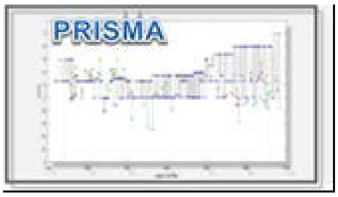
EUROPEAN CENTRAL BANK
EUROSYSTEM

Occasional Paper Series

Chiara Osbat, Cristina Conflitti, Gian-Pietro Bellocca, Martin Eiglsperger, Bernhard Goldhammer, Friderike Kuik, Jan-Oliver Menz, Fabio Rumler, Marta Saez Moreno, Lina Segers, Boriss Siliverstovs, Anaëlle Touré, Elisabeth Wieland

Measuring inflation with heterogeneous preferences, taste shifts and product innovation: methodological challenges and evidence from microdata



No 323

Price-setting Microdata Analysis Network (PRISMA)

This Occasional Paper contains research conducted within the Price-setting Microdata Analysis Network (PRISMA). PRISMA (2018-22) consisted of economists from the European Central Bank (ECB) and the national central banks (NCBs) of the European System of Central Banks (ESCB). PRISMA was coordinated by a team chaired by Luca Dedola (ECB) and consisting of Chiara Osbat (ECB), Peter Karadi (ECB) and Georg Strasser (ECB). Fernando Alvarez (University of Chicago), Yuriy Gorodnichenko (University of California Berkeley), Raphael Schoenle (Federal Reserve Bank of Cleveland and Brandeis University) and Michael Weber (University of Chicago) acted as external consultants (for further information, see Price-setting Microdata Analysis Network (PRISMA).

This work is part of a set of papers within the ECB's Occasional Paper Series, resulting from the report of the ECB's PRISMA network, which is summarised here.

Set of Occasional Papers related to the ECB's PRISMA network

No 319, "Price adjustment in the euro area in the low-inflation period: evidence from consumer and producer micro price data"

No 320, "E-commerce and price setting: evidence from Europe"

No 321, "Some implications of micro price-setting evidence for inflation dynamics and monetary transmission"

No 322, "Micro price heterogeneity and optimal inflation"

No 323, "Measuring inflation with heterogeneous preferences, taste shifts and product innovation -- methodological challenges and evidence from micro data"

No 324, "Price setting during the coronavirus (COVID-19) pandemic"

No 325, "Inflation heterogeneity at the household level"

Contents

Abstract

This paper provides an extensive literature review and analyses some open issues in the measurement of inflation that can only be explored in depth using micro price data. It builds on the analysis done in the context of the ECB's strategy review, which pointed at directions for improvement of the Harmonised Index of Consumer Prices (HICP), including better quantification of potential biases. Two such biases are the substitution bias and the quality adjustment bias. Most analyses of substitution bias rest on the concept of the cost of living, positing that preferences are stable, homogeneous and homothetic.

Consumer behaviour is characterised by preference shifts and heterogeneity, which influence the measurement of the cost of living and substitution bias. Climate change may make the impact of preference shifts particularly relevant as it causes the introduction of new varieties of "green" goods and services (zero-kilometre food, sustainable tourism) and a shift from "brown" to "green" products. Furthermore, PRISMA data show that consumption baskets and thus inflation vary across income classes (e.g. higher-income households tend to buy more expensive goods), pointing to non-homotheticity of preferences.

When preferences are heterogeneous and/or non-homothetic, it is important to monitor different experiences of inflation across classes of consumers/citizens. This is particularly important when very large relative price changes affect items that enter the consumption baskets of the rich and the poor, the young and the old, in very different proportions.

Another open area of analysis concerns the impact of quality adjustment on measured inflation. Evidence based on web-scraped prices shows that the various implicit quality adjustment methods can produce widely varying inflation trends when product churn is fast. In the euro area specifically, using different quality adjustment methods can be an overlooked source of divergent inflation trends in sub-categories, and, if pervasive, shows up in overall measured inflation divergence across countries.

Keywords: inflation, consumer prices, heterogeneity, micro data.

JEL codes: E31.

1 Introduction: different inflation concepts for different economic questions

Inflation is a key macroeconomic indicator. From a practical point of view, it is a thermometer for the general public of what money can buy, it affects decisions on consumption and savings, it serves as a parameter for important contracts, such as the indexing of pensions, and it is a factor in wage negotiations, albeit nowadays less automatically than in the past.[1] From a theoretical point of view, controlling inflation is the cornerstone of modern monetary policy. However, there is no single definition of inflation that fits each use.

Inflation is the change over time in the aggregated prices of goods and services produced or consumed in an economy. This paper focuses on consumer price inflation, which can be measured in various ways to address different questions and different economic concerns. Diewert (2001) indicated three such purposes: to measure general inflation, to measure the cost of living and to deflate consumption. In turn, these purposes shape the choice of price index into which individual prices are aggregated.

Cost-of-goods indices (COGIs) aim to isolate pure price changes by measuring the expenditure required to purchase a fixed basket of goods, or a basket of goods of fixed quality.[2] Comparing "like with like" is very important in this approach, so that adjustments for quality are central to the methodology. The Harmonised Index of Consumer Prices (HICP) is a COGI measured on the consumption of goods and services acquired in a given territory by the household sector, through monetary transactions, from other sectors of the economy. The ECB Occasional Paper "Inflation measurement and its assessment in the ECB's monetary policy strategy review" (WIM, 2021) gives a detailed analysis of why the HICP remains the best index for the ECB to use as a gauge for price stability, its methodology, its improvements over time, and remaining potential areas for improvement. This paper covers complementary aspects: it offers an overview of certain open knowledge gaps of particular interest for macroeconomists – namely, how to gauge substitution bias arising from the use of fixed baskets and biases due to quality adjustment – and how the PRISMA databases can help to close them.

Cost-of-living indices (COLIs) aim to measure the relative cost to households of achieving a given utility when facing two different sets of prices. This is an inflation concept rooted in consumer theory that is included in economic models, particularly in dynamic stochastic general equilibrium (DSGE) and trade models that focus on welfare analysis. The scope of COLIs is not restricted to goods and services that are subject to monetary transactions: it includes non-market goods and

---

1 See Koester and Grapow (2021) for a discussion of the types of wage indexation schemes prevalent in the euro area.

2 According to Eurostat's description of HICP methodology, "The HICP is a 'pure price index', meaning that only changes in prices should be reflected in the HICP measure between the current and the reference period". See Eurostat Statistics Explained: HICP methodology.

services, such as clean air and public health, which can affect the standard of living.[3] COLIs also take into account that consumers substitute some goods for others as prices change. In this sense, the COLI accounts for the substitution bias that, by design, is not taken into account by the COGI. For this reason, when estimating substitution bias in consumer price indices, some approximation of a COLI has mostly been used in the literature: this is what Triplett (2006) calls the "classic substitution bias paradigm drawn from Konüs (1925)".[4] However, practical COLI implementations come with their own distortions; a very important one is the effect of violating the common assumption of stable, homogeneous and homothetic preferences under which COLIs are commonly derived. Section 2 in this paper reviews the literature on how realistic this assumption is, with illustrations from PRISMA data, and discusses areas of research into the implications for using COLIs as yardsticks to measure substitution bias and to conduct welfare analysis.

The private consumption deflator converts household consumption from nominal euro terms to real volume terms. We do not cover it in this paper; please see work stream on digitalisation (2021) for a discussion of new measurement challenges in the personal consumption deflator posed by digitalisation.

The Cost of Nominal Distortions Index (CONDI) aims to capture the distortionary costs that inflation imposes on the economy. This fourth inflation concept is not discussed by price statisticians but arises in New Keynesian models, where inflation costs are driven by nominal frictions that may cause inefficient price dispersion, misallocation and adjustment costs. Recent theoretical and empirical developments in this literature and their implications for the euro area are discussed in the paper by Santoro and Weber (2023) on micro price heterogeneity and optimal inflation.

1.1 Open questions on measurement where the PRISMA data can help

Three main areas of possible further improvement in the HICP have been highlighted by the WIM (2021), in a report that analyses in depth some of the open methodological questions in inflation measurement, with specific reference to the HICP and the COGI framework. It highlights three areas for improvement: first and foremost, in terms of scope, it supports the inclusion of a measure of owner-occupied housing; second, it highlights the importance of quantifying the HICP measurement bias; and third, it calls for further harmonisation of implementation practices across countries, for example as regards quality adjustment. The PRISMA datasets described in Appendix 1 have been used in WIM (2021) to investigate the

---

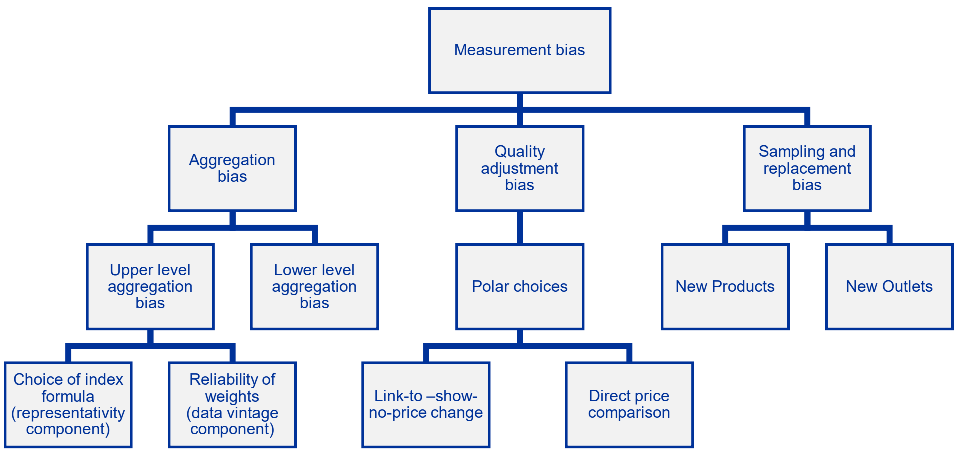
3 For the practical difficulties involved in measuring the weights and prices of non-market goods for constructing feasible COLIs, see WIM (2021).

4 See, for example, Braithwait (1980), Boskin (1998), Gordon (2000, 2006) and Hoffmann (1998); however, the use of COLI as a yardstick has been a controversial topic in the profession, as discussed by Triplett (2001, 2006).

substitution bias and its cyclicality and to explore the potential consequences of applying different choices for quality adjustment across countries.[5]

Substitution and quality adjustment are important sources of possible measurement bias. We reproduce here, for convenience, the stylised view of measurement bias in Figure 2 from WIM (2021). The diagram is organised around a COGI concept, where the problem of substitution bias is cast in terms of representativity and aggregation at the level of products (lower-level aggregation bias) and categories (upper-level aggregation bias). WIM (2021) discusses the various sources of bias in the HICP and how improvements in the HICP methodology may have mitigated these, while structural changes in retail, such as shorter product life cycles and the appearance of new outlet types, may have increased them. Ultimately, the authors conclude that a knowledge gap concerning the exact size of the HICP measurement bias remains, calling for further research. This paper takes a research point of view and focuses on two aspects relevant for consumer price indices in general, on which PRISMA data can be brought to bear: the methodological discussion of the COLI as a yardstick to measure substitution bias in general and an overview of the issues that may arise with quality adjustment. It also reviews issues related to sampling and replacement bias due to the introduction of new products and outlets.

Figure 1
Stylised overview: measurement bias



Source: WIM (2021).

In the next section we discuss substitution bias in the light of the literature that uses a cost-of-living concept as a reference, highlighting the importance of the assumptions of constant preferences, preference homogeneity and homotheticity when measuring the cost of living. We review the literature on measuring COLIs

5 In WIM (2021), see Box 9 "Is there a measurement bias from quality adjustment in Austria and Italy?". On "The cyclicality of upper and lower-level substitution bias", see Box 15 by Amann, Bachiller and Karadi: using the PRISMA household scanner data across Germany, France and the US, they find that the bias varies over time: the average bias is usually small, but its time variation is sizeable and can exceed 0.5 percentage points on average. Over two-thirds of the time variation can be attributed to the evolution of the lower-level bias.

under less restrictive hypotheses and show that purchase prices and consumption baskets vary by household income class and that homotheticity appears to be violated in our data. This suggests that using standard COLIs based on superlative indices as yardsticks for substitution bias can be problematic.

1.2 The cost-of-living framework: grounding inflation measurement in consumer theory

The economic theory of consumption can provide guidance on how to measure inflation when the aim is to characterise the impact of price changes on consumer welfare and to ask questions about how realistic the assumptions we need for this are in practice.

It is easier to understand substitution bias within the COLI framework if we outline the model of reference and clarify the definitions. The consumer has *N* goods available, will consume a bundle *c* of such goods and has a set of preference relations over such bundles. The preferences are indexed by *x*, a set of "environmental variables", which cannot be chosen by the consumer and which affect the ranking over the consumption bundles. Examples of these exogenous "environmental variables" could be public safety or the greenness of the environment, but might also be fads or immutable personal characteristics, such as age. The preference relations are represented by a utility function over consumption bundles *c* given environmental variables *x, u(c;x)*.

This definition allows us to distinguish an unconditional COLI, which varies according to environmental goods x, from a conditional COLI, defined for a given state of *x*.[6] Practical implementations of COLIs are necessarily conditional on a given level of state variables. This is both a significant limitation on the framework for measuring inflation practically and part of its appeal conceptually, as it allows us to characterise in economic models the effect on the cost of living of a change in the state of the world. Examples could be reduced public safety, as experienced, for example, during the coronavirus (COVID-19) pandemic, or a change in household perceptions of the importance of a clean environment.

A cardinal, "monetary" measure of utility is more useful for cost-of-living comparisons and welfare analysis. Indirect utility *v(p, I; x)* indicates the maximum utility achievable for every set of prices *p* and level of income *I.* It allows us to compute the change in welfare between two states indexed by a price vector and a level of income (at a certain state *x*). This can be done by computing the equivalent or compensating variation, which are money metrics used in welfare analysis.[7] Maximising indirect utility has a dual problem of expenditure minimisation, which yields the expenditure function *e(p, v)*: the minimum expenditure that will allow the

[6] Konüs (1925-39) gives the example of comparing the utility of a given bundle of goods in summer and winter.

[7] The equivalent variation is the additional income that the consumer would need, at current x and income and yesterday's prices, to be indifferent to the budget set defined by the new prices and income. In other words, the EV measures the additional income required to reach the final utility at the old prices.

consumer to reach a given indirect utility level. A COLI is the ratio of two such expenditure functions at different sets of prices.

The next "ingredient" of the COLI framework is a characterisation of the utility function in terms of properties. Stability is a convenient property and amounts to the separability of *x* and *c*: the shape of the utility function over *c* does not change as *x* changes. Another important property that is desirable from the point of view of tractability, but not necessarily from that of realism, is homotheticity: if consumption is multiplied by a scalar *a*, utility grows in proportion: $u(ac;x) = au(c;x)$.

Under homothetic preferences, many standard price indices can be derived and their properties analysed. By mapping utility levels at the base and reference periods to consumption baskets, the Laspeyres index provides an upper bound for the "true cost of living", because, following a change in relative prices, consumers can reshuffle their consumption bundles towards relatively cheaper goods in a way that allows them to keep the same utility for lower expenditure. By the same mechanism, the Paasche index gives a lower bound. Given these bounds, which are valid for any homothetic utility function, practical implementations of COLIs that approximate the "true cost-of-living index" are computed using "superlative" indices such as the Fisher index, which is the geometric average of a Laspeyres and a Paasche index.

The choice of index therefore depends on the preference structure we are willing to assume. Diewert (1976) suggested an approach that is appealing from the point of view of the economic modeller: starting with functional forms that are assumed to represent consumer preferences,[8] he proposes formulas for "exact" index numbers that are valid under those assumptions. The translog expenditure function is often used because it approximates any expenditure function to the second order, provided preferences are homothetic. The Törnqvist index is exact for this function (see Caves et al,1982). The Sato-Vartia index is exact for the constant elasticity-of-substitution (CES) expenditure function.

---

8 More precisely: for expenditure functions that are "flexible" in the sense that they provide a second-order local approximation of a true homothetic utility function.

2 From consumer theory to applied demand system estimation: how realistic are the standard COLI assumptions?

This consumer theory approach to inflation measurement relies on strong behavioural assumptions. It provides a direct link between how consumption choices are modelled and how inflation is measured, but it also puts a burden on the researcher to check the validity of underlying assumptions in terms of actual consumer behaviour. The next subsections discuss the assumptions of preference stability, homotheticity and homogeneity.

2.1 Measuring the cost of living with taste changes

The tension between macro assumptions and micro demand theory is evident in the assumption of stability of preferences from which aggregate price indices are derived. Redding and Weinstein (2020) study the impact of changing taste for individual varieties[9] based on CES preferences, which are extensive in the macro and trade literature. Focusing on continuing varieties, they highlight that the Sato-Vartia price index is consistent with CES preferences only if there are no demand shocks, but taste shocks are needed to estimate a CES demand system. This inconsistency leads to a bias in the Sato-Vartia COLI, which they call “taste-shift bias”.

Their estimate of the taste-shift bias in US supermarket scanner data from 2005 to 2013 is 0.4 percentage points a year on average when comparing against a Sato-Vartia index that also adjusts for entry and exit of goods but assumes constant preferences, and as much as 1.7 percentage points a year when comparing against a Laspeyres index.

The proposed solution is a new exact price index, the “CES unified price index”, which has three components: a Jevons index of the prices of common varieties between two periods, a correction for the entry and exit of varieties, and a term that captures changes in the degree of heterogeneity in taste-adjusted prices across common varieties. If the elasticity of substitution is greater than 1, then inflation will be positive (i.e., a given level of utility will be more expensive), not only if the Jevons term is greater than 1, but also if new varieties are less attractive than older ones and if the heterogeneity of taste-adjusted prices of common varieties decreases (because consumers have fewer opportunities to substitute for better varieties). The cost of living, measured this way, can rise in principle, even if

[9] It is useful to distinguish between “goods”, such as “carbonated beverages”, and varieties, such as “Coca-Cola - Coke Zero 2.00 litre”, which are identified by barcodes in scanner and web-scraped data.

observed prices do not change but taste for current varieties deteriorates. A normalisation on the average taste change avoids this. An example could be a reorientation of consumer taste away from “brown” to “green” products: this would increase the cost of living in a way not captured by standard price indices. Box 2 provides a back-of-the-envelope calculation of the potential importance of green versus brown products in various HICP categories, and thus the potential “exposure” of the consumption basket to taste shifts towards green consumption.

The analysis by Redding and Weinstein (2020)[10] **shows the importance of taste shocks for assessing changes in the cost of living (or for comparing the cost of living across geographic areas) but itself relies on assumptions**, such as homothetic CES preferences where varieties are substitutes.[11] Martin (2022) puts the critique of consumer price indices (CPIs) by Redding and Weinstein (2020) and their results into perspective by noting that the cost-of-living concept of reference for CPIs is a conditional COLI, while the bias documented by Redding and Weinstein refers (implicitly) to an unconditional COLI. He then proposes an exact index that is conditional upon tastes in the base or reference period in a CES setting. Also using scanner data, he finds that conditioning on one or the other set of tastes can lead to differences of a few percentage points per year depending on the category. This highlights how much the measurement of “inflation” depends on the preference framework of reference when the aim is to measure changes in the cost of living. Martin (2020) cautions against interpreting the discrepancy between indices solely as taste-shock bias in the Redding and Weinstein (2020) setting and simulates the effect of neglecting heterogeneity in substitution elasticities across groups of goods. His main result is that it is very easy to misdiagnose the impact of misspecification as “taste-shock bias” and calls for researchers that refer to the economic theory of price indices to estimate a variety of models to check the robustness of their results.

Modelling taste changes can also help to quantify uncertainty in price indices, another open question indicated by the WIM (2021). Feenstra and Reinsdorf (2007) use the fact that taste changes can be treated as stochastic to model uncertainty about weights and prices and map it into standard errors for exact index numbers. This is another area where scanner data can help with experimentation using alternative assumptions and methodologies, and WIM (2021), referring to sampling uncertainty, highlights the potential usefulness of estimated variances and confidence intervals of price indices and weights. Incidentally, the discussion in Feenstra and Reinsdorf (2007) also highlights the frequent chasm between the statistical and economic literature on inflation measurement: when describing the modelling assumption that inflation is composed of a common inflation trend and a component that contains relative price changes they cite the criticism by Diewert (1995) that the assumption of a common trend is “limiting”, but this distinction between a common (and equiproportional) factor and relative price trends is precisely the basis of the decomposition that Reis and Watson (2010) use to define

[10] Gábor-Tóth and Vermeulen (2018) reached similar conclusions on a different dataset.

[11] They do show that their result on the effect of taste shocks carries through in many more specifications.

the "pure inflation" that central banks should control in order to preserve the value of money.[12]

Box 1
How sensitive are components of the Harmonised Index of Consumer Prices to climate policies or related changes in consumer preferences? An introduction to classification approaches

The EU aims to reduce greenhouse gas (GHG) emissions by 55% by 2030 compared with 1990 and to net zero by 2050, and has proposed a set of measures which will entail wide-ranging changes to the economy and could also affect prices. To achieve the EU climate goals, changes in activities – and prices – that are associated with significant GHG emissions can be expected. Using two different approaches, this box explains how to identify which consumer prices could be affected by climate policies or changes in consumer preferences caused by such policies.

This box describes two classification approaches and initial results, which can be considered a starting point for further analyses. As a basis, we use a granular description of components of the Harmonised Index of Consumer Prices (HICP) (levels 3-5 of the Classification of Individual Consumption According to Purpose, COICOP). For the first approach, which enables us to obtain a rough overview, we map COICOP classes to "climate policy-relevant sectors" (Battiston et al., 2017) via links to the Eurostat NACE classification.[13] The second approach uses "consumption-based emissions", i.e., emissions associated with the whole production or value chain of a good or service, again linking them to COICOP classes via the NACE classification. A third possible approach, which is not discussed in more detail here, could entail the identification of COICOP links to sustainable consumption, for example by means of eco labels or energy efficiency labels.

Around 60% of HICP components in the euro area may be sensitive to climate policies (Chart A).[14] 5% and 6% of components can be associated with utilities and fossil fuels, respectively, which roughly corresponds to the HICP energy special aggregate (Chart B). 8%, 10% and 11% can be associated with agriculture, transport and buildings, respectively. Agriculture accounts for more than half of HICP unprocessed food. The agricultural sector (especially meat and dairy production) is responsible for high levels of GHG emissions and may be subject to changes in consumer preferences or climate policies.[15] 19% of HICP components can be associated with energy-intensive manufacturing, covering a large number of industrial activities and corresponding to almost 60% of HICP non-energy industrial goods (NEIG). However, it is important to note that different activities may be affected very differently by climate policies or changes in consumer preferences.

---

12 In a factor model, Reis and Watson (2010) decompose the common factors into two uncorrelated sets: "pure inflation" is the component that has an equiproportional effect on all prices and is uncorrelated with changes in relative prices at all dates.

13 Based on COICOP-NACE crosswalk by Kouvavas, Osbat, Reinelt and Vansteenkiste (2021).

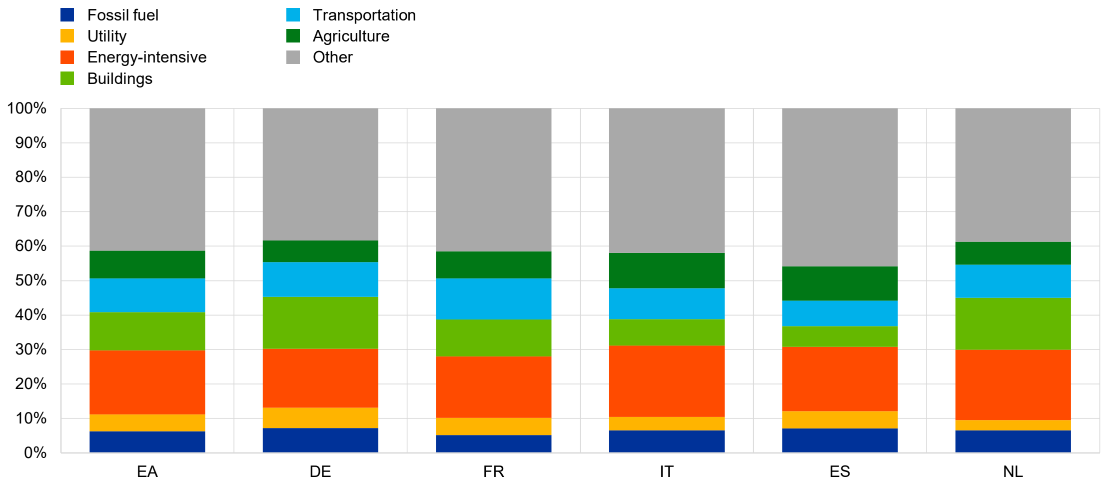
14 Applying 2021 weights.

15 In 2016, agriculture, forestry and land use accounted for around 19% of global GHG emissions (SOURCE).

Chart A

Mapping of COICOP level 5 to climate policy-relevant sectors, by country

(percentages, 2021 weights)

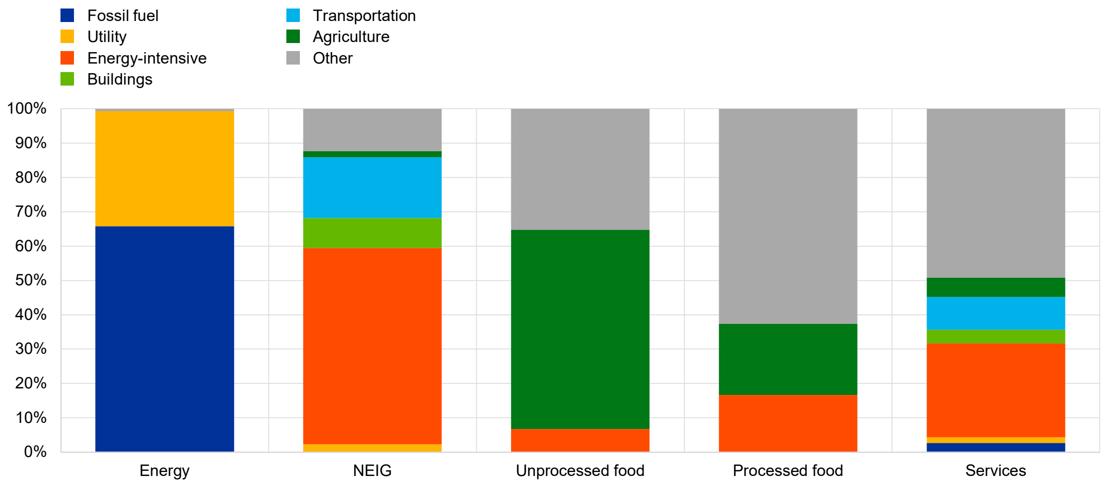


Sources: Eurostat, Battiston et al. (2017), Kouvavas et al. (2021) and ECB staff calculations.

Chart B

Mapping of COICOP level 5 to climate policy-relevant sectors, euro area, by HICP special aggregate

(percentages, 2021 weights)



Sources: Eurostat, Battiston et al. (2017), Kouvavas et al. (2021) and ECB staff calculations.

The identification of climate-policy-sensitive HICP components can be considered an initial rough assessment of the types of components that might be affected by climate policies or changes in consumer preferences. Within different climate policy-relevant sectors, there may be sizeable differences in the actual climate impact and therefore sensitivity to climate policies. For example, although there is little heterogeneity between countries in the allocation of HICP components to climate policy-relevant sectors (Chart A), substantial heterogeneities arise due to the types of fuels used in electricity production: while approximately 70% of Dutch electricity is produced using fossil fuels, only around 10% of French electricity is produced using them.[16]

[16] Eurostat, 2020 numbers.

Therefore, this approach may help to point to areas for future research, but a more in-depth assessment is necessary to draw conclusions on potential effects on inflation.

Consumption-based carbon accounting can attribute emissions along the supply chain to the final consumer. A production process consists of multiple steps in which emissions are generated. Multi-regional input-output (MRIO) tables provide a granular overview of all direct inputs – both domestic and imported – used in production. The production of inputs in turn requires inputs, which creates a recursive relation. Input-output analysis allows for the calculation of the total amount of indirect and direct inputs needed to satisfy a demand specification of interest (Davis and Caldeira, 2010). This framework of global production linkages can be extended to the computation of a footprint of external stressors, such as CO2 emissions.[17] Subsequent matching of industries or products to COICOP items can then help to associate the carbon footprint of final household consumption of a particular product or service with consumer prices.

Tracing the carbon footprint allows us to estimate more precisely the carbon emissions that can be associated with HICP components, thereby providing a more complete estimation of sensitivity to climate policies and shifts in consumer preferences. Here, the largest knowledge gains are in sectors heavily dependent on indirect inputs, such as the production of certain metals, but also the paper and cattle farming industries. The results suggest that the bulk of emissions stem from a small sub-group of items, mainly related to transportation or energy.[18] Additionally, items related to food and textiles feature prominently, but also some services categories that may be less obvious.

Climate-sensitive HICP components contribute to the overall volatility of euro area headline inflation, reflecting the volatility of energy prices (Chart C). Classifying HICP components into three categories – with items associated with the largest carbon footprint being at level 3 – shows a strong cyclical component, mainly in the items that are associated with a large carbon footprint and may thus be sensitive to climate policies. Part of this – as already discussed above – can be attributed to energy-related items, and to transport, textiles and food. The part of the HICP with a low carbon footprint consists of sectors such as education, maintenance and repair services and health care.

Ultimately, both approaches presented in this box can build a basis for future research on potential challenges that may arise for inflation measurement and for understanding inflation dynamics. For example, measuring cost-of-living changes can be harder if a range of new products is introduced quickly or if preferences regarding “clean” or “polluting” goods and services change, particularly if they change differently across different classes of consumers, such as the rich and the poor or the young and the old. Inflation dynamics will be affected if the decarbonisation of energy systems and industry proceeds rapidly and if relative price trends change significantly between different goods or services based on the type of energy they require as inputs.

---

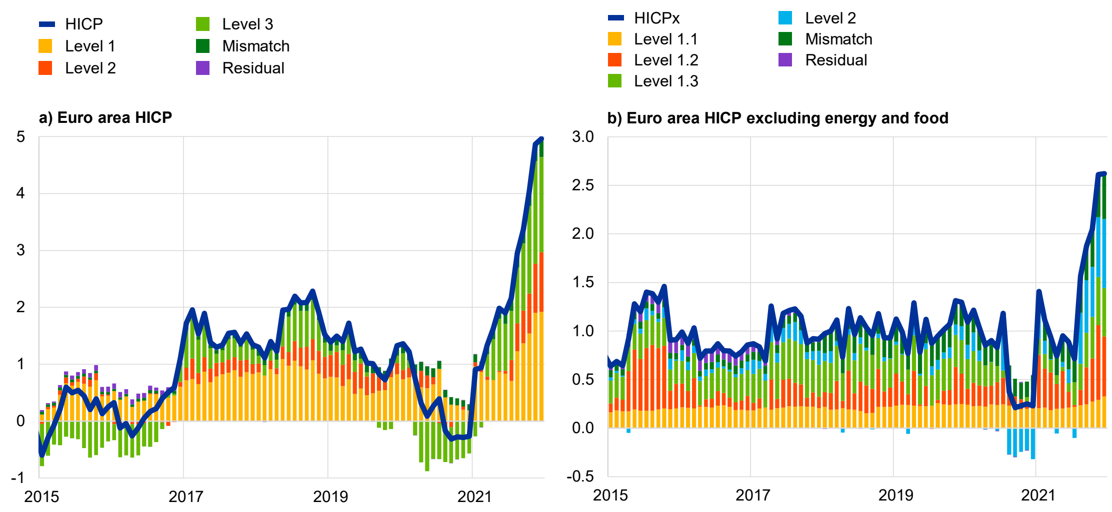
17 For the exact computations, see Miller and Blair (2009).

18 The results are based on a decomposition of the environment-extended MRIO tables from Exiobase3 into a carbon footprint associated with euro area household consumption of 163 industries and the subsequent matching to COICOP items.

Chart C

Decomposition of euro area HICP and HICP excluding energy and food into different carbon footprint levels

(annual percentage changes; percentage point contributions)



Sources: Exiobase, Eurostat and ECB staff calculations.
Notes: The carbon footprint is based on the environmentally extended multi-region input/output database from Exiobase 3 using the year 2018, reflecting the total carbon footprint of euro area household consumption. Exiobase industries are matched to COICOP items using COICOP correspondence tables, COICOP items that could not be matched are classified by “mismatch”. The residual in contributions arises for COICOP items without data extending to our full history. Classification of the COICOP3 sub-components ranges from level 1 (lowest footprint) to level 3 (highest footprint) and is based on a K-means clustering. Level 1 in the right-hand chart is further split into three sub-classes, ranging from the largest footprint (1.3) to the smallest footprint (1.1).

2.2 Measuring the cost of living when consumer preferences are non-homothetic: the income bias of superlative indices

Incorrectly assuming homotheticity is an important source of misspecification that is not easily addressed. Diewert (1976) provided guidance on how to derive exact indices under flexible functional forms for preferences, but his results do not cover all possible types of misspecification, with non-homotheticity potentially being a very difficult type to address. A violation of homotheticity would show up as an increase in the variance of an index estimated according to Feenstra and Reinsdorf (2007), but for economic analysis it is more meaningful to model non-homotheticity outright. Redding and Weinstein (2020) do so by modifying their CES unified price index (CUPI) to allow for a (constant) elasticity of consumption of each variety with respect to the consumption index.

Aggregation is a fundamental problem when assuming non-homothetic preferences, and very few models relax this assumption. Only homothetic and quasi-homothetic preferences aggregate, as discussed by Chipman (1974, 2006), which is why this assumption underlies models of representative consumers. Cavallari (2020) discusses the implications of a non-homothetic demand structure for monetary policy, adding to a CES utility function a component that is linear in consumption. This preference structure amplifies the real effects of monetary and technology shocks, attenuates the trade-off in the stabilisation of inflation and output and modifies the optimal monetary policy rule. Another example is Ravn et al. (2008), who explore the consequences of quasi-homothetic Stone-Geary preferences for the propagation of aggregate shocks over the business cycle. This approach, which incorporates variety-specific “subsistence points”, generates real rigidities and provides a basis for countercyclical mark-ups. Finally, Blanco and Diz (2021) explore the consequences of imposing a minimum subsistence point for food consumption, which decreases its elasticity of demand and makes food inflation less controllable by monetary policy, but also less relevant. The authors conclude that excluding food from the inflation index targeted by the central bank is optimal in this set-up. None of these studies addresses the measurement of inflation directly, but they have implications for welfare analysis and ultimately for cost-of-living comparisons.

Argente and Lee (2021) look at three margins of adjustment and their impact on the inflation rates experienced by poorer and richer households. The first margin is substitution to lower-quality varieties, the second is to lower-price retailers, and the third is the frequency of purchases of items on sale. They allow for non-homotheticities by introducing heterogeneity across income groups[19] and decompose the differences in price indices across income groups into changes in product prices, new-goods bias adjustment, product substitution, and shopping behaviour. They find that in the United States, from 2004 to 2016 almost half of the difference between the level of prices of the top and bottom 25% is explained by the product prices, i.e., the “pure price changes”, of the base-period basket. Another third is explained by substitution among varieties, and the rest equally by the new varieties correction and by shopping behaviour (e.g. shopping when items are on sale).

The relative importance of the various margins of adjustment varies over the business cycle. The decomposition into pure price changes, new variety adjustment, product substitution and shopping behaviour for the United States by Argente and Lee (2021) shows that the relative importance of these components varies in a recession. One reason is that richer households have more varieties and outlets in their choice set and can “trade down” more easily when their budget becomes more constrained.[20] They provide an estimate of the “quality Engel curve”, i.e. the relationship between income class and the quality of goods consumed, which for practical purposes is assumed to be indicated by the prices of varieties within a product category.[21] They find that rich households pay around 10-15% more for products in the same good category than poor households.

---

19 They allow for non-homotheticity by computing an income-class-specific Sato-Vartia index modified to account for new varieties. To do so, they estimate income-class-specific elasticities of substitution within each category. They find that the elasticities of substitution are very high, as can be expected when comparing varieties within a fine product group, but they are not substantially different across income groups.

20 See, for example, Li (2021).

21 See Bils and Klenow (2001). Clearly, the finer the product category, the more tenable this assumption.

2.3 Measuring the cost of living when consumer preferences are heterogeneous

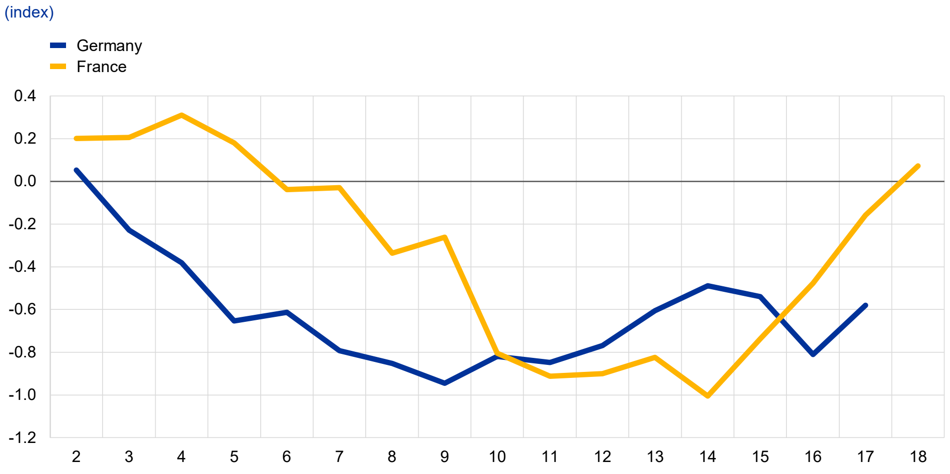
Next to stability and homotheticity, homogeneity is another important property of preferences from which standard COLIs are derived. Using standard indices to compute inflation for different groups of consumers, the paper by Strasser et al (2023) on household inflation heterogeneity documents that differences among households are mostly due to differences in baskets. Inflation heterogeneity is particularly important due to its impact on welfare comparisons and on the assessment of inequality: for example, Gürer and Weichenrieder (2020) find "pro-rich" inflation in Europe from 2001 to 2021, which results in the underestimation of the increase in income inequality as measured by Gini coefficients. Would these assessments be affected by the measurement of inflation with indices that account for the heterogeneity of consumers? If so, in which direction? This remains an open research question.

There are two approaches to constructing COLIs that can account for heterogeneity of consumers according to their income level: non-homothetic price indices and homothetic indices that allow for heterogeneous preference parameters.[22] Non-homothetic indices link the elasticity of substitution explicitly to the consumption level, as in the studies reviewed in the previous subsection. As an example of the second approach, Redding and Weinstein (2020) relax some homogeneity restrictions using a mixed CES specification where consumers are in groups and the elasticity of substitution as well as the taste parameters vary across groups. The price of each variety and the set of available varieties are common to all groups. This is in turn restrictive: for example, Li (2021) finds that, in India, urban and richer households consume more food varieties than rural and poorer ones. Argente and Lee (2021) find a similar result for the United States. In the PRISMA data, however, we see a different pattern: for example, in Germany and France, for a given year, product category and household size, the profile of the number of varieties (as gauged by the number of barcodes bought) across income classes is U-shaped instead, as shown in Chart 1. This different result could be due to the different status of food consumption in higher-income versus lower-income countries.

[22] See also the "primer" by Jaravel (2021), which also reviews the implications of non-homotheticity for optimal taxation and for the effectiveness of monetary policy and highlights the importance of having micro data on consumption baskets and prices paid for different sociodemographic groups in order to study these effects quantitatively.

Chart 1

GfK data: regression coefficient of barcodes per panellist on income



Source: GfK.
Notes: Regression of barcodes per panellist on the following factors: income, household size, product categories and years. Data: 2010-18 for Germany, 2014-18 for France.

Argente and Lee (2021) document the importance of income as an important dimension of preference heterogeneity by estimating "quality Engel curves". This concept was introduced by Bils and Klenow (2001) to estimate unmeasured quality change in a sample of goods in the United States. The quality Engel curve maps out the unit price of varieties of a good as overall consumption changes across consumers. The underlying assumption is that the variation in unit price across varieties of a good reflects various aspects of quality: some intrinsic and some related, for example to the different "quality" of the associated retail services. They find that richer households do pay higher prices for a given good than poorer households.

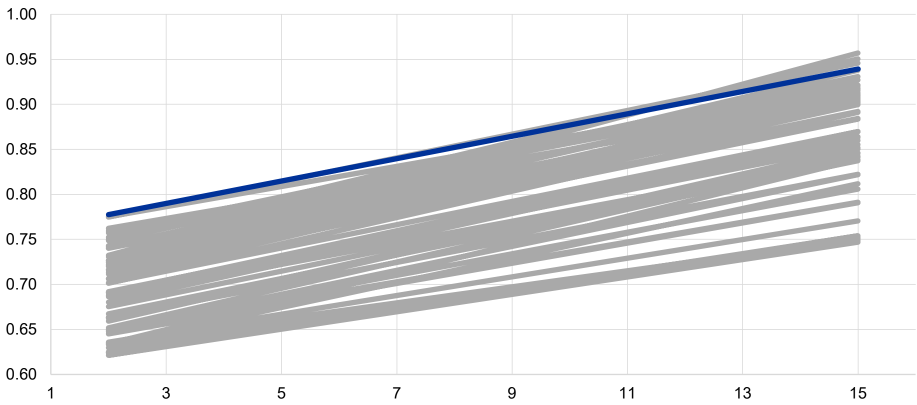
The PRISMA data indicate that, at product level, households in different income classes may pay different prices, mainly by choosing different varieties of that type of product. In principle, in scanner data, variation can also be observed in the prices paid for the same barcode, which could occur due to purchases in different kinds of shops or the concentration of more or fewer purchases on sales. An analysis of the German household panel data shows that the variation in prices paid in a year for the same barcode is minimal when adjusting for the median price paid. The next step in the analysis is to run a regression of the unit prices in each category on an income class dummy. Focusing on a reasonably homogeneous and large group, i.e., two-person households that shop at discounters,[23] a simple regression of average unit price per category in each quarter on the income class shows a remarkably linear relationship. The results are shown in Chart 2, where each line corresponds to a cross-section regression for a single quarter; the blue line corresponds to the last quarter in the sample: 2018q4.

[23] In this dataset, the number of products bought from discounters by far exceeds that bought from other store types.

Chart 2

Regression of unit price on income class for top category in Germany

(x-axis: income class, y-axis: mean value per volume)

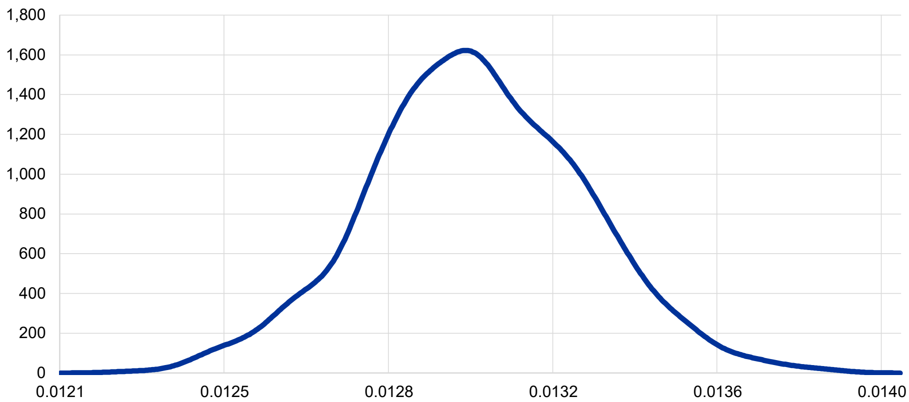


Sources: Gfk and PRISMA staff calculations.

Chart 3

Posterior density estimate of sensitivity of unit price to income category for top category in Germany

(density)



Sources: Gfk and PRISMA staff calculations.

This result is confirmed by a panel analysis. A panel regression was estimated using a Bayesian hierarchical model, where the conditional mean is modelled as a constant plus a time effect (to capture overall inflation across all products), plus a population slope parameter β that measures the sensitivity to changes in income class and is also allowed to change through time. Chart 3 shows the results for the largest category by total sales in Germany: fresh sausages. The corresponding results for the ten categories that appeared at least once in the top seven by total sales is shown in Table 1. Income class plays an important role in the prices paid for different varieties in each product category in this sample.

Table 1
Estimated coefficient of income class in price per volume paid: 95% interval

(cents)

Category	2.5%	Median	97.5%
Fresh bakery goods	0.51	1.65	2.71
Beer	0.80	0.96	1.11
Bread	2.26	2.42	2.58
Fresh meat	7.56	8.69	9.64
Fresh vegetables	3.64	3.85	4.05
Hard cheese	10.10	10.65	11.19
Fresh fruit	1.98	2.38	2.77
Coffee	8.37	9.48	10.67
Frozen goods	10.05	10.64	11.18
Fresh sausages	12.55	13.04	13.54

Sources: GfK and PRISMA staff calculations.
Notes: The table reports the median and the 95% credible interval of the posterior distribution of the slope in cents per volume for each category that showed up at least once in the top seven by expenditure share computed for quarters in the period 2005Q1 to 2018Q4.

2.3.1 Computing aggregate COLIs under the assumption of heterogeneous preferences

The problem of constructing COLIs based on preferences that are homogeneous in each group but vary across groups is that aggregation across groups requires assumptions on how to weight the preferences of each group. Decoster and Haan (2015) discuss the normative implications of preference heterogeneity in terms of ranking and aggregating across individuals. For example, while money metrics are convenient for aggregating welfare changes across individuals, using them becomes complex when reference prices as well as preferences are different for different groups. In a labour-leisure choice context, Decoster and Haan (2015) highlight the importance of making the “ethical priors” needed to make welfare aggregation and normative analysis transparent, and to study the robustness of welfare assessments across many such choices.

Such priors are in fact inherent, usually implicitly, in any aggregate index: standard indices based on average expenditure shares are called “plutocratic”, because they implicitly assign a greater weight to those who consume more. The Laspeyres and Paasche indices fall into this category. Indices that give each consumer the same weight are called “democratic”: see Fisher (2005) for a discussion of the value judgements required, concluding that neither is inherently superior, Ley (2005) for an interpretation and decomposition of the gap between a plutocratic and democratic index and, for example, Kokoski (2003) for an empirical comparison in the case of the US CPI.

Not only computing aggregate indices, but also any welfare comparison, is precluded in models that assume heterogeneous preferences across groups. As conceded by the authors, the approach of Argente and Lee (2021), where preferences are homothetic in each income class with different parameters across classes, precludes the possibility of comparing welfare gains between poor and rich households. Hottman and Monarch (2020) introduce an element of non-homotheticity in a two-tier preference structure: in each sector demand elasticity is constant and sector-specific, while across sectors they allow the parameters that govern taste shifts to vary by income class. Using US import data at supplier level from 1998 to 2014, they also find that poor households experienced the highest import price inflation and rich households the lowest. Handbury (2019) studies the implications of non-homotheticity for price comparisons across cities, taking into account the impact of product availability, like Li (2021) for India, and interacts it with income-dependent tastes. She addresses the aggregation problem by nesting income class-specific CES demand functions in a Cobb-Douglas utility function across expenditure categories. She finds that a specification where non-homothetic demand is modelled only in terms of preference for quality explains the differences between the choices of rich and poor households.

The studies reviewed so far model non-homotheticity by letting preference parameters vary across income classes. This approach is criticised by Beck and Jaravel (2021), who suggest a different approach based on Comin et al. (2021) to instead keep the CES structure with price elasticity of demand common across goods and income classes, but to introduce an expenditure elasticity of income. This yields a price index at household (or income class) level that can be represented as a Törnqvist index-like component (with average expenditure shares as weights) plus a component that accounts for non-homotheticities and difference in product varieties. Beck and Jaravel (2021) study purchase power parity (PPP), i.e., the relative cost of living across countries, and interpret their non-homothetic PPP index as a measure of compensating variation, which is a monetary measure of how much a consumer would be willing to pay to acquire the consumption bundle of the other countries. This also applies to comparisons between two periods, rather than two countries. Also in this approach, however, there is no clear way to aggregate the household – or income class – level price index to a country aggregate.

Assessing and relaxing the homotheticity assumption is a key element of the assessment of substitution bias in official CPIs, which either assume no substitution (e.g., the Laspeyres index used by the HICP) or use as yardsticks exact indices designed for homothetic preferences. Is the fact that sometimes the resulting superlative index is higher than the Laspeyres index an indication that the homotheticity assumption is violated? In other words, how large is the income bias in superlative implementations of COLIs, and how does this affect the assessment of substitution bias in the HICP? The possibility of such income bias in the Törnqvist index is well known conceptually, but the data requirements for assessing it quantitatively for the full scope of a consumer price index are very challenging: only microdata containing prices, quantities and consumer characteristics would allow it.

The curse of dimensionality bites when moving from inflation measurement grounded in consumer theory to practical computations based on estimating demand systems. Relinquishing the symmetry imposed by the CES assumption implies the need to estimate many demand elasticities with many products. The new empirical Industrial Organisation (IO) literature offers a framework and an econometric solution: recasting the problem from preferences over a continuum of products to preferences over a much smaller set of product characteristics makes it much more tractable. Also, the literature has developed faster and faster algorithms (see Conlon and Gortmaker,2020, for an overview).

PRISMA data can be used to estimate substitution and income biases and assess the potential impact of different COLI implementations. The limitation of this analysis lies in the restricted scope in terms of categories, but it can nonetheless be an important methodological contribution in the light of the open questions on COLI measurement and of the implications of non-homotheticity for measuring changes in welfare and for inequality.[24]

2.4 Measuring lower-level substitution bias: scanner data offer new opportunities, but also methodological challenges

The review of the literature above highlights that there are both general principles and specific computational methods for estimating COLIs that account for substitution, taste shocks and heterogeneity. However, they require observed prices and quantities consumed. Observing quantities is the harder problem in practice; there are consumption surveys for general allocation of expenditure and there are supply-side output measures classified according to industry or product classifications, but official consumption price collectors do not observe the quantity consumed of each variety of a given good or service in each outlet surveyed each month. For that reason, the first step in the computation of CPIs is to form elementary indices using unweighted averages of the price relatives between two periods.

There are two main choices for lower-level aggregation: the arithmetic or the geometric average. The arithmetic average of price relatives gives rise to a Carli index, the ratio of the arithmetic averages of base and reference period to a Dutot index and the geometric average of price relatives to a Jevons index. Levell (2015) gives an overview of the Carli and Jevons elementary indices, as well as a very clear discussion of the communication challenges faced by a national statistical institute (NSI) when changing the methodology of official statistical indicators so central to many contracts in the economy.[25] [26] In terms of technical properties, from the economic and axiomatic point of view, the Jevons index is preferred. In particular, it allows for some substitution, while Carli and Dutot do not and are biased upwards if substitution takes place. Silver and Heravi (2007) used scanner data to show that the difference between the Jevons and Dutot indices depends on the change over time in price dispersion, some of which is due to product heterogeneity.

---

24 See, for example, Handbury (2019).

25 See Bialek (2020a and 2020b) on computing confidence intervals for elementary indices.

26 For the United States, the BLS (2001) found that moving to a Jevons elementary index reduced annual CPI inflation by 0.2 percentage points.

The problem with lower-level substitution bias is that this is where the bulk of substitution bias arises, as the elasticity of substitution between varieties is higher than between different categories of goods and services.[27] But it is also at this level that no information on expenditure shares is available to compute adequate indices.

Scanner data offer new opportunities for evaluating the consequences of choosing different indices, not only because they contain data on expenditures but also because the barcode-level information allows to exclude the possibility that a price change could be due to quality.

Scanner data have also been introduced by NSIs in the production of official indices.[28] This innovation has been accompanied by much research, as using scanner data introduces practical challenges due to high volumes, the need for classification (see box in the paper by Strasser et al (2023) on online vs offline prices) and high product churn, but also purely methodological challenges.

While allowing, in principle, for demand systems to be estimated, scanner data pose a methodological problem when integrated in the NSI practice of producing chained indices. Scanner data provide current expenditure weights that are not available in traditional price collection, but the high product churn causes the chain-linked indices to drift down due to the "price bouncing" caused by sales. This is called chain drift, and multilateral indices such as the GEKS-Törnqvist (Gini, Eltetö, Köves, Szulc and Törnqvist) index, which is the geometric mean of all possible pairwise comparisons[29], address this problem.[30]

The literature on multilateral indices has exploded with the availability of scanner data for official statistical production.[31] Sands (2020) discusses index methods for scanner data extensively in the context of a quality framework developed to take decisions on what formulas to use for new collections based on big data (scanner and web-scraped).[32] The recommendation is that a multilateral GEKS index should be used when expenditure shares are available and a GEKS-Jevons in their absence. Eurostat also published a guide for the use of multilateral indices in the compilation of EU official price statistics.[33]

---

27 This is also what Tòth and Vermeulen (2018) find, for example, again using scanner data.

28 See Feenstra and Shapiro (2007) for an early overview of opportunities and challenges.

29 GEKS indices take their names from Gini (1931), Eltetö and Köves (1964) and Szulc (1964).

30 See, for example, Ehrlich et al. (2020). Zhen (2019) extends the methodology to "panel" multilateral indices, where the multilateral comparison is not only across time periods but also across different regions.

31 See, for example, Ivancic et al. (2011) and de Haan, J. and van der Grient, H.A. (2011) for an empirical study of their results.

32 The report can be found here.

33 See Eurostat (2022).

3 Measurement bias due to new products and outlets and to quality adjustment

Other dimensions of potential bias in consumer price indices relate to new types of products and outlets and to quality adjustment. It is important to distinguish between the appearance of new products and the introduction of new varieties (replacement). As formalised by Feenstra (1994), measurement of the cost of living must take into account the introduction of new goods because consumers have a taste for variety: if the range of varieties increases over time, conventional indices will overstate the change in cost of living. Similarly, when fewer varieties become available, conventional indices will understate the increase in the cost of living. Broda and Weinstein (2010) showed that new goods bias is important because of its cyclical nature, with fewer varieties becoming available during recessions. This lack of availability was extreme during the early phases of the COVID-19 pandemic, when entire categories of goods, and especially services, became unavailable: see the paper by Henkel et al (2023) on pricing during the pandemic.

Beyond this conceptual impact on the measurement of the cost of living, the introduction of new varieties gives rise to practical methodological questions on how to deal with product replacement in the compilation of price indices. These questions fall under the umbrella of "quality adjustment". A preliminary observation, also apparent when referring earlier to quality Engel curves, is that the term "quality" is not precisely defined in theory and is even harder to measure in practice. For example, Ueda et al. (2019) distinguish "quality", a permanent and time-invariant product characteristic, from "fashion", a temporary high volume of sales in new products. They measure the effect of product turnover along both components on a COLI for Japan using the approach put forward by Feenstra (1994) and find that the fashion effect is large, while quality effects decreased through time in Japan. They also find that the discrepancy between the COLI they estimate and the COLI generated from a matched sample of products is not very large. This could be an idiosyncratic feature of Japanese data due to the very low inflation over the whole sample.

The introduction of new goods or new outlets is best explained using the framework of the new empirical IO, which solves the curse of dimensionality in estimating demand systems by mapping preferences over many products to preferences over a much smaller number of product characteristics. This is at the basis of hedonic regressions, which underly explicit quality adjustment practices for some product categories by some national statistical institutes. The literature on hedonic adjustment, as well as the practice by NSIs, is a century old, starting with Haas (1922) and Court (1939) and popularised by Griliches (1961),[34] but the increased availability of data and of methods for analysing their characteristics has

[34] See the reviews in Goodman (1998) and Pakes (2005) but also Colwell and Dilmore (1999) for the history of the idea.

prompted continuous innovation. For example, Crawford and Neary (2021) look at the extensive margin of quality, i.e., the addition or deletion of characteristics, in addition to the "intensive margin" of upgrading existing characteristics. They apply their method to new car prices in the United Kingdom and find that it adds a substantial amount to the ballpark Boskin Commission estimate (for US inflation in general)[35] of the new goods and quality bias in measured inflation, at least in the product categories where the extensive margin of quality innovation is important, i.e., when new features are frequently introduced. As an example of the use of big data and AI for hedonic "regressions", Bajari et al. (2023) use deep learning on data on tens of millions of apparel items on sale in the Amazon store and find that their hedonic Fisher price index decreased between 2013 and 2017. Importantly, the conceptual basis of hedonic adjustment also assumes homogeneity of consumer taste and relaxing this assumption would further complicate the practice of hedonic price adjustment.

Heterogeneity is also an important factor in the impact of new varieties on inequality: as discussed by Jaravel (2021), the market for high-end products has grown faster, creating incentives for firms to add new varieties that cater to the rich ("premiumisation"). This in turn, via the preference for varieties channel, further increases inflation for poor households relative to rich ones.

The next subsection discusses bias due to new products and outlets and Section 3.2 discusses bias from quality adjustment and, in particular, the role of the choice of methods.

3.1 Bias due to the introduction of new products and outlets.

The term "new products" is only apparently self-explanatory, and the concept needs to be elaborated. If "new product" indicates a new variety of an existing product item, or a new product item in a product category already included in the CPI, then the treatment of new products boils down to sampling and quality adjustment, posing the measurement questions discussed in the next subsection. In this vein, biases can occur if the product replacement is delayed (the new product is introduced too late and the sample is no longer representative, also leading to a lower-level aggregation bias).

When a new, innovative product arrives on the market, two other sources of bias exist: bias due to missing welfare gains and bias due to late introduction. This is the case when the new product cannot be compared with existing product items and is hard to fit into the classification of the consumer price index. This occurs most often with technological goods, for example smart phones or smart watches.

The bias due to missed welfare gains can be explained for a CPI based on the COLI concept. In this case, the welfare gains associated with the introduction of the

[35] The Boskin Commission Report estimated an overall bias in US CPI of 1.1 percentage points annually, of which 0.6 was due to quality and new goods biases. See Boskin (1998) for a summary of the Boskin Commission Report.

innovative product should be taken into account to evaluate the cost of living. The use of reservation prices has been proposed for valuation (Hausman 1996). However, this has two drawbacks: the reservation prices would also be needed when products exit (Ahnert and Kenny, 2004), leading to zero inflation in the long term if the demand curves for estimating the reservation prices are stable (as for a conditional COLI). One practical problem is that no common methodology for estimating reservation prices exists, as the estimation results differ widely, depending on the underlying preference concept (Diewert and Feenstra, 2019).

Bias due to late introduction arises if an innovative product is included too late in the CPI. In this case, the CPI is biased as long as the product is absent from the CPI basket. A prominent example was presented by Hausman (1999), who showed that the late introduction of mobile telecommunication in the US CPI led to a bias of up to 1.9 percentage points in the telecommunication services part of the index.[36] Such a bias applies to both concepts of inflation measurement: the welfare-based COLI and the COGI, based on the purchasing power of money.

Similar reasoning applies to the "new outlet bias". If a new type of outlet is established, its prices are not compared with those of traditional outlets. Examples of this are the arrival of discount supermarkets in the 1970s and 1980s and of e-commerce in the 2000s. In these cases, the price decreases experienced by consumers when changing to a different outlet and the related potential welfare gains are not taken into account by a CPI following the fixed basket approach. Additionally, if the outlet type enters the CPI too late its price development over time will be missed, also leading to a bias. One important aspect, which differs from the case of new products, is that new outlet types might be accompanied by new price-setting policies, which can also lead to measurement biases if not taken into account when setting up the price collection.[37]

In order to assess the measurement bias related to new products and e-commerce (as an example of a new outlet type) of the HICP, a survey of NSIs was conducted during the monetary policy strategy review of the ESCB (Goldhammer et al., 2021; a short summary can also be found in WIM, 2021). The survey investigated only issues that are relevant within a COGI framework: the timing of the introduction of innovative products, changes in their prices, allocation to the European Classification of Individual Consumption According to Purpose (ECOICOP), the share of e-commerce and its inclusion in the basket, coverage of e-commerce price collection and treatment of delivery fees.[38] The survey found substantial heterogeneity in the treatment of new products in the HICP; however, "…size and direction of a potential bias arising from the inappropriate timing of product introduction remain uncertain" (WIM, 2021, p. 39). Rather, the survey revealed 62 cases of avoided biases,[39] with the potential bias being both downwards

---

36 They first appeared in the market in 1983 but were not included in the basket until 1998.

37 For an example, see Blaudow and Burg (2018).

38 The survey also covered more organisational issues not in the focus of PRISMA, like the detection of innovative products, the inclusion strategy, or how to deal with foreign e-commerce retailers; see Goldhammer et al. (2021).

39 Avoided bias since "… the non-inclusion of the innovation would have led to a bias…" (Goldhammer et al., 2021, p. 8).

(in 21 cases, especially for services) and upwards (in 41 cases, especially goods). However, long time lags in the introduction of innovations into the basket between countries (over ten years for mobile internet, for example) introduces limitations on the methodological harmonisation across countries regarding the timing of the introduction of innovative products. In the case of e-commerce, 23 out of 28 countries surveyed already include e-commerce in their baskets; those that do not show e-commerce shares below 7% of the overall market.[40] The survey also revealed that the inclusion of e-commerce started with the first country as early as 2000, rapidly expanding in the second half of the past decade. The products covered most frequently in the e-commerce price collection are electronics and clothing. On average, the collection covers 39 out of 108 product groups of non-energy industrial goods. The countries also stated that the number of products was steadily increasing over time. Therefore, any bias from the too-late inclusion of the e-commerce channel can be expected to be limited, although not enough data were provided to judge whether the price trends of the e-commerce distribution channel diverge systematically from those of other outlet types. The paper by Strasser et al (2023) on online and offline prices analyses some of these issues in detail.

3.2 Bias due to quality adjustment and the impact of quality adjustment methods

When producing official statistics product churn poses a problem: is the variety available in the reference period identical for all practical purposes to the one available in the base period? Is the price change "pure" or is it due to a change in quality? To address this problem, statistical institutes use implicit and explicit methods to carry out quality adjustments when comparing prices of comparable but slightly different products over time.[41] In the case of implicit quality adjustment, the "pure" price change is estimated or inferred indirectly from other information, whereas explicit adjustment methods rely on product characteristics. In the EU, the HICP manual (Eurostat, 2018) offers a menu of methods that NSIs can use for quality adjustment, which are described in Box 2.

Implicit methods can be used under specific assumptions and can be problematic if these are not met. For example, the "link-to-show-no-price-change" method requires any difference in price level to be a measure of quality difference. However, strategic price setting upon introduction or a decreasing price trajectory over the life cycle of the product may invalidate the results.[42] In fact, the HICP

40 The survey was carried out by Eurostat and targeted all NSIs in the European Economic Area; two NSIs did not respond. All countries in the euro area responded.

41 This applies to permanent replacements due to product life cycle, whereby a product ceases to be available in shops, as well as to temporary replacements for seasonal products.

42 See, for example, von der Lippe (2007). If prices decrease over the product life cycle, as is typically the case for clothing and electronics, then the index may be affected by downward drift (Keating/Murtagh, 2018).

regulation[43] is very restrictive on the use of this method and establishes that it should in principle not be used in the HICP, unless duly justified.[44]

The use of the bridged overlap method should be avoided when the prices involved are atypical. This method has been newly regulated by Eurostat's HICP recommendation on bridged overlap of June 2021. Essentially, it should be avoided when the prices involved are atypical: if the last price of the replaced product or the first price of the new product is a reduced price, or if the introduction price is atypically high, or if the prices in the matched sample include in turn atypical prices or show downward life cycle trends.

In practice, as Eurostat (2021) explains: "There is no single best alternative to bridged overlap and the choice depends on circumstances", and it is important to assess the impact of bridged overlap regularly. Such an impact assessment was carried out using PRISMA web-scraped data on beer prices by Goldhammer et al. (2019), as detailed in Box 2 and quoted in Eurostat (2021). It found that an index constructed using bridged overlap lies below link-to-show-no-price-change, and that both indices show significant downward trends compared with direct comparison.

Box 2
Quality adjustment bias due to the link-to-show-no-price-change and bridged overlap method

All quality adjustment methodologies aim to split the nominal price difference $\Delta\mathrm{np}$ between two product items into a price component $\Delta\mathrm{p}$ and a quality component $\Delta\mathrm{qu}$:

$$\Delta\mathrm{np} = \Delta\mathrm{p} + \Delta\mathrm{qu} \qquad (1)$$

Each method carries out this split in a different way. There are explicit and implicit methods for quality adjustment (FSO Germany, 2009; Eurostat, 2018). Explicit methods, such as hedonic quality adjustment, supported judgement or option pricing, estimate the quality difference using product characteristics. By contrast, implicit methods try to estimate the quality difference using general assumptions, regardless of the product characteristics. The most important implicit methods are:

Direct price comparison (DPC), assuming no quality difference: $\Delta\mathrm{np} = \Delta\mathrm{p}; \Delta\mathrm{qu} = 0$.

Link-to-show-no-price-change (LNP), sometimes also referred to as "simple overlap", assuming that the price difference is equal to the quality difference: $\Delta\mathrm{np} = 0; \Delta\mathrm{p} = \Delta\mathrm{qu}$.

Bridged overlap (BO): the price difference equals the average percentage price change of all observed products in the same or similar product category in the sample and the remainder is considered quality difference; in other words, the price change in replacement situations is the same as the price change during the average product life cycle.

43 Commission Implementing Regulation (EU) 2020/1148 of 31 July 2020 laying down the methodological and technical specifications in accordance with Regulation (EU) 2016/792 of the European Parliament and of the Council as regards harmonised indices of consumer prices and the house price index (OJ L 252, 4.8.2020, p. 12–23).

44 See Article 11(2): "Member States shall make a quality adjustment equal to the whole price difference between the replaced product in month m-1 and its replacement in month m only if this can be justified as an appropriate estimate of the quality difference".

Implicit methods are easy to apply, but they can be problematic under certain circumstances. For LNP, price changes accompanying the introduction of new varieties are disregarded (FSO Germany, 2009). If prices of products decrease over their life cycle and price increases happen only at the time of product replacement, a downward drift in the index may occur (Keating and Murtagh, 2018). Therefore, the first Harmonised Index of Consumer Prices regulation[45] in 1996 already restricted the use of LNP.[46]

The BO method also has limitations. The prerequisite for meaningful results of quality adjustment with BO is that the price development of the observed product items on the market reflects the price development accompanying the introduction of the replacement model (FSO Germany, 2009). Hence, in markets in which the product life cycle follows the "regular price – sales price – replacement" pattern, the application of BO "…would lead to a devastating downward bias in the index" (Dalén and Tarassiouk, 2013, p. 11). A similar problem arises when prices are constantly declining over the life cycle of a product item and price increases occur only when new items are introduced. Therefore, a new Eurostat recommendation advises against the use of BO under such circumstances (Eurostat, 2021).

To illustrate the biases resulting from the inappropriate application of LNP and BO, research was carried out using data from the PRISMA web-scraping exercise. In German supermarkets, sales of beer are a common tool in the marketing strategies of retailers and breweries. By calculating price indices for beer as a simulation, the exercise entailed treating the end of the sales period of a certain brand of beer like a replacement situation, applying the three implicit quality adjustment techniques. In this exercise, the "outgoing" beer variety is "replaced" by itself, which makes the DPC the unbiased benchmark.

For this study, 28,698 price quotations for beer (cans, bottles and boxes) were used, scraped from 29 August to 7 November 2018 (60 days), including 1,888 discount quotations (6.6%). After data cleaning, 24,149 price observations remained, with 1,662 discounts.

The price index simulation was carried out using unweighted indices, in both the Jevons (geometric mean) and the Dutot (arithmetic mean) forms. As ingredients for the price indices in this simulation, it is necessary to calculate quality-adjusted prices for each beer product item. These "calculated prices" $\mathrm{pc_{it}}$ were calculated by using Additive Adjustment Factors ($\mathrm{AAF_{it}}$) that were subtracted from the observed price $\mathrm{po_{it}}$:

$$\mathrm{pc_{it}} = \mathrm{po_{it}} - \mathrm{AAF_{it}} \qquad (2)$$

The calculation of $\mathrm{AAF_{it}}$ depends on the quality adjustment methodology. It always starts with $\mathrm{AAF_{i0}} = 0$. Then, for the following periods, it is calculated as follows:

(a) $\text{if}\ (\text{discount}_{\text{it}-1} = \text{false or discount}_{\text{it}} = \text{true}){:}\ \ \mathrm{AAF_{it}} = \mathrm{AAF_{it-1}}$ (3)

else

(b) Index calculated with DPC: $\mathrm{AAF_{it}} = 0$ (4)

[45] Commission Regulation (EC) No 1749/96 of 9 September 1996 on initial implementing measures for Council Regulation (EC) No 2494/95 concerning harmonized indices of consumer prices (OJ L 229, 10.9.1996, p. 3-10).

[46] See Article 5(5): "In no case shall a quality change be estimated as the whole of the difference in price between the two product-offers, unless this can be justified as appropriate."

(c) Index calculated with LNP $\mathrm{AAF}_{\mathrm{it}} = \mathrm{po}_{\mathrm{it}} - \mathrm{pc}_{\mathrm{it-1}}$ (5)

(d) Index calculated with BO $\mathrm{AAF}_{\mathrm{it}} = \mathrm{po}_{\mathrm{it}} - \mathrm{pc}_{\mathrm{it-1}} * b_t$ (6)

b_t is the bridge factor, whose calculation depends on the index types (Jevons or Dutot). Let us define the set of beer product items not being "replaced" in t as $\Psi_t = \{discount_{it-1} = false\ OR\ discount_{it} = true\}$. Then, the bridge factor is defined as follows:

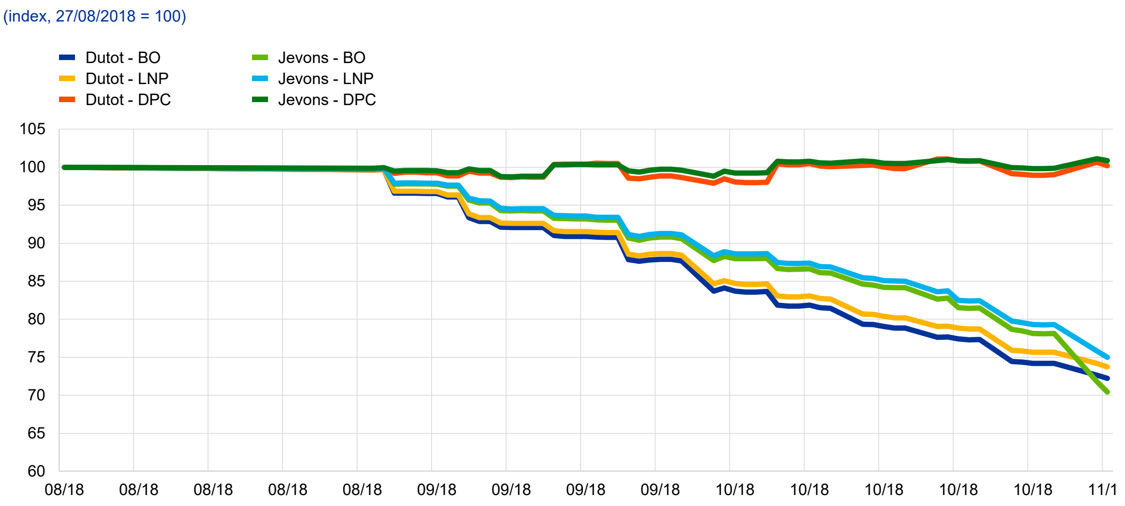
For the Dutot index: $b_t = \frac{\Sigma_{\Psi_t} pc_{it}}{\Sigma_{\Psi_t} pc_{it-1}}$ (7)

For the Jevons index: $b_{Jevons,t} = \sqrt[|\Psi|]{\prod_{\Psi_t} \frac{pc_{it}}{pc_{it-1}}}$ (8)

As the three quality adjustment methods are combined with two index types, six resulting series emerge. The results can be seen in Chart A and Table A.

Chart A

Test calculations for different quality adjustment methods



Source: ECB calculations.
Note: DPC: direct price comparison; LNP: link-to-show-no-price-change; BO: bridged overlap.

Table A

Test calculations for different quality adjustment methods

Index type	Value at 2018-11-07
Dutot – DPC	100.2
Dutot – LNP	73.7
Dutot – BO	72.2
Jevons – DPC	100.9
Jevons – LNP	75.0
Jevons – BO	70.4

Source: ECB calculations.
Note: DPC: direct price comparison; LNP: link-to-show-no-price-change; BO: bridged overlap.

After 60 periods, which correspond to less than three months, we can observe a clear downward trend in both the LNP and the BO indices compared with the DPC index. This is irrespective of the index formula, but is even more pronounced for BO than for LNP, showing a "price decline" of almost 30% for the combination of Jevons and BO.

In conclusion, the exercise showed that disregarding price changes in replacement situations can lead to a downward drift in a price index. Therefore, LNP and BO as implicit methods for quality adjustment should be handled with care and only employed if the underlying assumptions are met. This may often not be the case: for example, price differences may not be a measure of quality difference, as assumed by LNP, if prices are set due to marketing strategies, such as the discounting of old models or skimming of market segments (von der Lippe, 2007, pp. 282-283). Specifically, BO and LNP are not suitable for goods with downward moving prices over the product life cycle and price jumps in replacement situations. The new Eurostat guidelines on the treatment of BO (Eurostat, 2021) will help NSIs to improve their quality adjustment practices in this respect.

Another assessment was performed by Conflitti et al. (2021), who used the PRISMA CPI microdata for Italy and Austria to investigate whether the different choices made by NSIs lead to results that lie within plausible boundaries, i.e. if "too strong" quality adjustment can be ruled out. These data are particularly interesting for this kind of analysis because Statistik Austria only applies explicit quality adjustment methods, while ISTAT only applies implicit quality adjustment methods. The authors compute price indices for a number of NEIG[47] using the two opposite cases of direct comparison and link-to-show-no-price-change and using the flags provided in the micro datasets by the NSIs. They find that, in general, the latter lie within the bounds, indicating no evidence of "excessive" quality adjustment (Tables 2 and 3). However, they find that the choice of quality adjustment method may lead to economically meaningful differences in the inflation rates of those categories. This suggests that different methodological choices in different EU countries could lead to persistent trend deviations in the inflation rates of categories that experience high product churn.

A third study of quality bias and quality adjustment performed on PRISMA data, by Menz et al. (2022), focuses on the risk of persistent trend deviations due to national methodological choices. Menz et al. note that despite the requirement to harmonise methodologies in the euro area, many homogeneous and tradable goods, such as mobile phones and washing machines, exhibit divergent price trends over time. They analyse the non-harmonised treatment of quality changes in national HICPs as one candidate explanation. Box 3 describes their methodology and results.

[47] Specifically, they use 12 for Austria (bedroom furniture, sofa set, dishwasher, electrical razor, toothbrush, washing machine, lawn mower, sink, laundry detergent, notebook/tablet, PC and men's jeans) and ten for Italy (men's pants, women's pullovers, bedroom furniture, washing/dryer machine and dishwasher, appliances for heating and air conditioners, laundry detergent, TV, fridge/freezer, jewellery and clocks, and small electronic appliances (razor, toothbrush).

Table 2

Austria: average inflation for different quality adjustment assumptions (2011-17)

(index)

Products	DPC	QA	LNP
Bedroom furniture	4.3	3.8	1.7
Sofa set	2.9	1.8	1.2
Dishwasher	0.1	1.2	0.4
Electrical razor	-1.0	0.1	-2.0
Toothbrush	0.6	0.3	-0.3
Washing machine	0.2	0.1	-0.6
Lawn mower	0.7	0.4	-0.2
Sink	3.2	1.0	0.8
Laundry detergent	-1.2	-5.3	-6.0
Notebook/tablet	-0.1	-3.1	-5.3
PC	1.3	0.6	-1.7
Men's jeans	-0.6	-0.5	-1.4

Source: Conflitti et al. (2021).
Note: DPC – direct price comparison; QA – quality-adjusted price development according to the quality adjustment method used by Statistik Austria; LNP – link-to-show-no-price-change.

Table 3

Italy: average inflation for different quality adjustment assumptions (2011-18)

(index)

Products	DPC	QA	LNP
Men's pants	0.0	0.0	0.1
Women's pullovers	-0.2	-0.2	-0.1
Washing/dryer machine and dish washer	0.0	0.0	0.0
Bedroom furniture	0.2	0.2	0.2
Laundry detergent	0.4	-0.1	-0.1
Fridge/freezer	-0.9	-1.3	-1.3
Appliances for heating and air conditioners	0.6	0.7	0.7
TV	0.3	0.2	0.2
Small electronic appliances (razor, toothbrush)	-0.1	-0.1	-0.1
Jewellery and clocks	0.3	0.3	0.3

Source: Conflitti et al. (2021).
Note: DPC – direct price comparison; QA – quality-adjusted price development according to the quality adjustment method used by ISTAT; LNP – link-to-show-no-price-change.

As argued in Box 3, depending on the pervasiveness of the discrepancies in the practical implementation choices and on the weight of the categories affected, wedges in trend price index differentials could even affect the aggregate indices. This is discussed at length in WIM (2021) and, indeed, Eurostat has been active in exploring these problems and issuing new recommendations.

Box 3
The impact of quality adjustment on euro area inflation[48]

Euro area inflation as measured by the Harmonised Index of Consumer Prices (HICP) may be affected by heterogeneous quality adjustment procedures applied by national statistical institutes. Various quality adjustment procedures are currently available for national statistical institutes in the euro area, but without any binding rules, indicating scope for further harmonisation (WIM, 2021). Notably, homogeneous and tradable goods, such as mobile phones and washing machines, exhibit pronounced inflation differentials. For example, the average price change of mobile phones in the HICP since 2016 ranges from +5% in Portugal to -17% in Ireland.[49] Given the homogeneity and tradability of this item, such large change differentials are surprising. One possible explanation for diverging price trends – notably for industrial products with continuous technological improvements – could be the heterogeneity of quality adjustment practices across euro area Member States. We address this question in two ways.

A first approach builds on the official inflation series published by Eurostat and selects product categories whose prices we judge to be materially affected by quality change. The selection of quality-adjusted products is backed by a survey of Eurostat's individual HICP Monitoring Reports and German consumer price index microdata, for which information on quality adjustment is available at the product level; the latter also confirms that most quality-adjusted products can be found in the categories of household appliances (e.g. washing machines and freezers), transport (new cars) and recreational electronic goods (TVs and game consoles). Therefore, we have selected categories in both a broad and a narrower sense, in order to make our results more robust. Next, for each of these product categories, we compute the minimum and maximum across the countries' cumulative inflation series. We then replace the countries' official inflation series for the selected products with the minimum and maximum series. By re-aggregation to the euro area level, we obtain a range for euro area headline and core inflation that we interpret as an estimate for the impact of heterogeneous quality adjustment methods. Of course, quality adjustment procedures applied by national statistical institutes are not the only source of persistent price change differentials: these are also driven by different market structures, preferences and living conditions. We try to control for these influences with the help of a simple panel regression explaining the inflation rates of quality-adjusted products with national gross domestic product (GDP) per capita.

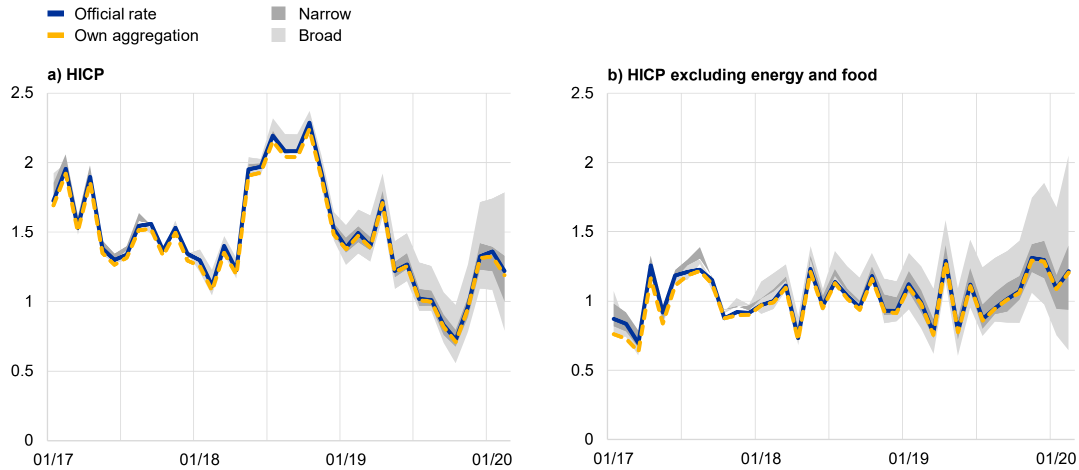
[48] This box is a summary of findings by Menz, Wieland and Mehrhoff (2022).

[49] Note that the HICP is computed using prices that include indirect taxes on consumption such as VAT and excise duties, so changes in taxes over time may also contribute to deviations.

Chart A

The impact of quality adjustment on euro area inflation over time

(percentages)



Sources: Eurostat and own calculations.
Notes: The figure shows the annual inflation rate of euro area headline and core inflation as published by Eurostat ("official rate"), and aggregate from the disaggregate COICOP5 series ("own aggregation"). "Narrow" and "broad" denote the inflation rates using the lowest and highest inflation rates by country and product group assumed to be affected by quality changes.

A second approach aims to illustrate the impact of heterogeneous quality adjustment methods on euro area inflation by means of transaction price data from Growth from Knowledge (GfK) for washing machines in ten euro area countries, as used by Fischer (2012). For the periods 2000-05 and 2017-21, we compute different experimental price indices for each country in the same way. We then compute a euro area experimental price index, in order to compare it with the official benchmark series published by Eurostat.

We find that our estimate of the impact of heterogeneous quality adjustment methods not only blurs the price trends of some product groups, but also translates strongly into aggregate inflation. Controlling for the impact of income differentials between countries, our estimate can make up to ±0.2 percentage points for headline inflation and ranges between 0.1 and 0.3 percentage points for core inflation (Chart A). Generally, we find our macro-based estimate to be positive, implying that inflation would be somewhat lower if quality adjustment procedures were harmonised across euro area Member States. Moreover, based on the micro price evidence, we find that, compared with the corresponding official HICP benchmark, euro area inflation on washing machines would have been about 3.5 percentage points lower during the first few years of the euro area and about half a percentage point in recent years, if the same quality adjustment method had been used across countries.

4 Summary and conclusions

For the credibility of central banks, it is important that when aiming for a price stability objective they use an inflation index that is representative, reliable and timely. The ECB, in its strategy review, decided that the HICP remains the most appropriate index for this purpose, but that it would be more representative if it also included owner-occupied housing. It also pointed to remaining knowledge gaps regarding potential biases in the HICP, relating mostly to substitution and to quality adjustment.

Quantifying these biases is a very open field of research, both in theory and in practice. Most theoretical literature grounds the quantification of inflation bias in consumer theory: an important result in this literature is that given conditions on the preference structure different "superlative" indices can be constructed that are "exact" measures of the change in the cost of living, i.e., in this definition, of consumer price inflation. The same preference structures, based on stability, homogeneity and homotheticity, are also a staple of the workhorse models used for welfare comparisons, including the welfare costs of inflation, as well as for developing monetary policy rules. Computing COLIs is much harder in practice than computing COGIs such as the HICP, particularly in a timely manner. However, they have long been considered a useful benchmark for measuring biases, and the Federal Reserve, having a COLI at its disposal (the Personal Consumption Expenditure or PCE index) has decided to use this as its main benchmark.

This paper does not address the diatribe between supporters and critics of COLIs versus COGIs as a reference measure for inflation, but takes a different perspective: inflation measurement can be grounded in consumer theory, but can inflation be measured taking into account evidence on consumer behaviour? In other words, what is the evidence on preferences being stable, homogeneous and homothetic?

The review of the literature shows that preferences change and that taste shocks are important in measuring changes in the cost of living, and modifications of price indices based on constant elasticity of substitution have been developed. For example, Redding and Weinstein (2020) found that in US supermarket scanner data the bias was as large as 1.7 percentage points a year when compared with a Laspeyres index. Martin (2022), using a different concept, found that the bias was smaller but nevertheless a few percentage points, depending on the product category and warned of the difficulty of discerning the effects of taste shocks from those of heterogeneity. This short review shows how lively the literature on unstable and heterogeneous preferences is today; the impact of taste shocks is particularly interesting as a research area, as climate change has led to the introduction of new varieties of "green" goods and services (zero-kilometre food, sustainable tourism) and a shift from brown to green products. Box 1 shows the potential exposure of sub-categories of the HICP to climate transition policies.

The literature also documents the fact that consumer preferences are not homogeneous across different types of consumers: preferences over baskets of goods and services vary according to age, income and other characteristics. Evidence based on PRISMA data in this paper and the paper by Strasser et al (2023) on inflation heterogeneity also shows that the prices charged, the number of varieties bought as well as inflation vary, for example across income classes, pointing to the non-homotheticity of preferences.

The violation of the homogeneity and homotheticity of preferences is a challenge for inflation measurement: it is a problem in theory, because it undermines the value of superlative indices as benchmarks to quantify substitution bias, and it is a problem in practice, because constructing COLIs that reflect the evidence on consumer behaviour requires more complex theory, more complex computation and, especially, much larger amounts of data at a granular level, not only on prices but also on quantities and on the characteristics of purchasers. Scanner data, in particular household scanner data, are fit for this purpose but do not cover the full consumption basket.

Measuring inflation when preferences are heterogeneous and/or homothetic is not only important for computing better gauges of substitution bias: it also gives central bankers an overview of the various experiences of inflation This is particularly important when very large relative price changes affect items that appear in very different proportions in the consumption baskets of low and high-income (energy and food) and young and old consumers (education and health care). The public discourse on inflation at this time of energy price surges clearly has an impact on the credibility of central bankers with civil society. Communication may be greatly enhanced by sharing information on different experiences of inflation, i.e., what can be measured using the consumption baskets of different groups, as carried out by Charalampakis et al. (2022).[50]

The paper also covers another open area of research on inflation measurement, which is more technical but no less far-reaching: what is the impact of quality adjustment on measured inflation? In particular, as already suggested by the work stream on inflation measurement, what could happen if quality adjustment methods are not applied in the same way across categories and countries in the euro area? Box 2 shows, using PRISMA web-scraped data, that using one or the other implicit quality adjustment method may produce widely varying inflation trends when product churn is fast. Product churn has accelerated, particularly in semi-durable categories, such as consumer electronics and clothing. This has had an impact, not only on optimal inflation as documented by Santoro and Weber (2023) in their paper on micro price heterogeneity and optimal inflation, but also on inflation measurement. In the euro area specifically, using different methods to adjust for quality changes may be a hidden source of divergent inflation trends in sub-categories. If pervasive it could show up in overall inflation divergence, as

[50] To perform their study, Charalampakis et al. (2022) used data from Eurostat's Household Budget Survey and ISTAT on consumption baskets by broad COICOP categories. However, these are available with a considerable delay, and the analysis of heterogeneity of experienced inflation would benefit greatly from more timely availability of data. Claeys et al (2022) and Cardoso et al (2022) performed similar studies.

shown in Box 3. Practitioners might be tempted to extend the use of explicit hedonic adjustment methods to solve this problem, also on account of the easier availability of product characteristics offered by scanner and web-scraped information and new data processing technologies. However, hedonic methods are grounded in the same consumer theory as COLIs and are subject to the same problem of preference stability and heterogeneity, and as such are often perceived by the public as untransparent and unrepresentative.

PRISMA data have already shone some light on some of the aspects mentioned above, particularly regarding quality adjustment methods and inflation heterogeneity. Projects on the measurement of inflation under less restrictive preference structures are ongoing, enabled by the scanner data, and may produce results relevant for policy, offering a range of inflation measures that can make the assessment of economic conditions and the transmission of shocks more robust, and enrich communication, particularly during times of substantial swings in relative prices.

Uncovering evidence on the structure of preferences is not only important for measuring inflation, but also for exploring the most promising deviations from the modelling of consumer behaviour in terms of representative agents and for modelling sources of real rigidities, such as idiosyncratic subsistence points, like Ravn et al. (2008). This is an ambitious research agenda; for its success it is of paramount importance to support initiatives designed to enhance the collection and availability of microdata.

References

Ahnert, Henning and Kenny, Geoff (2004), “Quality adjustment of European price statistics and the role for hedonics”, *Occasional Paper Series*, No 15, ECB, Frankfurt am Main, May.

Almas, Ingvild (2012), “International Income Inequality: Measuring PPP Bias by Estimating Engel Curves for Food”, *American Economic Review*, Vol. 102, No 2, pp. 1093-1117.

Argente, David O., Hsieh, Chang-Tai and Lee, Munseob (2023), “Measuring the Cost of Living in Mexico and the US”, *American Economic Journal: Macroeconomics, Vol. 15, No 3, pp. 43-63.*

Argente, David O. and Lee, Munseob (2021), “Cost of Living Inequality During the Great Recession”, *Journal of the European Economic Association*, Vol. 19, No 2, pp. 913-952.

Atkin, D., Faber, B., Fally, T. and Gonzalez-Navarro, M. (2020), “Measuring Welfare and Inequality with Incomplete Price Information”, *NBER Working Papers*, No 26890, National Bureau of Economic Research, March.

Bajari, Patrick, Cen, Zhihao, Chernozhukov, Victor, Manukonda, Manoj, Wang, Jin, Huerta, Ramon, Li, Junbo, Leng, Ling, Monokroussos, George, Vijaykunar, Suhas and Wan, Shan (2023), “Hedonic prices and quality-adjusted price indices powered by AI”, *Cemmap Working Papers*, No 8, Centre for Microdata Methods and Practice, Institute for Fiscal Studies and Department of Economics, University College London.

Battiston, S., Mandel, A., Monasterolo, I., Schütze, F. and Visentin, G. (2017), “A climate stress-test of the financial system”, *Nature Climate Change*, Vol. 7, pp. 283-288.

Beck, Günter and Jaravel, Xavier (2021), *Prices and Global Inequality: New Evidence from Worldwide Scanner Data*, Mimeo.

Berardi, N., Gautier, E. and Bihan, H. L. (2015), “More Facts about Prices: France Before and During the Great Recession”, *Journal of Money, Credit and Banking*, Vol. 47, No 8, pp. 1465-1502.

Berry, S., Levinsohn, J. and Pakes, A. (2004), “Differentiated Products Demand Systems from a Combination of Micro and Macro Data: The New Car Market”, *Journal of Political Economy*, Vol. 112, No 1, pp. 68-105.

Białek, Jacek (2020a), “Comparison of elementary price indices, *Communications in Statistics – Theory and Methods”,* Vol. 49, No 19, pp. 4787-4803.

Białek, Jacek (2020b), “Basic Statistics of Jevons and Carli Indices under the GBM Price Model”, *Journal of Official Statistics*, Vol. 36, No 4, pp. 737-761.

Bils, Mark and Klenow, Peter J. (2001), “Quantifying Quality Growth”, *American Economic Review*, Vol. 91, No 4, pp. 1006-1030.

Blanco, Cesar and Diz, Sebastian (2021), “Optimal monetary policy with non-homothetic preferences”, *MPRA Papers*, No 107427, University Library of Munich, April.

Blaudow, C. and Burg, F. (2018), “Dynamic pricing as a challenge for consumer price statistics”, *EURONA*, No 1, pp. 79-92.

Boskin, Michael J. (1998), “Consumer Prices, the Consumer Price Index, and the Cost of Living”, *Journal of Economic Perspectives*, Vol. 12, No 1, pp. 3-26.

Braithwait, Steven D. (1980), “The Substitution Bias of the Laspeyres Price Index: An Analysis Using Estimated Cost-of-Living Indexes”, *American Economic Review*, Vol. 70, No 1, pp. 64-77.

Broda, Christian and Weinstein, David E. (2010), “Product Creation and Destruction: Evidence and Price Implications”, *American Economic Review*, Vol. 100, No 3, pp. 691-723.

Bureau of Labor Statistics (2001), The experimental CPI using geometric means (CPI-U-XG), last modified 16 October 2001.

Cardoso, Miguel, Ferreira, Clodomiro, Leiva, José Miguel, Nuño, Galo, Ortiz, Álvaro Ortiz and Tomasa, Rodrigo, (2022) "The Heterogeneous Impact of Inflation on Households’ Balance Sheets," Working Papers 176, Red Nacional de Investigadores en Economía (RedNIE).

Cavallari, Lilia (2020), “Monetary policy and consumers’ demand”, *Economic Modelling*, Vol. 92, Issue C, pp. 23-36.

Cavallo, A. (2017), “Are Online and Offline Prices Similar? Evidence from Large Multi-channel Retailers”, *American Economic Review*, Vol. 107, No 1, pp. 283-303.

Caves, Douglas W., Christensen, Laurits R. and Diewert, W. Erwin (1982), “The Economic Theory of Index Numbers and the Measurement of Input, Output, and Productivity”, *Econometrica*, Vol. 50, No 6, pp. 1393-1414.

Charalampakis, Evangelos, Fagandini, Bruno, Henkel, Lukas and Osbat, Chiara (2022), “The impact of the recent rise in inflation on low-income households”, *Economic Bulletin*, Issue 7, ECB, Frankfurt am Main.

Chipman, John S. (1974), “Homothetic preferences and aggregation”, *Journal of Economic Theory*, Elsevier, Vol. 8, No 1, pp. 26-38.

Chipman, John S. (2006), “Aggregation and Estimation in the Theory of Demand”, *History of Political Economy*, Vol. 38, No 5, pp. 106-129.

Claeys, Grégory, Conor McCaffrey, Conor and Welslau, Lennard (2020), “Does inflation hit the poor hardest everywhere?”, Bruegel blog post, 28 November 2022.

Conlon, Christopher and Gortmaker, Jeff (2020), “Best practices for differentiated products demand estimation with PyBLP”, *RAND Journal of Economics*, Vol. 51, No 4, pp. 1108-1161.

Colwell, Peter F. and Dilmore, Gene (1999), “Who Was First? An Examination of an Early Hedonic Study”, *Land Economics*, Vol. 75, No 4, pp. 620-626.

Comin, D.A., Lashkari, D. and Mestieri, M. (2021), “Structural Change with Long-Run Income and Price Effects”, *Econometrica*, Vol. 89, No 1, pp. 311-374.

Conflitti, Cristina, Goldhammer, Bernhard and Rumler, Fabio (2021), *Is There a Measurement Bias from Quality Adjustment in Austria and Italy?*, Mimeo.

Court, A.T. (1939), *Hedonic price indexes with automotive examples. The Dynamics of Automobile Demand*, General Motors, New York, p. 98.

Crawford, Ian and Neary, J. Peter (2021), “New characteristics and hedonic price index numbers”, *The Review of Economics and Statistics*, pp. 1-49.

Dalén, J. and Tarassiouk, O. (2013), “Replacements, quality adjustments and sales prices”, paper for the Ottawa Group, Copenhagen.

Davis, S.J. and Caldeira, K. (2010), “Consumption-based accounting of CO2 emissions”, *Proceedings of the National Academy of Sciences*, Vol. 107, No 12, pp. 5687-5692.

De Haan J. and van der Grient, H.A. (2011), “Eliminating Chain Drift in Price Indexes based on Scanner Data”, *Journal of Econometrics*, Vol. 161, pp. 36-46.

Deaton, Angus and Muellbauer, John (1980), “An Almost Ideal Demand System”, *American Economic Review*, Vol. 70, No 3, pp. 312-326.

Decoster, A.M. and Haan, P. (2015), “Empirical welfare analysis with preference heterogeneity”, *International Tax Public Finance*, Vol. 22, No 2, pp. 224-251.

Diewert, W. Erwin (1976), “Exact and superlative index numbers”, *Journal of Econometrics*, Vol. 4, No 2, pp. 115-145.

Diewert, W. Erwin (1995), “On the Stochastic Approach to Index Numbers”, *Discussion Papers*, No 31, University of British Columbia, September.

Diewert, W. Erwin (2001), “The Consumer Price Index and Index Number Purpose”, *Journal of Economic and Social Measurement*, Vol. 27, pp.167-248.

Diewert, W.E. and Feenstra, R. (2021), “Estimating the Benefits of New Products: Some Approximations”, in Abraham, Katharine G., Jarmin, Ron S., Moyer, Brian and Shapiro, Matthew D. (eds.), *Big Data for Twenty-First-Century Economic Statistics*, University of Chicago Press, pp. 437-473.

Diewert, W.E. and Fox, Kevin J. (2022), “Measuring Real Consumption and CPI Bias under Lockdown Conditions”, *Canadian Journal of Economics*, Vol. 55, pp. 480-502.

Ehrlich, Gabriel, Haltiwanger, John, Jarmin, Ron, Johnson, David and Shapiro, Matthew D. (2020), "Re-engineering Key National Economic Indicators", *NBER Chapters*, in: Big Data for Twenty-First-Century Economic Statistics, pages 25-68, National Bureau of Economic Research, Inc..

Eltetö, Ö. and Köves, P. (1964), "On a Problem of Index Number Computation Relating to International Comparisons", *Statisztikai Szemle*, Vol. 42, pp. 507-518.

EU Commission Regulation (EC) No 1749/96 of 9 September 1996 on initial implementing measures for Council Regulation (EC) No 2494/95 concerning harmonized indices of consumer prices (OJ L 229, 10.9.1996, p. 3), consolidated version of 12 May 2007.

Eurostat (2018), *Harmonised Index of Consumer Prices – Methodological Manual*, Publications Office of the European Union, Luxembourg.

Eurostat (2021), *HICP recommendation on bridged overlap*, Publications Office of the European Union, Luxembourg.

Eurostat (2022), *Guide on multilateral methods in the Harmonised Index on Consumer Prices (HICP)*, Publications Office of the European Union, Luxembourg

Faber, Benjamin and Fally, Thibault (2022), "Firm Heterogeneity in Consumption Baskets: Evidence from Home and Store Scanner Data", *Review of Economic Studies,* Vol. 89, pp. 1420-1459.

Federal Statistical Office of Germany (2009), "Handbook on the application of quality adjustment methods in the Harmonised Index of Consumer Prices", *Statistics and Science*, Vol. 13.

Feenstra, R.C. and Shapiro, M.D. (2007), "Scanner Data and Price Indexes", *Studies in Income and Wealth*, Vol. 64, University of Chicago Press.

Feenstra, Robert C. and Reinsdorf, Marshall B. (2007), "Should Exact Index Numbers Have Standard Errors? Theory and Application to Asian Growth", *Hard-to-Measure Goods and Services: Essays in Honor of Zvi Griliches*, pp. 483-513.

Fischer, C. (2012), "Price convergence in the EMU? Evidence from micro data", *European Economic Review*, Vol. 6, pp. 757-776.

Fisher, Franklin M. (2005), "Price Index Aggregation: Plutocratic Weights, Democratic Weights, and Value Judgments", *Annales d'Économie et de Statistique*, No 79/80, pp. 749-757.

Gábor-Tóth, Eniko and Vermeulen, Philip (2018), "The Relative Importance of Taste Shocks and Price Movements in the Variation of Cost-of-Living: Evidence From Scanner Data", *SSRN* 3246221, September.

Gini C. (1931), "On the Circular Test of Index Numbers", *Metron*, Vol. 9, No 9, pp. 3-24.

Goldhammer, Bernhard, Kouvavas, Omiros, Beka, Jan and Krasnopjorovs, Olegs (2021), “Innovative products and e-commerce – survey results”, document for the ESS HICP Workshop meeting, Mimeo, 29-30 June 2021.

Goldhammer, Bernhard, Traverso, Raffaella and Henkel, Lukas (2019), “Bias related to the bridged-overlap method”, poster presented at the 16th meeting of the Ottawa Group, Rio de Janeiro, Brazil.

Goodman, Allen C. (1998), “Andrew Court and the Invention of Hedonic Price Analysis”, *Journal of Urban Economics*, Vol. 44, No 2, pp. 291-298.

Gordon, Robert J. (2000), “The Boskin Commission Report and its Aftermath”, *NBER Working Papers*, No 7759, National Bureau of Economic Research, June.

Gordon, Robert J. (2006), “The Boskin Commission Report: A Retrospective One Decade Later”, *NBER Working Papers*, No 12311, National Bureau of Economic Research, June.

Griliches, Zvi (1961), “Hedonic Price Indexes for Automobiles: An Econometric of Quality Change”, *The Price Statistics of the Federal Government*, pp. 173-196.

Gürer, Eren and Weichenrieder, Alfons (2020), “Pro-rich inflation in Europe: Implications for the measurement of inequality”, *German Economic Review*, Vol. 21, No 1, pp. 107-138.

Haas, G.C. (1922), *Sale prices as a basis for farm land appraisal*, University of Minnesota, Minnesota Agricultural Experiment Station.

Hamano, Masashige and Zanetti, Francesco (2018), “On Quality and Variety Bias in Aggregate Prices”, *Journal of Money, Credit and Banking*, Vol. 50, No 6, pp. 1343-1363.

Hamilton, Bruce W. (2001), “Using Engel’s Law to Estimate CPI Bias”, *The American Economic Review*, Vol. 91, No 3, pp. 619-630.

Handbury, Jessie (2019), “Are Poor Cities Cheap for Everyone? Non-Homotheticity and the Cost of Living Across U.S. Cities”, *Econometrica*, Vol. 89, No 6, pp. 2679-2715.

Handbury, Jessie, Watanabe, Tsutomu and Weinstein, David E. (2013), “How Much Do Official Price Indexes Tell Us about Inflation?”, *NBER Working Papers*, No 19504, National Bureau of Economic Research, October.

Hausman, Jerry (1996), “Valuation of New Goods under Perfect and Imperfect Competition”, in Bresnahan, T. and Gordon, R. (eds.), *The Economics of New Goods*, University of Chicago Press, pp. 207-248.

Hausman, Jerry (1999), “Cellular Telephone, New Products, and the CPI”, *Journal of Business & Economic Statistics*, Vol. 17, No 2 pp. 188-194.

Henkel, Wieland, E., Błażejowska, A., Conflitti, C., Fabo, B., Fadejeva, L., Jonckheere, J, Karadi, P., Macias, P., Menz, J-O, Seiler, P, and Szafranek, K., (2023), “Price-setting during the COVID-19 pandemic”, ECB OP no 324

Hoffmann, Johannes (1998), “Problems of Inflation Measurement in Germany”, *Discussion Papers*, No 1, Economic Research Group of Deutsche Bundesbank.

Hottman, Colin J. and Monarch, Ryan (2020), “A matter of taste: Estimating import price inflation across U.S. income groups”, *Journal of International Economics*, Vol. 127, Issue C.

Ivancic, L., Diewert, W.E. and Fox, K.J. (2011), “Scanner Data, Time Aggregation and the Construction of Price Indexes”, *Journal of Econometrics*, Vol. 161, No 1, pp. 24-35.

Jaravel, Xavier (2019), “The Unequal Gains from Product Innovations: Evidence From the US Retail Sector”, *The Quarterly Journal of Economics*, Vol. 134, No 2, pp. 715-783.

Jaravel, Xavier (2021), “Inflation Inequality: Measurement, Causes, and Policy Implications”, *Annual Review of Economics*, Vol. 13, pp. 599-629.

Kaplan, Greg and Schulhofer-Wohl, Sam (2017), “Inflation at the Household Level”, *Journal of Monetary Economics*, Vol. 91, pp. 19-38.

Keating, J. and Murtagh, M. (2018), “Quality adjustment in the Irish CPI”, paper for the Meeting of the Group of Experts on Consumer Price Indices, Geneva.

Koester, G. and Grapow, H. (2021), “The prevalence of private sector wage indexation in the euro area and its potential role for the impact of inflation on wages”, *Economic Bulletin*, Issue 7, ECB, Frankfurt am Main.

Kokoski, Mary (2003), “Alternative Consumer Price Index Aggregations: Plutocratic and Democratic Approaches”, *Working Papers*, No 370, US Bureau of Labor Statistics, December.

Konüs, A.A. (1939), “The Problem of the True Index of the Cost of Living”, translated in *Econometrica*, Vol. 7, pp. 10-29.

Kouvavas, Omiros, Osbat, Chiara, Reinelt, Timo and Vansteenkiste, Isabel (2021), “Markups and inflation cyclicality in the euro area”, *Working Paper Series*, No 2617, ECB, Frankfurt am Main, November.

Levell P. (2015), “Is the Carli index flawed?: assessing the case for the new retail price index RPIJ”, *Journal of the Royal Statistical Society*, Series A (Statistics in Society), Vol. 178, No 2, pp. 303-336.

Ley, Eduardo (2005), “Whose Inflation? A Characterization of the CPI Plutocratic Gap”, *Oxford Economic Papers*, Vol. 57, No 4, pp. 634-646.

Li, Nicholas (2021), “An Engel Curve for Variety”, *The Review of Economics and Statistics*, Vol. 103, No 1, pp. 72-87.

Martin, Robert S., (2020), “Changing Tastes Versus Specification Error in Cost-of-Living Measurement”, *Working Papers*, No. 531, US Bureau of Labor Statistics.

Martin, Robert, S. (2022), “Revisiting Taste Change in Cost-of-Living Measurement”, *Journal of Economic and Social Measurement,,* Vol. 46, pp.109-147.

Menz, J.-O., Wieland, E. and Mehrhoff, J. (2022), “Estimating the impact of quality adjustment on consumer price inflation”, *Discussion Papers*, No 49*,* Deutsche Bundesbank.

Miller, R.E. and Blair, P.D. (2009), *Input-Output Analysis: Foundations and Extensions*, Cambridge University Press.

Nakamura, E. and Steinsson, J. (2008), “Five Facts about Prices: A Reevaluation of Menu Cost Models”, *The Quarterly Journal of Economics*, Vol. 123, No 4, pp. 1415-1464.

Nevo, Aviv (2000), “A Practitioner’s Guide to Estimation of Random Coefficients Logit Models of Demand”, *Journal of Economics and Management Strategy*, Vol. 9, No 4, pp. 513-548.

Nevo, Aviv (2001), “Measuring Market Power in the Ready-to-Eat Cereal Industry”, *Econometrica*, Vol. 69, No 2, pp. 307-342.

Nevo, Aviv (2003), “New Products, Quality Changes, and Welfare Measures Computed from Estimated Demand Systems”, *The Review of Economics and Statistics*, Vol. 85, No 2, pp. 266-275.

Pakes, A. (2005), “Hedonics and the Consumer Price Index”, *Annales d’Économie et de Statistique*, No 79/80, pp. 729-748.

Patel, Nikhil and Villar, Agustín (2016), “Measuring inflation”, in Bank for International Settlements (ed.), *Inflation mechanisms, expectations and monetary policy*, Vol. 89, pp. 9-21.

Pollak, R.A. (1989), *The Theory of the Cost of Living Index*, Oxford University Press, New York.

Ravn, Morten, Schmitt-Grohe, Stephanie and Uribe, Martín (2008), “Macroeconomics of subsistence points”, *Macroeconomic Dynamics*, Vol. 12, Issue S1, pp. 136-147.

Redding, S.J. and Weinstein, D.E. (2020), “Measuring Aggregate Price Indices with Taste Shocks: Theory and Evidence for CES Preferences”, *The Quarterly Journal of Economics*, Vol. 135, No 1, pp. 503-560.

Reis, Ricardo and Watson, Mark W. (2010), “Relative Goods’ Prices, Pure Inflation, and the Phillips Correlation”, *American Economic Journal: Macroeconomics*, Vol. 2, No 3, pp. 128-157.

Santoro, Sergio, and Weber, Henning (2023), “Micro price heterogeneity and optimal inflation”, *Occasional Paper Series, No.* 322, ECB Frankfurt am Main.

Schultze, Charles and Mackie, Christopher (2002), *At What Price? Conceptualizing and Measuring Cost-of-Living and Price Indexes*, National Academy Press, Washington, D.C.

Silver, Mick and Heravi, Saeed (2007), “Why elementary price index number formulas differ: Evidence on price dispersion”, *Journal of Econometrics*, Vol. 140, No 2, pp. 874-883.

Strasser, G, Messner, Teresa, Rumler, Fabio and Ampudia, Miguel (2023), “Inflation Heterogeneity at the Household Level”, *Occasional Paper Series*, no. 325, ECB Frankfurt am Main.

Strasser, G., Wieland, E., Macias,P., Błażejowska, A., Szafranek, K., Wittekopf, D., Franke, J., Henkel, L. Osbat, C. (2023), “E-commerce and price setting - evidence from Europe”, *Occasional Paper Series*, no. 320, ECB Frankfurt am Main.

Szulc, B. (1964), “Indexes for Multiregional Comparisons”, *Przeglad Statystyczny*, Vol. 3, pp. 239-254.

Triplett, Jack E. (2001), “Should the Cost-of-Living Index Provide the Conceptual Framework for a Consumer Price Index?”, *The Economic Journal*, Vol. 111, No 472, pp. F311-F334.

Triplett, Jack E. (2006), “The Boskin Commission Report After a Decade”, *International Productivity Monitor*, Vol. 12, Centre for the Study of Living Standards, pp. 24-60.

Ueda, Kozo, Watanabe, Kota and Watanabe, Tsutomu (2019), “Product Turnover and the Cost of Living Index: Quality vs. Fashion Effects”, *American Economic Journal: Macroeconomics*, Vol. 11, pp. 310-347.

Uras, Burak R. and van Buggenum, Hugo (2022), “Preference heterogeneity and optimal monetary policy”, *Journal of Economic Dynamics and Control*, Vol. 134.

Von der Lippe, P. (2007), *Index Theory and Price Statistics*, Peter Lang, Frankfurt am Main.

Work stream on digitalisation (2021), “Digitalisation: channels, impacts and implications for monetary policy in the euro area”, *Occasional Paper Series*, No 266, ECB, Frankfurt am Main.

Work stream on inflation measurement (2021), “Inflation measurement and its assessment in the ECB’s monetary policy strategy review”, *Occasional Paper Series*, No 265, ECB, Frankfurt am Main.

Zadrozny, Peter (2021), "Full and Implicit Quality Adjustment of a Cost of Living Index of an Estimated Generalized CES Utility Function", *Working Papers*, No 515, US Bureau of Labor Statistics.

Zhen, C., Finkelstein, E.A., Karns, S.A., Leibtag, E. and Zhang, C. (2019), "Scanner Data-Based Panel Price Indexes", *American Journal of Agricultural Economics*, Vol. 101, No 1, pp. 311-329.

Acknowledgements
This report has been coordinated by Chiara Osbat with input and comments on all sections by Bernhard Goldhammer, as well as Boriss Siliverstovs, Martin Eiglsperger, Gian-Pietro Bellocca*, Friderike Kuik, Marta Saez Moreno, Lina Segers* and Anaëlle Touré* on Section 2 and Cristina Conflitti, Jan-Oliver Menz, Fabio Rumler and Elisabeth Wieland on Section 3.
*The work was carried out while the author was based at the ECB.
The authors would like to thank Luca Dedola for valuable comments and suggestions and Marta Oliva Riera for excellent editorial support.

Chiara Osbat
European Central Bank, Frankfurt am Main, Germany; email: Chiara.Osbat@ecb.europa.eu

Cristina Conflitti
Banca d'Italia, Rome, Italy; email: Cristina.Conflitti@bancaditalia.it

Gian-Pietro Bellocca
European Central Bank, Frankfurt am Main, Germany; email: gpebellocca@gmail.com

Martin Eiglsperger
European Central Bank, Frankfurt am Main, Germany; email: Martin.Eiglsperger@ecb.europa.eu

Bernhard Goldhammer
European Central Bank, Frankfurt am Main, Germany; email: Bernhard.Goldhammer@ecb.europa.eu

Friderike Kuik
European Central Bank, Frankfurt am Main, Germany; email: Friderike.Kuik@ecb.europa.eu

Jan-Oliver Menz
Deutsche Bundesbank, Frankfurt am Main, Germany; email: Jan-Oliver.Menz@bundesbank.de

Fabio Rumler
Oesterreichische Nationalbank, Vienna, Austria; email: fabio.rumler@oenb.at

Marta Saez Moreno
European Central Bank, Frankfurt am Main, Germany; email: Marta.Saez_Moreno@ecb.europa.eu

Lina Segers
European Central Bank, Frankfurt am Main, Germany; email: Lina.Segers@eui.eu

Boriss Siliverstovs
Latvijas Banka, Riga, Latvia; email: Boriss.Siliverstovs@bank.lv

Anaëlle Touré
European Central Bank, Frankfurt am Main, Germany; email: anaelletoure@gmail.com

Elisabeth Wieland
Deutsche Bundesbank, Frankfurt am Main, Germany; email: Elisabeth.Wieland@bundesbank.de

Postal address 60640 Frankfurt am Main, Germany
Telephone +49 69 1344 0
Website www.ecb.europa.eu

PDF ISBN 978-92-899-6152-3, ISSN 1725-6534, doi:10.2866/182061, QB-AQ-23-014-EN-N