mark-ups and profits. Alternatively, they might keep prices constant and accept lower profits, thus dampening the pass-through to final consumer prices, or somewhere in-between.

At the import price stage, the exchange rate pass-through is related to the degree of competition across industries. The degree to which firms can adjust mark-up in response to an exchange rate change depends on their pricing power, which is a function of how easily their products can be substituted with other similar ones and the degree of market concentration. In short, the greater the capacity for substitution between domestic and imported products and the higher the number of firms servicing the UK market, the lower would be the pass-through to import prices in sterling.

The upper panel of Figure 4 shows that the depreciation of sterling was followed first by a sizeable increase in inflation for imports of inputs to manufacturing and then a somewhat larger increase in inflation for manufacturing inputs overall. The lower panel shows inflation for output producer prices and consumer prices, with a rescaled vertical axis to make the changes more visible. The increase in inflation for output producer prices (factory gate prices) was much lower than the inflation rates shown in the upper panel and the increase for consumer prices was even more muted. These findings are exactly in line with what we would expect from the indirect effects described earlier.

Figure 4: The impact of depreciation on output producer price inflation and consumer price inflation was lower and with more of a lag than on import price inflation and input producer price inflation

Data download

Source: Office for National Statistics

Import price inflation rose from negative 7.2% in August 2015 to 13.6% in January 2017, a rise of 20.8 percentage points. Input price inflation rose from a low of negative 14.6% in August 2015 to a high of 19.9% in January 2017. It is likely that the rise in energy prices in this period contributed to the increase in input producer prices, compounding the effect of the depreciation.

Stylised fact 3: The exchange rate depreciation was followed by large increases in the inflation rate for imported commodities and for inputs to the manufacturing process, and then more muted increases in output producer prices and consumer prices

Focusing on the last stage of the pricing chain, namely consumer prices, we expect that the pass-through will be higher for durable goods and lower for non-durable goods. The impact of an exchange rate change on non-energy industrial goods inflation is to a large extent transmitted via the prices of durable goods. The empirical literature has shown that the observed relationship between exchange rate and prices depends on sector and product characteristics.

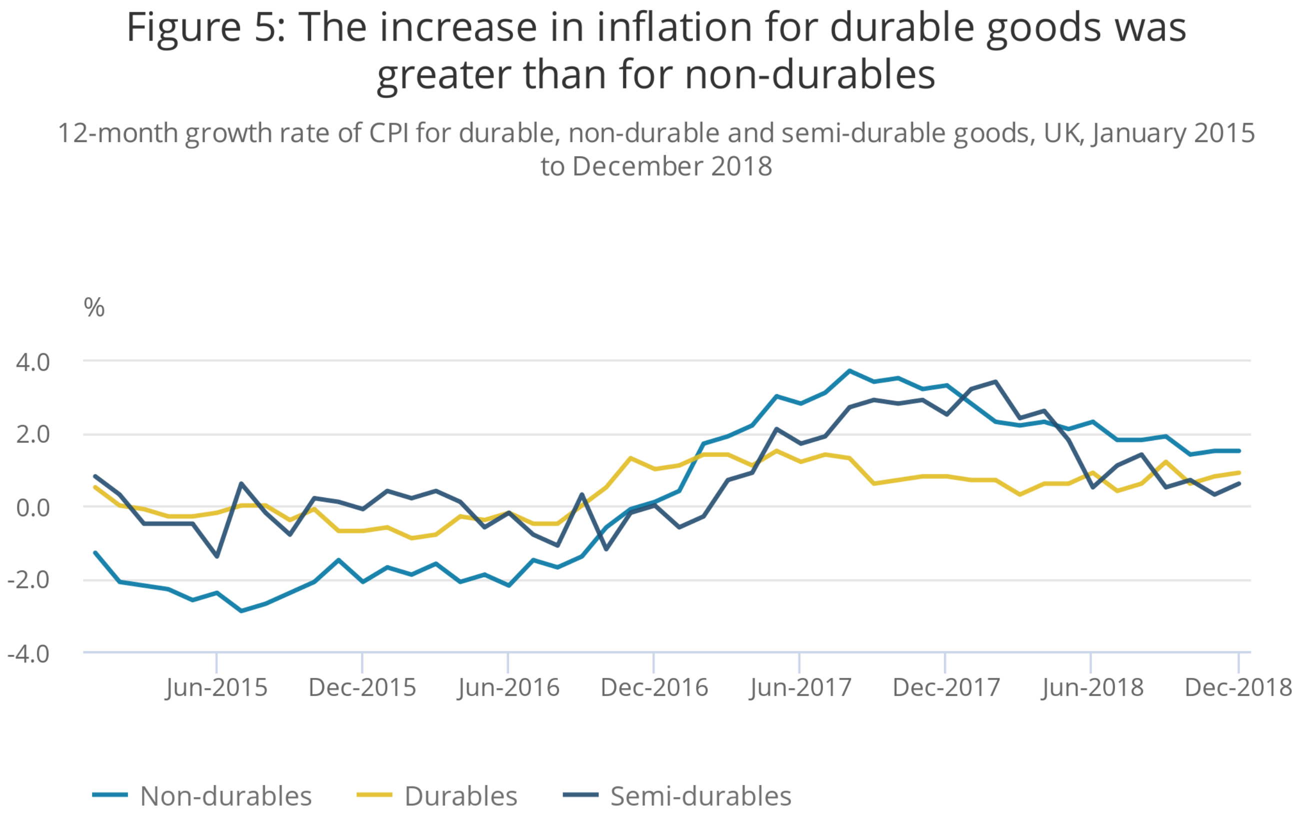
Of the components making up the CPI excluding energy and food, non energy industrial goods (NEIG) prices are the most sensitive to movements in the exchange rate. This is particularly the case for durable goods because durables are traded more extensively and have higher import intensity compared with non-durables. In fact, a large proportion of international trade is in durable goods comprising more than 60% of imports and exports for Organisation for Economic Co-operation and Development (OECD) countries, whereas the share increases to 70% after excluding raw materials and energy products (Engel and Wang, 2007). Figure 8 shows that this pattern observed in previous episodes was repeated in the 2015 to 2016 depreciation. The increase in inflation for durable goods was greater than for non-durables.

As the size and speed of the exchange rate pass-through seems to differ across product categories this indicates that cost structures and pricing decisions at the firm level are important factors determining the exchange rate effects at the aggregate price level. These differences at the goods category level can be related to different industry characteristics.

Stylised fact 4: There was a marked contrast between the change in inflation for goods and the more stable inflation rate for services following the depreciation and there was also a noticeably greater impact on inflation for durables compared with non-durables

Figure 5: The increase in inflation for durable goods was greater than for non-durables

12-month growth rate of CPI for durable, non-durable and semi-durable goods, UK, January 2015 to December 2018



Source: Office for National Statistics - Consumer Prices Index

6 . Conclusion

Exchange rate pass-through refers to the degree to which movements in the exchange rate are transmitted to import prices and subsequently domestic prices. This reflects the higher prices of goods imported for direct consumption as well as through changes in the costs of imported goods which are subsequently used as inputs into domestic production.

In this analysis we use the depreciation of sterling in 2016 as a case study which enables us to investigate the exchange rate transmission through import and producer prices to consumer prices. The picture that emerges is of a rise of the rate of inflation after the depreciation and one that was markedly higher for goods with higher import intensity. The depreciation was transmitted both through higher prices for goods imported for consumption and through higher import prices of goods used as inputs in productions. Given the number of factors that influence it, however, further research is required to understand the speed and magnitude of pass-through.

We should note that monitoring the impact of past exchange rate depreciation on the inflation should be an ongoing task. Pass-through models suggest that the impacts are spread over several quarters, and the exchange rate pass-through may be difficult to detect if it is offset by other factors including the pricing power of firms.

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8 . Authors

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Compendium

New data sources in consumer price statistics: July 2019

Explaining our research and plans to use scanner data and web-scraped data as alternative data sources in our measures of consumer price inflation.

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1 . Main points

- Our aim is to incorporate scanner and web-scraped data into our measures of consumer price inflation from early 2023.
- Scanner data have some unique advantages when used to produce price statistics.
- Experimental analysis on web-scraped data has yielded promising results for their future inclusion in consumer price inflation measures.
- When used in combination, scanner data, web-scraped data and data from existing sources will give us an unprecedented level of insight into how prices change across the economy.

2 . Overview

In this article, we will:

- briefly explain what our alternative data sources are
- provide our first status update for scanner data and explain why these data are so valuable
- expand the experimental web-scraped analysis by increasing our time series and providing further commentary
- provide greater detail on our plans for these alternative data sources

3 . Introduction to alternative data sources

We are researching the suitability of two new alternative data sources to inform our measures of consumer price inflation. We plan to incorporate these data sources in the first quarter (Jan to Mar) of 2023 . These data sources are:

- scanner data: prices automatically generated from point-of-sale customer transactions
- web-scraped data: prices automatically scraped from websites

We will look to use these data sources in conjunction with the existing (mostly manually collected) data sources. These include local collections (prices obtained from shop shelves), administrative data and some central collections that cannot be replaced by web scraping (such as telephone calls used to collect prices for local services such as hairdressing).

We are aiming to integrate these alternative data sources as part of a phased approach. In the first quarter of 2023, we plan to integrate alternative data sources for spending categories where early data acquisition is possible. These categories account for around 100 of the approximately 700 items covered by the current basket of goods and services. The categories we plan to focus on in 2023 are:

- technological goods (laptops, desktops, tablets and smartphones)
- chart-collected items (CDs, DVDs, Blu-rays and books)
- package holidays
- clothing
- rail fares
- used cars
- groceries (which will likely cover the largest retailers in this sector)

From 2024 onwards, we would then look to expand upon this list, incorporating alternative data sources for additional areas of the basket of goods and services.

In May 2019, we used these alternative data sources and published some early experimental indices and analysis on web-scraped data with a five-month time series.

4 . Scanner data: an update

The UK's largest retailers generate vast quantities of data on consumer spending at the point of sale, through scanner machines in-store or through online sales ("scanner data" will be used to refer to both data sources). These data can provide powerful information on consumer spending patterns and so are a highly valuable source of information for producing consumer price statistics. We are in ongoing discussions with several of the largest UK retailers to make use of the wealth of information that these data sources offer.

Following a period of research, provided the data are suitable, we are planning to produce our first set of experimental results using the scanner data in December 2019.

Crucially, no customer information will be collected in these data feeds. This ensures customers will not be identifiable in these data sources. Instead, these data will solely provide information on the prices and total sales of products.

Scanner data are considered an ideal data source for measuring consumer price statistics because of a unique set of advantages over existing collection methods and web-scraping alternatives.

Scanner data provide greater market coverage

It is estimated that scanner data will provide hundreds of millions of rows of consumer spending data per year. Just a single large retailer can provide an annual dataset with hundreds of millions of rows of data. Such a scale of data has never been used in UK consumer price statistics before. This is achievable as scanner data are not as limited by ongoing data collection costs.

The sample size improvements brought about by scanner data carries numerous potential benefits, such as:

- improved precision for low-level indices
- the potential to use new methods that require more data than is available using existing data sources
- the potential to produce regional analysis by using store location information
- improved market coverage, allowing us to expand the definitions of an item (for example, potentially expanding the definition of a banana to include plantains)
- long-term, we may even be able to expand on the types of items covered by our basket (for example, including home gym equipment)

Scanner data allow us to calculate an exact product average price

Scanner data provide us with the expenditure (that is, total spending) and number of sales for each individual product sold by the retailer over a period (generally a month). Dividing total expenditure by total sales gives an exact monthly average price.

The ability to create this exact average figure across the month is unique to scanner data. In existing collections, most prices are collected once per month on a specific day. Price changes within a month will not be accounted for. We can improve our estimation of the product average price by collecting prices weekly and taking an average. This is done in current collections for more volatile areas of the basket (such as motor fuels) and is the standard for indices produced using web-scraped data.

Even so, this does not account for more regular price changes. Nor does it account for instances where spending is spread unevenly over the month and a weighted average is required (for example, in November, more spending may be expected on Black Friday compared with the rest of the month).

In the past, we have only had access to prices and not expenditure or number of sales. We can use these new figures to understand and account for how consumers are reacting to price changes.

This allows us to produce more accurate representative prices for our products, allowing us to better capture changes in market dynamics such as price and sales movements.

Scanner data can provide comprehensive information on the number of each item purchased

When calculating expenditure shares required to produce consumer price statistics, we currently rely on survey data to estimate the relative importance of one item category (for example, laptops) against another (for example, desktops). Scanner data give us another data source to make these types of comparison.

More importantly, scanner data provide a data source to weight at product level (for example, laptop A compared with laptop B). This is a first for price statistics; no other data source can provide this level of detail. This will allow us to see how consumers react in their spending after price changes.

For item categories where we have scanner data from more than one retailer, we can also accurately compare how much consumers are spending at each retailer for each item group. We can supplement this with market research to account for retailers where we do not have scanner data.

It is important to note that we will not publish individual retailer expenditure shares or any other data of a commercially sensitive nature. These will instead be used to produce more precise aggregate figures that will then be published at this higher level.

The improvements in weighting will allow us to better understand where consumers are spending their money: at which retailers, on which types of items and on which products themselves.

Scanner data may provide us with a back series

Retailers may be able to provide a substantial amount of scanner datasets for years and months in the past. We can then conduct long-term analysis from the point at which we receive the data. We will be able to retrospectively compare indices produced using scanner data against historic consumer price statistics measures when producing our planned impact assessments in 2021.

This is not possible with web-scraped data, as we are only able to obtain data from the point at which we have created our scrapers. This means having to wait for a long time series to build up before we can conduct long-term analysis.

Scanner data cannot be our only source of data

Despite their many advantages, scanner data cannot be the only data source for our consumer price inflation figures. The main challenge comes from data availability. Many small and medium-sized enterprises (SMEs) would find it challenging to produce and provide regular data feeds on consumer spending patterns.

Even if they were able to, from most recent estimates there are 5.7 million SMEs (PDF, 818KB) and it would be unfeasible for us to hold discussions with enough retailers to fully represent the SME market. SMEs make up 52% of private sector turnover, so it is important to be able to represent these enterprises in our price statistics.

To provide the best possible coverage of retailers, we will need to use multiple different data sources. For example, for groceries, we may use scanner data first and foremost, use web-scraped data where scanner data are not available, and supplement with local collections to account for SMEs such as independent grocery outlets.

5 . Web-scraped data: experimental analysis

Like scanner data, web-scraped data have the potential to provide substantially more information than manually collected data. However, unlike scanner data, web-scraped data are unable to provide us with exact average prices or expenditure shares.

The main advantage that web-scraped data provides is the ability to quickly obtain data from many different retailers, provided we meet the website's terms and conditions. When used in conjunction with scanner data, the two data sources can cover a substantial portion of consumer spending.

In May 2019, we published experimental indices over a five month time series for four technological goods . Using the same methods, we can now extend this time series. It is important to note that these are experimental results and are subject to change given ongoing research into the suitability of methods applied to the data, some of which will be touched on in the analysis. For this reason, we have also not compared them with the existing published indices for these items.

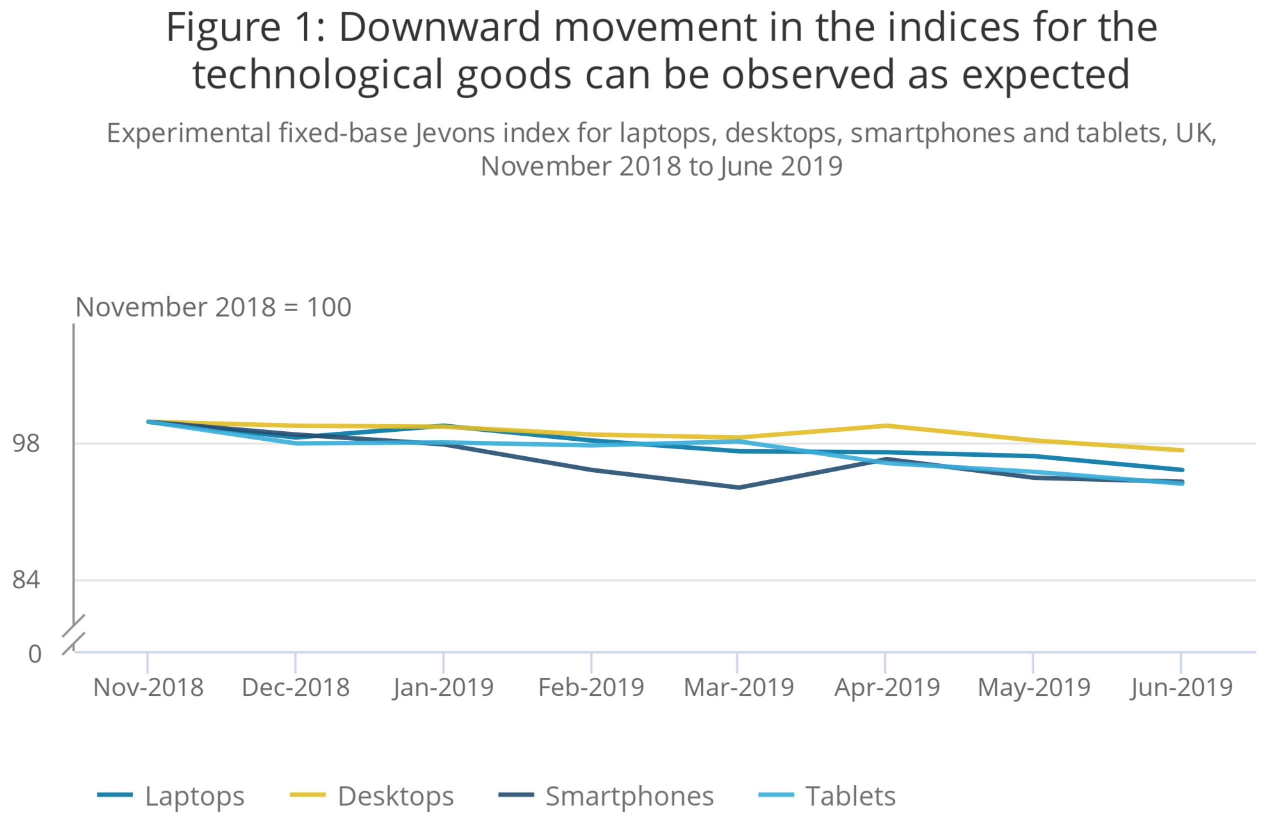
In our previous publication, we noticed some fluctuations in the indices for our technological goods (laptops, desktops, smartphones and tablets). The most noticeable phenomenon was a drop in the laptops index in February 2019. After further investigation, it appears that the performance of the indices was being reduced by a single retailer where small sample sizes and inconsistency in product coverage was causing volatility in the overall index.

We can now present updated indices for these technological goods with this retailer removed for laptops, desktops and tablets. We have retained this retailer for smartphones because of a desire to ensure sufficient retailer coverage. Notice, however, that the smartphones index appears more volatile than the other three as a result.

Figure 1 gives the experimental aggregate indices for our four technological items: laptops, desktops, smartphones and tablets.

Figure 1: Downward movement in the indices for the technological goods can be observed as expected

Experimental fixed-base Jevons index for laptops, desktops, smartphones and tablets, UK, November 2018 to June 2019



Source: Office for National Statistics, Prices web-scraped data

The index presented here is a fixed-base Jevons. This is the most commonly used unweighted index method in the Consumer Prices Index including owner occupiers' housing costs (CPIH). For each month in turn, this method compares each product's price in the current month against the same product's price in the base month (November 2018). Since technological goods become more affordable over time, we would expect that the indices slowly fall over time. Our experimental indices follow this behaviour – a promising sign for use in our consumer price statistics.

Product churn as a potential source of volatility

There are months where the indices rise in value, most notably for laptops in January 2019 and desktops in April 2019. We are currently investigating what may be causing these increases. However, a potential explanation could be because of product churn.

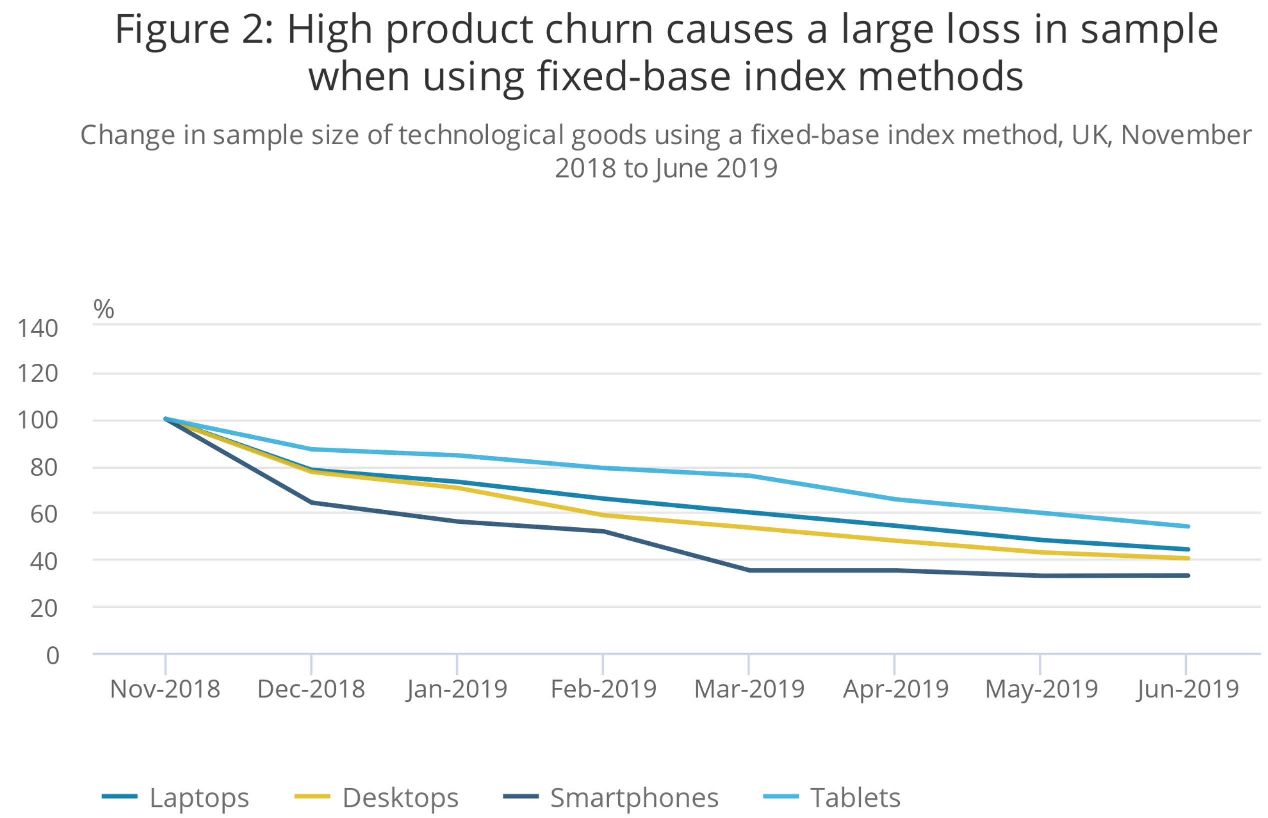
Product churn is the rate at which products enter and leave the market. Technological goods such as laptops have high levels of product churn since the market is constantly refreshing its products. By comparison, gaming consoles have low levels of product churn, as the most popular gaming consoles stay on the market for several years.

In the traditional methodology, discontinued products are manually replaced with a similar product and (if needs be) quality adjusted, allowing a stable sample to be followed over time. However, this manual approach is not feasible given the larger size of the web-scraped data. We are currently investigating methods of automatic comparable replacement but at this stage, if a product is no longer available, it is then dropped from the sample rather than a replacement being found.

This means that for a fixed-base index in this analysis, a product is only included in the sample for calculating the index for a given month if its price can be observed in both the base month (November 2018) and the month in question. As Figure 2 shows, this leads to a sample size that continuously falls when using a fixed-base method because of product churn.

Figure 2: High product churn causes a large loss in sample when using fixed-base index methods

Change in sample size of technological goods using a fixed-base index method, UK, November 2018 to June 2019



Source: Office for National Statistics, Prices web-scraped data

The high levels of product churn we have observed is what we would expect in a market where continuous improvements cause products to become technically obsolete quickly. To make full use of all the data we are collecting, we may look to use an automatic approach to finding comparable replacements, or indeed find alternatives to fixed-base index methods that allow for new products to be introduced over time rather than just when the base period updates.

We will now look at two of the new methods that may be used to process web-scraped data, and the effects that they have on our indices.

Classification

When we scrape a web retailer's laptops section, we may pick up products that are commonly sold alongside laptops. For example, this may include laptop bags, mice and keyboards. We may also pick up laptops that we do not currently include in our index, such as refurbished laptops. We use classification to sort the products we do and do not want to include in our index.

Figure 3 shows the indices produced based on whether we apply our current method of classification. In our previous publication, classification had a relatively small impact on the indices produced. In the months since, this gap has widened. This suggests that without applying classification, bias may be introduced into our indices.

Figure 3: Classification can affect the indices produced

Fixed-base Jevons index for laptops, desktops, smartphones and tablets, with and without classification, UK, November 2018 to June 2019

[Data download]

Source: Office for National Statistics, Prices web-scraped data

Our current method of classification is rules-based. We specify a set of keywords and if they are included in the product name, the product is removed from the sample. In the case of laptops, we search for words such as “bag” and “mouse”.

To generate the list of keywords, we take a sample of our data and manually label what each product is. Products that are not to be included in the laptops index are given reasons for exclusion. We then use a program to automatically identify the most common words used to exclude products and these can then be used as our keyword filters.

We can test the quality of this classification method. Price collectors have labelled a sample of the web-scraped data. We can compare what the price collector determines a product to be against what our classifier predicts the product to be. This produces a “confusion matrix”. Table 1 provides the confusion matrix for our first month for laptops and shows the classification method to perform relatively well.

Table 1: The confusion matrix shows our rules-based classifier performs well when there is a lot of labelled data to draw from

	Actual: laptop	Actual: non-laptop
Predicted: laptop	3,608	119
Predicted: non-laptop	26	1,493

Source: Office for National Statistics, Prices web-scraped data

Using Table 1, we can calculate the percentage of the time that we accurately predict laptops. This is calculated using the following formula:

$$\frac{3608}{26+3608} \approx 99.3\%$$

We can also calculate the percentage of the time that we accurately predict non-laptops. This is calculated as follows:

$$\frac{1493}{119+1493} \approx 92.6\%$$

We can take the average of these two figures to give us a metric called balanced accuracy (BA). This can be used as a measure of the quality of our classifier:

$$\mathrm{BA}_{\text{Laptops, Month 1}} \approx \frac{99.3+92.6}{2} \approx \ 96.0$$

We can test the performance of our classifier over time. We can label a sample of our data in a second month and repeat the previous steps as follows:

$$BA_{\text{Laptops, Month 2}} \approx 96.9$$

Based on these results, it appears that classification is relatively stable over time for laptops. It seems that the keywords identified in the earlier month were generalisable towards the later month.

We can now produce similar results for desktops as follows:

$$\mathrm{BA}_{\text{Laptops, Month 1}} \approx 92.3$$
$$\mathrm{BA}_{\text{Laptops, Month 2}} \approx 73.6$$

While the performance for month one for desktops was relatively high (albeit lower than the scores for laptops), this dropped substantially in month two. Upon further research, we found that the classifier predicted desktops well (96.5%) but did poorly at predicting non-desktops (50.7%). This suggests that the keywords generated in the first month were not generalisable enough to perform well in the second month.

We believe that the main reason for this is because we used a much larger sample to generate our keywords for laptops in month one than for desktops. This may have resulted in a more comprehensive list of keywords that were more generalisable over the months.

We are now exploring alternative methods of classification drawing on machine learning methods, which we believe may improve classification performance for more complex cases when rules-based keyword filtering may not be suitable (for example, clothing). We can use metrics such as balanced accuracy to compare the performance of different classification methods to ensure high-quality classification.

Imputation

As previously discussed, product churn can cause a loss in sample size, potentially increasing volatility.

Product churn can be:

- temporary – for example, where a retailer runs out of stock for a product
- permanent – for example, where a product is discontinued

We would not want to include discontinued products in our indices as these products can no longer be said to represent consumer spending in the market. However, there may be a case for imputing missing prices when a product has been temporarily taken off the market.

This leads to the option of imputing data (where a missing product price is filled). While there are several different methods available, we are currently exploring a fill forward method. This means a missing price is filled with the latest available price, up to a maximum of a specified number of months. An example of this is given in Table 2.

Table 2: How different imputation methods react to a product price (£30) disappearing in February before returning to the market in April at a higher price of £35

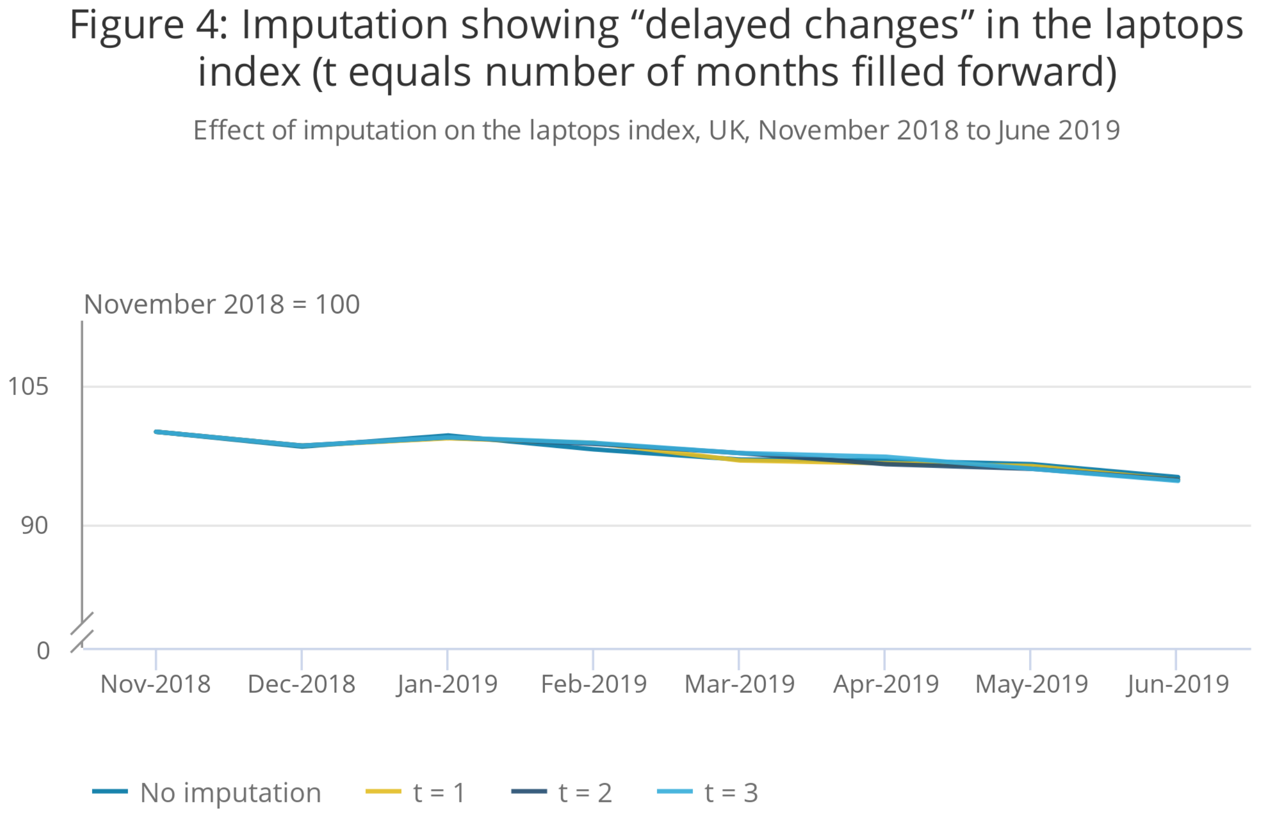
Imputation method	January	February	March	April
No imputation	30	Missing	Missing	35
One month fill forward	30	30	Missing	35
Two month fill forward	30	30	30	35

Source: Office for National Statistics, data for illustrative purposes

In the results discussed so far, we have not used imputation. We can now explore what happens if we do use this method of imputation. If t equals the number of months from which we can fill forward, then Figure 4 shows what happens as t varies from 0 (that is, no imputation) to 3.

Figure 4: Imputation showing "delayed changes" in the laptops index (t equals number of months filled forward)

Effect of imputation on the laptops index, UK, November 2018 to June 2019



Source: Office for National Statistics, Prices web-scraped data

Imputation generally does not have a large impact on the indices produced, as seen in Figure 4. However, it can cause interesting effects. Where rises and falls in the index are because of product churn, imputation can delay the change in the index.

For example, consider the laptops index shown in Figure 4. Without imputation, a fall in the index is observed between January 2019 and February 2019. It appears that this drop is because of product churn as imputation reduces this drop substantially, suggesting the dropped products accounted for the rest of the movement in the index.

However, when imputation is used, this drop is not prevented entirely, but rather delayed. For example, when t equals 1, the drop is displaced to March; when t equals 2, the drop is displaced to April; and when t equals 3, the drop is displaced to May. The reason for this is that these are the months from which the imputation methods stop being able to pull forward values from January that went missing in February.

If imputation primarily imputed temporarily missing data, then such drops in the index would have been prevented rather than delayed. This suggests that imputation is mostly imputing discontinued rather than out-of-stock products. This means that imputation may not be preferable for the technological goods.

Which index method should be used?

Up until now, all indices presented in this article have used a fixed-base Jevons index. This is the most commonly used unweighted index method in the Consumer Prices Index including owner occupiers' housing costs (CPIH). However, there are many different index methods that could be applied to alternative data sources, such as chained versions of the fixed based indices and new multilateral methods that use prices from more than two periods (for example, GEKS-J). These alternatives are shown in Figure 5.

For more information on these index methods, please see ONS methodology working paper series number 12 – a comparison of index number methodology used on UK web-scraped price data .

Figure 5: Differences are emerging in the values of different index methods

Alternative methods for calculating price indices, UK, November 2018 to June 2019

Data download

Source: Office for National Statistics, Prices web-scraped data

In our previous publication, the limited time series available meant that the choice of index did not seem to have a large impact on the results. In the months since, larger gaps have opened, particularly for the laptop and smartphone indices.

We have previously discussed fixed-base methods (particularly Jevons), where prices are compared in the current month against the base month. These can be contrasted to the high-frequency chaining methods (chained Jevons; chained Dutot), where prices in the current month are compared with the previous month. Chained methods have been considered as a means of getting around the product churn problem. By only requiring prices in two consecutive months, sample sizes are kept high.

Note, however, that high-frequency chained methods show the largest drops in the indices for three of the four technological goods. The price decrease is significant even though new items are being introduced into the sample over time because of the chaining. This is because we are not making any comparable replacements at the moment, so even if a comparable item comes in at a higher price to one that went out of stock, this increase in price will not get captured in the period that the new item is introduced. Instead, it will take until the second period for any price change to be captured for the new item, and in most cases for technological goods, this will be a downward movement. This means that chained indices may not be suitable for this type of item in future.

As part of our research on alternative data sources, we will be producing a framework for assessing the quality of consumer price indices produced using alternative data sources. This work will summarise the properties of a desirable index calculated using these big datasets and provide recommendations on how a final index method (out of the many alternatives available) could be selected for our initial specified categories. The recommendations from this will feed into our final decision on which method/s to choose for implementation.

6 . Plans for alternative data sources

We will be looking to integrate alternative data sources into consumer price statistics in the first quarter (Jan to Mar) of 2023. In this section, we present a high-level roadmap that summarises the main phases of our implementation plan (Figure 6).

Throughout the process we will be working with our users and the Office for Statistics Regulation, and we plan to hold a formal consultation in 2022 prior to the final implementation phase. We will notify users of progress or changes to this roadmap subject to further exploration of the data and methods.

Figure 6: Our aim is to use alternative data sources in the production of consumer price statistics by Quarter 1 (Jan to Mar) 2023

Timeline of integrating alternative data sources into consumer price statistics

Source: Office for National Statistics - Survey name/Data source

Notes:

Our aim is to use alternative data sources in the production of consumer price statistics by January 2023.

2019

In May 2019 we released our [first set of experimental results using web-scraped indices](), which have now been expanded upon in this Economic review.

We are expecting imminent scanner data feeds (see Scanner data: an update section) and will now focus on ensuring that these data feeds can be used for producing price statistics. Provided they are suitable, we intend to produce our first set of experimental indices from scanner data in December 2019.

To produce indices from these new alternative data sources, a new processing pipeline is being developed in a secure in-house virtual environment (the Data Access Platform), allowing us to process vast quantities of data. 2019 will see prototype builds of the system being produced, allowing the experimental results to be produced. For more information on the Data Access Platform, please see the [Systems section of our May 2019 release]().

2020 and 2021

Several stages of data processing are required to transform price quotes (and quantities where available) into price indices. Examples include needing to:

- classify products to match the Office for National Statistics (ONS) basket of goods and services
- choose an index method for a product group
- determine how to weight retailers to account for product market share

Ongoing research is exploring how we choose and then parameterise these methods that underpin the construction of price indices (for more information, please see the Further research section in Using alternative data sources in consumer price indices: May 2019).

The first half of 2020 will see the release of several methodological articles on the main areas of research. This puts us in a position to begin making recommendations to our advisory panels on the methods and parameters that we should use for constructing price indices for our initial specified categories. Upon agreement with our advisory panels, we will then apply these methods to publish initial impact assessments for these categories over the period to mid-2021.

Subject to having a sufficient time series in place, these assessments will allow us to understand how using these alternative data sources for these specific categories will affect our headline measures of consumer prices over time.

During and following the publication of the research reports, the statistical methods required for processing prices data will continue to be built into the processing pipeline, ensuring the system contains all the methods needed to produce our indices. Systems development will finish in December 2021, resulting in a final system for producing prices data.

2022

In 2022 we will run a parallel year where existing systems and new systems run concurrently. We will produce quarterly experimental results on the alternative data sources using established business processes, drawing comparisons with existing data sources and methods. We will run a consultation open to all users for users to provide feedback.

2023 and beyond

Our goal is to see alternative data sources used in consumer prices for the first time from Quarter 1 (Jan to Mar) 2023 as part of a phased approach. In 2023, we will focus on integrating alternative data sources for the categories listed in the background section.

2024 and beyond will see alternative data sources used in additional areas of the basket. Longer-term, we may also be able to use alternative data sources to expand the basket to cover new items that are not currently included in the existing consumer basket.

7 . Conclusion

Web-scraped and scanner data will allow us to collect more data than ever before, allowing us to improve the precision of our statistics, especially at more granular levels. This may also allow us to adopt methods and report on levels that were previously not possible because of limitations in sample size.

Scanner data have some useful unique properties that can allow us to address some of the limitations that current data sources have. For example, we can:

- calculate exact product price averages, accounting for change in price throughout the month
- understand how price changes (including price increases and sales) affect the number of sales and expenditure
- improve our understanding of where consumers are spending their money (on what products, on which types of item, and at which retailers)

The experimental web-scraped analysis we have conducted so far shows promising results. Technological goods generally lose value over time and this effect is reflected in a downward movement in the indices that we have produced.

The main challenge observed in our web-scraped data is in instances where product churn is high. When using fixed-base index methods, this can reduce sample size over time and increase volatility. When using chained methods, this can cause chain drift. We are exploring other index methods that we hope will allow us to account for this problem.

Our plan is to incorporate these alternative data sources in consumer price statistics by the first quarter (Jan to Mar) of 2023. Between now and then, we will conduct research, build IT systems, conduct impact assessments and engage with stakeholders. This will allow us to be transparent with any changes we intend to make and how they may affect our consumer price statistics.

8 . Author

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