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Estimating the impact of quality adjustment on consumer price inflation

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Price-setting Microdata Analysis Network (PRISMA)

This paper contains research conducted within the Price-setting Microdata Analysis Network (PRISMA). PRISMA consists of economists from the ECB and the national central banks (NCBs) of the European System of Central Banks (ESCB).

PRISMA is 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) act as external consultants.

PRISMA collects and studies various kinds of price microdata, including data underlying official price indices such as the Consumer Price Index (CPI) and the Producer Price Index (PPI), scanner data and online prices to deepen the understanding of price-setting behaviour and inflation dynamics in the euro area and EU, with a view to gaining new insights into a key aspect of monetary policy transmission (for further information see https://www.ecb.europa.eu/pub/economic-research/research-networks/html/researcher_prisma.en.html)

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This paper is released in order to make the results of PRISMA research generally available, in preliminary form, to encourage comments and suggestions prior to final publication. The views expressed in the paper are the author's own and do not necessarily reflect those of the ESCB.

Abstract

How important is quality adjustment in measuring consumer price inflation? We address this question using different sources of micro and macro price data. For Germany, based on micro price data covering 85% of the CPI basket, but lacking some items subject to quality adjustment, we find that price adjustments due to quality changes reduce headline inflation by only 0.06 percentage points on average. This is offset by an increase of the same amount due to quantity adjustments (e.g. smaller package size). However, scanner data analysis suggests a larger impact for goods subject to quality adjustment, leading to an overall estimate of 0.6 percentage points for Germany. For the euro area, we show that the use of heterogeneous quality adjustment practices across member states has a significant impact on cross-country inflation differentials and distorts the level of inflation. Using scanner data for consumer and household electronics, we find that cross-country inflation differentials may be overestimated by about 0.5 percentage points, and the euro area (Big-5) inflation rate by about 0.3 percentage points due to non-harmonised quality adjustment methods.

JEL Classification: E31, C43.

Keywords: inflation measurement, quality adjustment, inflation differentials, consumer prices, scanner price data.

Non-technical summary

The measurement of consumer price inflation remains a key question for both statisticians, central bankers and policy makers. One of the most important challenges consists of adequately accounting for changes in product quantity and quality, not only in a single country but also between members of the euro area if the adjustment practices are not harmonised sufficiently. This issue has also been identified as a crucial knowledge gap in the strategy review of the Eurosystem (ECB, 2021).

We contribute to filling this gap by estimating the impact of quality adjustment using different sources of micro and macro price data. First, we present evidence on the extent and the size of quality and quantity adjustment in the German inflation rate, using micro data covering 85% of the CPI basket. Second, we approximate the impact of heterogeneous QA practices across member states on euro area inflation by using disaggregate HICP data. And third, we illustrate the impact of heterogeneous QA methods on euro area inflation using scanner price data for 15 product categories, mainly related to consumer and household electronics, which are generally subject to quality adjustment.

For Germany, we find that price adjustments due to quality changes have lowered the headline inflation rate by about 0.06 percentage points between 2015 and 2020, which was offset by an increase caused by quantity adjustments of around the same magnitude. However, the effect of quality adjustment is substantially larger for industrial goods and services, also because our dataset excludes some electronic goods that are typically adjusted for quality changes. Using scanner data, which mainly include goods that are subject to quality adjustment and which we lack in the German CPI micro data, the estimated impact of quality adjustment on price changes for these goods is 3.7 percentage points. Adding this to the results from the CPI micro price data gives an estimate of 0.6 percentage points for overall inflation in Germany, which is quite close to earlier findings in the literature.

Regarding the euro area, our findings suggest that the use of non-harmonised quality adjustment methods increases price differences across member countries. According to our estimates using official HICP data, the range of headline inflation could be overestimated by $\pm$ 0.2 percentage points and core inflation by up to $\pm$ 0.3 percentage points, taking into account income differences across countries. Applying a harmonised quality adjustment to our scanner dataset leads to very similar results. The range of cross-country inflation rates for the available product categories is reduced from around 10 percentage points to around 4 percentage points. Multiplied by the corresponding HICP weight of 1.5%, this gives a range of 0.1 percentage points in terms of headline inflation caused by non-harmonised quality adjustment methods. Assuming that the reduction in inflation differences also applies to product categories that are likely to be affected by quality changes but for which we do not have scanner data, the effect on headline inflation increases to 0.5 percentage points.

Finally, our findings suggest that the use of non-harmonised quality adjustment methods or the lack of quality adjustment of some product groups in some countries also leads to a bias in the euro area inflation rate. On average, our quality-adjusted inflation rate based on scanner data is about 3.5 percentage points lower than the official inflation rate for the same product groups. Multiplied by the corresponding HICP weight, this implies a measurement bias of +0.3 percentage points for headline inflation, if a similar bias is assumed for typical quality-adjusted products.

Turning to the implications for policymakers, we find that heterogeneous QA procedures across euro area member states are a source of non-negligible measurement bias affecting euro area inflation. Our estimate of the impact of heterogeneous QA procedures on euro area inflation is similar in magnitude to the measurement bias in the HICP due to substitution effect or the absence of owner-occupied housing (ECB, 2021). As this bias is not constant over time, it poses a double problem for policymakers: not only does it lead to an overestimation of euro area inflation, but it also contributes to larger inflation differentials between countries. This creates difficulties in terms of communication, but also in terms of measuring the stance of monetary policy. Hence, this would support the call for further harmonisation of QA methods across member states. In this line, more efforts should be made to quantify both the size and the direction of the impact of quality adjustment in euro area inflation with greater accuracy and on a regular basis.

1 Introduction

There are several challenges to the correct measurement of consumer price inflation. Measurement bias can arise if new products, outlets and changes in consumption patterns are only taken into account with a certain time lag.[1] Moreover, price statistics should measure the "pure" price change by disentangling a price decrease or increase due to an improvement or deterioration in the quality of a product. Hence, inflation will be overestimated if price increases are not adjusted for improved product quality, or if products of different quality are treated as close substitutes.

Concerning potential measurement bias in a CPI, quality adjustment was found to explain more than half of the measurement error for US inflation (Boskin et al., 1996). For Germany, Hoffmann (1998) argues that pre-euro inflation may have been biased upwards by about 0.75 percentage points (p.p.), mainly because of difficulties in accounting for changes in product quality. However, little is known about the impact of quality adjustment on consumer price inflation for a more recent period, which may be due to the lack of more granular information on the underlying methods and the magnitude of the price adjustments at the product level.

In the euro area, an additional source of measurement bias may arise not only from the lack of quality adjustment (QA) itself, but also from heterogeneous national QA practices. To date, different QA procedures exist for national statistical institutes (NSIs) in the euro area, but without any binding rules, suggesting scope for further harmonisation (ECB, 2021). Heterogeneous QA practices may also contribute to the surprisingly large price differentials for certain products in the euro area. For example, the average price change of mobile phones in the HICP since 2016 ranges from +5% in Portugal to -17% in Ireland. Given the homogeneity and tradability of this item, such large price differentials are surprising; one possible explanation for diverging price trends – especially for industrial products with continuous technological improvements – could be heterogeneous QA practices across euro area member states. Likewise, a case study of Austrian and Italian Consumer Price Index (CPI) micro data by Conflitti et al. (2022) suggests that the choice of QA methods can well explain the divergent HICP rates in the two countries. In the context of its 2020-21 strategy review, the Eurosystem has also stressed the importance of gaining a better understanding of the various sources of measurement bias in euro area inflation

[1] Camba-Mendez (2003) offers a discussion of four potential measurement biases in the euro area Harmonised Index of Consumer Prices (HICP): substitution bias, quality bias, outlet bias and new good bias. Concerning substitution bias, product variety, and taste shocks, Beck and Jaravel (2021) provide a comprehensive empirical assessment for more than 30 countries using scanner data for fast-moving consumption goods.

and has identified a knowledge gap regarding the bias due to quality adjustment (ECB, 2021).

We contribute to filling this gap by estimating the impact of quality adjustment using different sources of micro and macro price data. First, we update the earlier findings of Hoffmann (1998) and present evidence on the extent and the size of quality and quantity adjustment in the German inflation rate, using micro data covering 85% of the official consumer basket of the CPI. Second, we try to approximate the impact of heterogeneous QA practices across member states on euro area inflation.[2] For this purpose, we build on the official inflation series published by Eurostat and select product categories whose prices are typically affected by quality change. Based on the dispersion of cumulative inflation rates across member states, we derive a range for euro area headline and core inflation, which we interpret as an estimate of the impact of quality adjustment on the HICP. Finally, we illustrate the impact of heterogeneous QA methods on euro area inflation using scanner price data for 15 product categories that are generally subject to quality adjustment. Our data mainly cover products in the area of consumer and household electronics and are available for the five largest euro area economies (France, Germany, Italy, the Netherlands and Spain), covering 80% of the euro area in terms of HICP country weights.

Overall, our main findings can be summarised as follows. First, accounting for changes in quantity and quality has only a very small impact on headline inflation in Germany. Quantity changes in this context refer to changes in the "size of a unit" supplied, such as the package size of a product or the length of a music lesson. Quality changes, on the other hand, refer to changes in the nature of a product, such as improved features of a particular mobile phone. According to this definition, a lower *quantity* of products should lead to higher inflation, while a higher *quality* of products, such as improved mobile phone features should lead to lower inflation. In fact, our results suggest that since 2015, inflation has been increased by +0.06 p.p. on average due to a lower underlying quantity, but has decreased by about the same amount due to quality improvements. This small effect may seem surprising, but it should be borne in mind that we lack data for a number of products that are typically adjusted for quality changes such as computers, smartphones and used cars. Including these products in our analysis would certainly give rise to a larger impact of quality changes in official German inflation. Indeed, our analysis

[2] A precise estimate could only be derived from detailed micro price data. Although the Eurosystem's Price-setting Microdata Analysis Network (PRISMA) has gone some way in this direction, a direct comparison of the HICP micro price data across countries is hampered by the lack of information on quality adjustment and by centrally collected prices such as electronics, which are often subject to quality adjustment (see Gautier et al., 2024).

using scanner data that primarily comprise goods that are subject to quality adjustment and that we lack in the German CPI micro data, gives an estimated impact of quality adjustment on price changes for these goods of 3.7 p.p. Adding this to the results from the CPI micro price data gives an estimate of 0.6 p.p. for overall inflation in Germany, which is quite close to earlier findings in the literature (Hoffmann, 1998).

Second, the use of non-harmonised quality adjustment methods increases price differences across euro area countries. According to our estimates using official HICP data, the range of headline inflation could be overestimated by ± 0.2 p.p. and core inflation by up to ± 0.3 p.p., taking into account income differences across countries. Applying a harmonised quality adjustment to our scanner dataset leads to very similar results. The range of cross-country inflation rates for the available product categories is reduced from around 10 p.p. to around 4 p.p. Multiplied by the corresponding HICP weight of 1.5%, this gives a range of 0.1 p.p. in terms of headline inflation caused by non-harmonised quality adjustment methods. Assuming that the reduction in inflation differences also applies to product categories that are likely to be affected by quality changes but for which we do not have scanner data, the effect on headline inflation increases to 0.5 p.p.

Third, the use of non-harmonised quality adjustment methods or the lack of quality adjustment of some product groups in some countries also leads to a bias in the euro area inflation rate. On average, we find that our quality-adjusted inflation rate based on scanner data was about 3.5 p.p. lower than its official counterpart. Multiplied by the corresponding HICP weight, this implies a measurement bias of +0.3 p.p. if a similar bias is assumed for a set of typical quality-adjusted products. Note that this estimate is a lower bound: If we assume that about one third of the consumption basket is subject to quality adjustment, as is the case of Statistics Sweden (2019), we obtain an estimated bias in euro area inflation of about 0.9 p.p.

The outline of this paper is as follows. Section 2 presents some stylised facts and a literature review on the impact of quality adjustment in consumer price statistics. Section 3 provides an estimate of the impact of quantity and quality adjustment on German inflation using CPI micro prices for the period 2010-2020. Section 4 discusses the role of quality adjustment for euro area inflation. First, we estimate the impact of heterogeneous QA methods on euro area headline and core inflation using official national inflation rates and a predefined list of typical quality-adjusted products (Section 4.1). Second, we illustrate the impact of heterogeneous QA methods in the euro area using scanner price data for 15 product categories that are generally subject to quality adjustment and cover the five largest euro area economies (Section 4.2). Section 5 concludes.

2 Stylised facts and literature overview

While there is a large literature on the impact of quality adjustment on inflation measurement, there is much less evidence on its potential impact on explaining price differences across countries. As part of the traditional debate on measurement error, quality adjustment was found to explain more than half of the measurement error for US inflation (Boskin et al., 1996). Building on this seminal contribution, several studies for euro area countries have made similar efforts to quantify the measurement bias in domestic inflation, e.g. Hoffmann (1998) for Germany, Lequiller (1997) for France and Neves and Sarmento (1997) for Portugal.[3] Hoffmann (1998) argues that German inflation before the introduction of the euro may have been biased upwards by about 0.75 p.p., mainly because of difficulties in accounting for changes in product quality. Based on a model of price formation, the author states that – if inflation is moderate – the quality adjustment bias *"might be approximately 1/2 percentage point if the average advance in quality is 1% per annum"*, with non-linearities depending on the level of inflation.[4] In view of digitalisation and product innovation, the question of the impact of quality adjustment on consumer prices has become even more relevant today (Reinsdorf and Schreyer, 2019). However, to the best of our knowledge, Statistics Sweden seems to be the only institute that regularly publishes the impact of its quality adjustment on national inflation; according to its annual quality report, about 27% of the products in the Swedish consumption basket are adjusted for quality changes. Without quality adjustment, the prices of these groups would be 1.2% higher, resulting in a total effect on headline inflation of +0.3 p.p. (Statistics Sweden, 2019).

For the euro area, in addition to a bias caused by missing or inadequate quality adjustment

[3] Several studies also focus on the measurement bias in the HICP stemming from the underlying index formulae. Herzberg et al. (2021) calculate the upper-level aggregation bias arising from product substitution and delayed data availability in Germany and the euro area. They find that official HICP inflation has been biased upwards by about 0.1 p.p. In contrast, Gabor-Toth and Vermeulen (2019) argue that the choice of the index formula at the micro level, the elementary index bias, is quantitatively more important than the upper-level substitution bias.

[4] See Hoffmann (1998), p. 154: *"Below this area, i.e. given falling prices, the bias increases rapidly. As a maximum it could be in the region of one percentage point per annum. If inflation is higher, the bias might also be over 1 percentage point p.a."*

itself, a measurement bias may arise from country-specific quality adjustment; either because some countries choose to adjust prices of certain goods for quality changes and others do not, or because countries use different QA methods. Already in the early days of monetary union, Ahnert and Kenny (2004) point to differences in price trends in the HICPs for PCs and clothing, which may *"reflect the chosen quality adjustment method rather than actual price developments."* Similarly, Byrne (2019) shows that there are substantial differences in the price trends of the HICP for mobile phones in the EU, with a range of average annual price decreases of 9 p.p. over the period 2014–18.[5] Figure 1 shows price trends for mobile telephones (including smartphones) and personal computers across euro area countries; it plots the corresponding HICP subindex and the cumulated inflation rate from January 2016 onwards.[6] Given that products in the mobile phone category are assumed to be fairly homogeneous, we would expect prices to behave rather similarly across countries.[7] Nevertheless, we observe remarkable price differentials ranging from a cumulative price decrease of more than 60% in Estonia to an increase of about 2% in Portugal. A similar pattern emerges for prices of personal computers, as shown in the bottom panel of Figure 1.

In its strategy review, the ECB (2021) identified a knowledge gap on the potential bias from quality adjustment in the euro area HICP. In the euro area, there are several recommendations on how to implement quality adjustment, which basically distinguish between two main approaches (see Eurostat, 2024, Chapter 6): *Explicit methods* infer quality changes by assumption or by direct calculation using product characteristics. In contrast, *implicit methods* estimate the impact of quality changes from other information, such as observed price differences for similar individual products. Nevertheless, NSIs can choose from a wide range of quality adjustment methods and strategies for selecting replacement products.[8] In a case study of Austrian and Italian CPI micro prices, Conflitti et al. (2022) show that heterogeneous QA practices may well explain divergent HICP rates and trends across countries. While Statistics Austria uses mainly explicit QA methods, Istat uses only implicit methods. For a selection of non-energy industrial

[5]Note that this difference is smaller than for a wider group of countries (G7, Australia, China, Finland, Korea, and New Zealand), indicating at least some efforts at harmonisation.

[6]The lowest level of aggregation of the HICP, which refers to the 5-digit level of the European Classification of Individual Consumption according to Purpose (ECOICOP), only starts in 2015 for most euro area countries.

[7]Note that the HICP index "08.2.0.2 - Mobile telephone equipment" covers only mobile phone handsets, while the mobile phone tariff falls under ECOICOP "08.3.0.2 - Wireless telephone services".

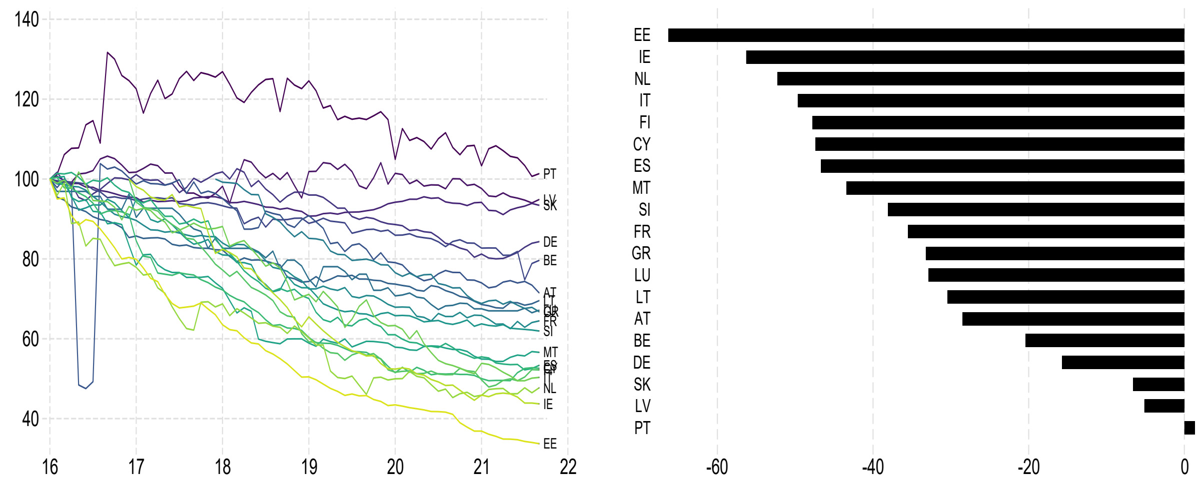
[8]See Eurostat (2024), p. 156: *"Statisticians need to make some important choices among the various quality adjustment methods available, in addition to the strategy for selecting the replacement individual product. Both dimensions to quality adjustment have traditionally varied across Member States, which presents a challenge for harmonisation."*

Figure 1: Price developments for selected products

HICP for mobile telephone equipment

Index

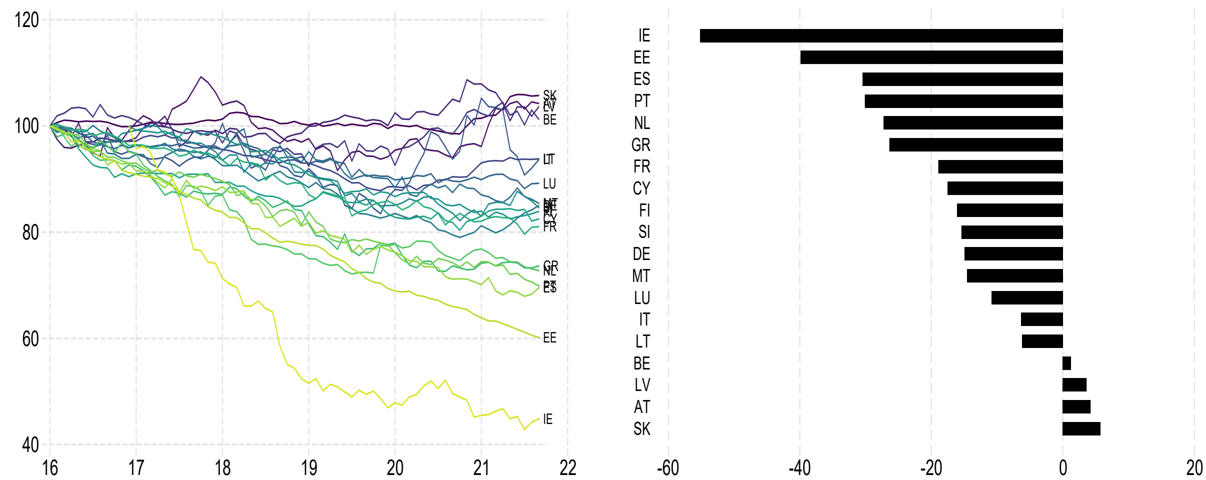
Cumulated inflation rate



HICP for personal computers

Index

Cumulated inflation rate



Note: The figure shows the HICP indices "08.2.0.2 Mobile telephone equipment" and "09.1.3.1 Personal computers" indexed to January 2016=100 and as cumulated inflation rate between January 2016 and September 2021. Data for Ireland and Finland are only available from December 2016 onwards. For Greece, HICP data on mobile telephone equipment only start in December 2017.

goods, the study finds no strong measurement bias due to quality adjustment. Between the two countries, however, the results suggest that the implicit adjustment used in Italy explains a larger share of price changes due to product replacement with quality changes than the explicit methods used in Austria. Overall, to the best of our knowledge, no study has estimated the impact of quality adjustment on euro area inflation.

3 The impact of quality adjustment on the German CPI

In this section, we make use of the micro price data underlying the German CPI to estimate the impact of quality adjustment on inflation. Moreover, this analysis also underpins our selection of products that are typically subject to quality adjustment in Section 4.1.

3.1 Data and definitions

According to the Federal Statistical Office of Germany (Destatis), various methods of quality adjustment are applied to the German CPI.[9] These include option pricing (e.g. for airbags in new cars) and (supported) judgmental quality adjustment (e.g. washing machines with modified water and electricity consumption). Hedonic methods are applied to about 1.4% of the German CPI basket, including products such as desktop PCs, tablet PCs, notebooks, smartphones, printers and used cars. Finally, Destatis also accounts for changes in the quantity (e.g. package size) of a given product.

The micro price data underlying the German CPI have recently been made available for research purposes and have been used by Adam et al. (2022) to analyse changes in relative prices over time and Gautier et al. (2024) to study price setting in the euro area.[10] Prices are collected each month at the product level, i.e. in a given retail store or by service provider in a given region. To construct price indices, micro prices are aggregated at the lowest elementary index level (product-outlet-region level) using the Dutot formula (see Destatis, 2023). The resulting average price is compared to a given base period (e.g. 2015 = 100). The subsequent aggregation to the overall CPI by Destatis follows the Laspeyres formula by using a weighting pattern for i) outlet types, such as supermarkets, discounters, and internet trading, ii) for the 16 federal states in Germany, and iii) for goods and services at the so-called COICOP-10 level.

Our micro price sample covers the period from 2010:01 until 2020:12. After excluding imputed prices and aggregated price measures, the dataset consists of about 50 million observations,

[9] General information on the QA procedures used in the German CPI is provided by Destatis online here.
[10] See appendix A.1 for a description of the dataset.

representing about 85% of the HICP. The coverage varies somewhat between components, from 77% for unprocessed food to 79% for non-energy industrial goods, 90% for services, 94% for processed food and 100% for energy. In total, the data cover 716 different product groups at the COICOP-10 level. Note that the dataset contains a statistical break in 2015:01, as Destatis usually revises the price collection and the underlying methods every five years when a new consumption basket is introduced. Therefore, any analysis at the product level needs to be split into the periods before and after 2015. Concerning quality-adjusted products, the dataset lacks some centrally collected goods that are considered to be strongly affected by quality changes, such as computers, smartphones, and used cars. Our analysis will therefore provide a *lower benchmark* on the impact of quality changes on German inflation.

From the micro price data, we estimate the impact of quantity and quality changes on consumer prices as follows. The dataset contains two price variables: p^{raw} denotes the raw price as observed by the price collector in the store. p^{adj} is the quantity- and quality-adjusted price which enters the official CPI compilation.[11] Among many other product information, the dataset provides information on the quantity and unit of measurement of a product. For example, we know how many grams of rice are in a package or how many millilitres of milk are in a bottle, but also how many minutes are spent per guitar lesson.[12] The quantity-adjusted price is then computed in two steps. First, we define the unit-value price $p_{i,t}^{unit}$ by dividing the raw price $p_{i,t}^{raw}$ of a given product i in month t by its corresponding quantity $quan_{i,t}$:

$$p_{i,t}^{unit} = \frac{p_{i,t}^{raw}}{quan_{i,t}} \tag{1}$$

Second, we follow the approach of Destatis, which calculates the quantity-adjusted price relative to the corresponding quantity of the base period, i.e. the years 2010 and 2015. However, as the reference quantity is not reported in our dataset, we use the first available quantity of each product spell instead. Thus, with $t = 1$ as the reference period, the quantity-adjusted price

[11] A detailed variable description can be found in the corresponding meta data report (Research Data Centres of the Statistical Offices of the Federation and the Federal States, 2022).

[12] We cleaned these variables beforehand to avoid spikes in the data due to redefinitions of units of measurement and the like.

$p_{i,t}^{quan}$ is given by:

$$p_{i,t}^{quan} = \frac{p_{i,t}^{unit}}{p_{i,t=1}^{unit}} p_{i,t=1}^{raw} \tag{2}$$

Third, regarding quality changes, our dataset contains a variable $qual_{i,t}$ which indicates the price difference in euros with respect to the previous month that is caused by a change in product quality; this is the case whenever the price collector samples a replacement product that differs in terms of quality from the predecessor product. We define the quality variable in such a way that *negative* values indicate *quality improvement*, i.e. the raw price is reduced due to an increase in product quality. Likewise, a deterioration in quality is captured by positive values. Thus, the quality-adjusted price is defined as:[13]

$$p_{i,t}^{qual} = p_{i,t}^{raw} + qual_{i,t} \tag{3}$$

Finally, to assess the impact of changes in product quantity and quality on inflation, individual product prices have to be aggregated to derive inflation measures. We follow the official aggregation scheme as described above and end up with four measures of inflation: π_t^{adj} denotes inflation derived from the adjusted price as reported in the micro dataset, and π_t^{raw} from the raw price. π_t^{quan} and π_t^{qual} denote inflation derived from the quantity- and quality-adjusted price, respectively. As shown in Table A.1, the resulting micro price inflation rates move very closely with the official inflation rates, as reflected by a correlation coefficient generally above 0.8.[14]

3.2 Impact of quality and quantity adjustment on German inflation

Using these definitions, we first take a closer look at the scope and the size of quantity and quality adjustments at the product level. To this end, in Tables 1 and 2, we present results for 20 product groups in the German CPI with the largest quantity and quality adjustment (in absolute terms) for the two sub-samples 2010-2014 and 2015-2020, sorted by the most recent

[13]Note that, if a product is replaced by a product of higher or lower quality, we count all price observations of the replacement product as quality-adjusted.

[14]In Figure A.1 in the appendix, we plot the inflation rates over time and show that our measures of micro price inflation track official inflation very well. Although the correlation seems rather low for non-energy industrial goods and services, this seems to be due to limited periods at the beginning of the sample and to the missing service component "package holidays", which is highly volatile in Germany (see Sch, 2024).

period.

Quantity adjustments in the German CPI mainly affect food prices (e.g. apple juice, leeks, lamb) and non-durable and semi-durable consumer goods (e.g. bird food, blank CDs, clothing). The share of adjustment varies between products, from about 80% for grapefruit, kiwi and cauliflower to about 7% for fresh fish and apple juice, but also between sub-samples. For example, only 5% of the prices of kiwis, pineapples and mangoes were adjusted for quantity before 2015, compared to about 80% afterwards. The size of the quantity adjustment is typically *positive*, meaning that the raw price of a given product is adjusted upwards because it is sold with a lower quantity. Exceptions are some clothing products (children's and men's underwear) and hair shampoo. Also note that the size varies markedly between the two sub-samples under consideration.

Table 1: Quantity-adjusted products in the German CPI

COICOP-10		% share		avg. size		HICP weight
		1014	1520	1014	1520	1520
934201200	Bird food	13.2	19.0	2.8	19.5	0.05
122311100	Apple juice or similar fruit juice	8.7	7.8	0.2	14.6	0.11
117119200	Leek or celery	7.7	15.9	1.9	14.4	0.01
112300100	Lamb	16.3	15.0	8.1	13.1	0.02
116115100	Grapefruit	78.2	79.4	27.8	12.4	0.01
914210100	Blank CDs	22.7	14.7	3.4	12.2	0.00
520301100	Table cloth, table runner or the like	0.8	4.7	1.0	12.2	0.02
312343100	Children's underwear	18.6	27.7	3.1	-11.2	0.02
116111100	Oranges	40.3	38.3	10.4	10.9	0.05
1213105300	Wet shaving razor, razor blades or the like	18.8	18.4	14.5	10.7	0.03
312161200	Men's underwear	10.7	18.9	-2.0	-9.8	0.02
116170200	Kiwis, ananas or mangos	5.2	78.8	6.9	9.6	0.05
121201100	Black tea or green tea	13.4	13.1	5.0	9.0	0.02
117121100	Cauliflower	81.2	83.4	4.7	8.1	0.01
113500100	Smoked fish	13.8	13.2	18.4	8.1	0.05
113100100	Fresh fish	2.8	6.5	5.1	8.1	0.05
116165100	Grapes	16.1	15.4	6.4	8.0	0.08
113200100	Frozen fish	21.8	36.6	4.7	7.9	0.04
114501100	Hard cheese	25.7	15.5	10.7	7.9	0.09
1213211100	Hair shampoo	15.0	28.9	4.8	-7.6	0.06

Note: The table shows the 20 COICOP-10 groups with the largest absolute quantity adjustment from 2015 to 2020. *% share* denotes the share of products adjusted for quantity changes, and *avg. size* gives the average absolute size of the adjustment in percentage terms. 1014 and 1520 refer to the sub-samples 2010-2014 and 2015-2020. *HICP weight 1520* reports the average COICOP share in the HICP.

Quality adjustment mainly affects the prices of durable goods and some services. This is especially true for insurance premiums, where the price adjustment has been the largest of all products. Interestingly, the quality of these insurances has deteriorated, as is suggested by the positive price adjustment. By contrast, the quality adjustment for the remaining products has mainly led to a price decrease, especially for cars, tools, washing machines and the like.

Finally, in Table 3, we compute the impact of quantity and quality adjustment on German

Table 2: Quality-adjusted products in the German CPI

COICOP-10		% share		avg. size		HICP weight
		1014	1520	1014	1520	1520
1255000200	Premium for legal protection insurance	5.5	47.2	-0.8	5.5	0.17
1255000100	Premium for personal liability insurance	0.0	10.4	0.0	5.1	0.24
551102100	Impact drill	8.3	19.9	-0.7	-2.5	0.04
921101100	Camper	67.4	79.2	-1.1	-1.8	0.11
1120201100	Campsite fee	0.0	28.4	0.0	-1.7	0.04
531201200	Washing machine	53.2	60.1	-1.0	-1.6	0.12
711100100	New passenger car	66.1	67.8	-2.2	-1.6	2.39
531102100	Freezer or chest freezer	51.4	44.4	-1.6	-1.5	0.03
932111100	Football or other sports ball	5.1	7.1	-0.3	1.4	0.01
911250100	Satellite kit	17.3	11.0	-0.6	1.3	0.03
914920100	USB flash drive	11.7	9.0	-0.2	-1.2	0.04
712004100	Moped	0.0	17.6	0.0	-1.1	0.03
551102200	Cordless screwdriver or cordless drill	10.0	8.9	-0.0	-1.1	0.05
1111112100	Soups, hotel	5.4	5.8	0.1	1.0	0.00
1270402100	Classified advertisement in a newspaper	3.1	1.9	0.4	1.0	0.05
532900200	Electric kettle, egg boiler or the like	8.7	7.1	0.6	0.9	0.02
911210200	Television	40.5	60.8	-0.3	-0.9	0.34
531101100	Refrigerator	50.8	39.6	-1.9	-0.9	0.06
531103100	Fridge-freezer	54.5	55.2	-2.6	-0.8	0.05
531203100	Tumble dryer	46.2	51.7	0.0	-0.8	0.04

Note: The table shows the 20 COICOP-10 groups with the largest absolute quality adjustment from 2015 to 2020. *% share* denotes the share of products adjusted for quality changes, and *avg. size* gives the average absolute size of the adjustment in percentage terms. 1014 and 1520 refer to the sub-samples 2010-2014 and 2015-2020. *HICP weight 1520* reports the average COICOP share in the HICP.

headline inflation, as well as on the five main aggregates unprocessed food, processed food, energy, non-energy industrial goods, and services. Two findings stand out.

First, the share of both quantity and quality adjustments has increased over time. From 2010 to 2014, about 3.5% of headline inflation was quantity-adjusted, compared with 6.1% since 2015. As suggested earlier, accounting for changes in the package size mainly affects food prices, and also, to a lesser extent, prices of services and industrial goods. Quality adjustment is somewhat less important (bearing in mind that we lack prices for some electronic products that are largely adjusted for quality changes), amounting to 2.8% and 4.4% for headline inflation mainly stemming from non-energy industrial goods and services. Second, we find that taking into account changes in quantity and quality has a very small impact on headline inflation. From 2010 to 2014, inflation was quantity-adjusted downwards by -.02 p.p. and quality-adjusted by -0.06 p.p. In the more recent sample since 2015, inflation has been increased by +0.06 p.p. due to a lower underlying quantity, but reduced by about the same amount due to quality improvements. However, these effects are more pronounced at the more disaggregated level. Food prices have been adjusted upwards by about +0.3 p.p. in both sub-samples due to quantity changes, while prices for non-energy industrial goods and services have been lowered by about -0.1 p.p. due to

Table 3: Impact of quantity and quality adjustment on German inflation

	% quan	% qual	π_t	π_t^{raw}	$(\pi_t^{quan} - \pi_t^{raw})$	$(\pi_t^{qual} - \pi_t^{raw})$
			2010-2014			
Total	3.5	2.8	1.75	2.20	-0.02	-0.06
Unprocessed food	14.0	0.9	2.54	0.49	0.36	-0.01
Processed food	11.0	1.6	2.68	1.56	-0.14	-0.01
Energy	0.1	0.5	3.83	3.69	0.00	0.01
NEIG	2.8	7.6	0.86	1.56	0.02	-0.16
Services	3.1	2.4	1.41	2.48	-0.03	-0.06
			2015-2020			
Total	6.1	4.4	1.07	1.35	0.06	-0.06
Unprocessed food	13.0	0.7	2.14	1.08	0.33	-0.01
Processed food	11.1	0.9	1.81	1.29	0.23	0.00
Energy	0.4	0.2	-1.22	-1.95	0.00	0.00
NEIG	2.6	5.1	0.80	1.39	0.04	-0.11
Services	6.6	4.7	1.54	2.23	0.00	-0.08

Note: The table shows the impact of quantity and quality adjustment on German inflation. The columns *% quan* and *% qual* give the fraction of price observations that have been adjusted for quantity and quality changes weighted by the corresponding COICOP weights. π_t lists the official inflation rate published by *Destatis*, and π_t^{raw} the inflation rate derived from the raw price as reported in the micro price data. $(\pi_t^{quan} - \pi_t^{raw})$ and $(\pi_t^{qual} - \pi_t^{raw})$ report the difference between adjusted and unadjusted micro price inflation.

quality improvements.

Overall, we find a negative, but quantitatively small impact of quality adjustment on the German inflation rate. Thus, without quality adjustment (and abstracting from quantity adjustment), the average inflation rate over the period 2010-2020 would have been only about +0.1 p.p. higher. This is well below other estimates of consumer price inflation, e.g. for Germany in the pre-euro period (Hoffmann, 1998: +0.5 p.p. during a moderate inflation regime) and more recently for Sweden (Statistics Sweden, 2019: +0.3 p.p.). However, as mentioned above, the underlying CPI micro database lacks some centrally collected prices of products that are typically subject to quality adjustment. Thus, our results can be seen as a *lower* bound on the impact of quality adjustment on German inflation. If we include scanner data (see next section) that primarily comprise goods that are subject to quality adjustment and that we lack in the German CPI micro data, we obtain an estimated impact of quality adjustment on price changes for these goods of 3.7 p.p. Adding this to the results from the CPI micro price data gives an estimate of 0.6 p.p. for overall inflation in Germany, which is quite close to Hoffmann (1998).[15]

[15] This estimate is obtained as a weighted average of 0.06*0.85 (share of goods for which we have CPI micro data) and 3.7*0.15 (scanner data and remaining missing items). We assume here that the effect of quality adjustment derived from scanner data also applies to industrial goods such as mobile phones, for which we have no data.

4 The impact of quality adjustment on euro area inflation

Measuring the impact of quality adjustment on consumer price inflation in the euro area is challenging because of the lack of detailed and harmonised micro price information. We try to tackle this problem in two ways. First, we build on the official COICOP-5 inflation series and select product categories whose prices are typically affected by quality changes. Based on the dispersion across member states' cumulative inflation rates, we derive a range for euro area headline and core inflation, which we interpret as an estimate of the impact of quality adjustment on the HICP (Section 4.1). Second, we illustrate the role of heterogeneous QA methods across euro area countries using scanner price data for 15 product categories (Section 4.2).

4.1 Estimating the impact of quality adjustment in euro area inflation based on typical quality-adjusted products

While there is extensive documentation on available methods and recommendations for quality adjustment of the euro area HICP,[16] little is known about the detailed QA coverage of and methods applied at the product level. For the purpose of our study, we have collected the relevant information from country-specific HICP monitoring reports published on the Eurostat website.[17] Accordingly, Table 4 lists product groups whose prices are typically adjusted for quality changes in euro area member states.

Overall, almost all member states adjust the prices of cars, clothing and footwear and electronic goods. In some cases, prices of food (France, Latvia, Lithuania, Germany) or package holidays (Estonia, Slovakia) are also quality-adjusted. Regarding the share of quality-adjusted products, three countries provide detailed figures. In its 2015 monitoring report, Germany reports an adjustment of 5-10% of its HICP, followed by Austria with 4.6% in 2016 and Slovenia with 0.4% in 2019. In addition to the heterogeneous selection of product groups, the QA methods applied vary considerably between countries. Whereas a detailed discussion of the pros and cons of these methods is beyond the scope of this paper and has its own strand of literature (see, for example, Groshen et al., 2017), it is important to note that NSIs also consider price adjustment for a change in package size as a QA method. Therefore, quality adjustment should not only

[16] See, for example, Eurostat (2024).

[17] Appendix D of our Bundesbank Discussion Paper reproduces all public information from Eurostat's HICP monitoring reports on QA practices in euro area member states (Menz et al., 2022).

Table 4: Quality-adjusted product groups in the HICP

Country	Products
Austria	Clothing and footwear, recreation and culture (books, DVDs, CDs), telecommunication, durable goods and cars.
Belgium	Cars, video games, CDs, DVDs, books, clothing and footwear.
Cyprus	Electronics, cars.
Estonia	Cars, mobile phones, clothing and footwear, restaurants and cafes, package holidays.
Finland	Cars.
France	Durable goods, clothes, cars, newspapers, books.
Germany	Clothing and footwear, technical products, books, CDs, downloads, computer games, software, cars, electronics, residential property.
Greece	No information available.
Ireland	Clothing and footwear, cars, electronics, CDs, DVDs.
Italy	Clothing and footwear, processed or fresh food, electronics, DVDs, fuels, cars.
Latvia	Cars, electronics, fruit, vegetables, clothing and footwear, books.
Lithuania	Food and beverages, clothing and footwear, furnishings, household equipment, cars, electronics, books.
Luxembourg	Cars.
Malta	Cars, laptops, mobile phones, cameras, clothing and footwear, books, recording media, computer games.
Netherlands	Clothing and footwear, tobacco, cars, electronics, boats.
Portugal	Cars, clothing and footwear, mobile phones.
Slovakia	Package holidays, cars, clothing and footwear, books, CDs, computer games.
Slovenia	Electronics, household appliances, cars, clothing and footwear, books, DVDs, computer games, medicaments, audio-video equipment, PCs.
Spain	Cars, food, medicines, personal care, fresh food, clothing and footwear, furniture, household appliances, restaurants.

Note: List of product groups whose prices are adjusted for quality changes by NSIs. Information is collected from the individual HICP Monitoring Reports (until 2022) published at Eurostat's website: link.

be relevant if an existing product is replaced by a new one, but should also apply to the same product if only its quantity (e.g. package size) has changed.

Based on the list of quality-adjusted products in Tables 1 and 4, we define two sets of products which we believe to be fairly homogeneous and therefore whose price trends should not differ too much across euro area countries. In a narrow sense, this set consists of telephones, radio and television sets, photographic equipment, information processing equipment and data storage media. In a broader sense, we add major household appliances, small electric household appliances, pharmaceutical products, therapeutic appliances, cars and bicycles and consumer durables. In addition, we define a third set of products using only those HICP components for which we also have scanner data available, which we analyse in the next section. This set includes products from both the narrow and the broad product samples.[18] In terms of the euro

[18]Table A.2 in the appendix gives details of the selected products.

area HICP, the narrowly defined set of products represents 1.5% of the total basket, the GfK scanner data product group 1.8% and the more broadly defined set 8.7%. Compared to the NSI practice, our choice may well misclassify some products in some countries. Nevertheless, Reinsdorf and Schreyer (2019) argue that digitalisation should also affect the prices of products in categories such as restaurants, accommodation and other services, which would require an even larger set of products whose prices are likely to depend on quality changes. In this respect, our choice will be rather cautious instead of overstating the effect of quality adjustment on inflation. In order to classify quality-adjusted products as accurately as possible, we refer to the lowest index level in the HICP, the so-called COICOP-5. This has the disadvantage that for most countries inflation series at this level of aggregation will only be available from 2015 onwards or even later. Nevertheless, we have repeated the analysis at the higher level of COICOP-4 and obtained broadly similar results.

We then calculate a range for the impact of quality adjustment on euro area inflation as follows:

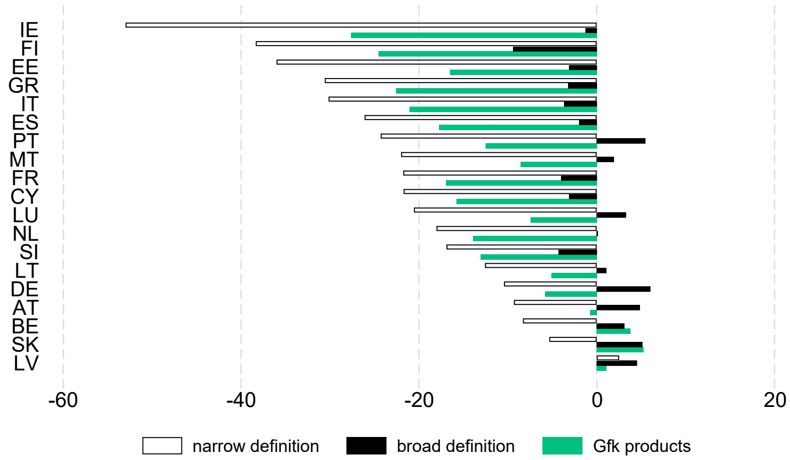
1. For all products according to the narrow or broad definition of quality adjustment, we calculate the minimum and maximum cumulative inflation rate across countries from January 2016 to September 2021, i.e. the rate of change between the first and last index period.

2. Next, we replace the countries' price indices for the selected products with the price index of the country with the lowest and highest cumulated inflation rate. Returning to the mobile phone example from Section 2, we find that Estonia has the lowest cumulated rate in our sample and Portugal the highest. We therefore replace the price index for mobile phones in all countries with the Estonian one when computing the lower range and with the Portuguese one when computing the upper range.

3. Using product and country weights, we aggregate the adjusted price series to obtain an upper and a lower bound for the quality-adjusted euro area headline and core inflation, which we interpret as an estimate of the impact of quality adjustment on the euro area HICP.

The resulting quality-adjusted inflation rates by country are shown in Figure 2. For the narrowly defined set of quality-adjusted products and the available GfK scanner data, the picture is broadly similar to that for mobile phones in Figure 1; cumulative rates of change are consistently negative across countries. In contrast, the pattern is quite different for the broad definition of products for which we observe as many negative as positive inflation rates.

Figure 2: Cumulated inflation rates of quality-adjusted products by country



Note: The figure shows the weighted average of the cumulated inflation rates of products affected by quality adjustment defined narrowly, broadly and by the available GfK scanner data from January 2016 until September 2021.

Of course, heterogeneous QA practices are not the only driver of inflation differentials across euro area countries. In a perfect world, their impact would be zero and homogeneous goods should only be priced differently according to the local individual preferences, market structure, local distribution costs and living conditions. Since the first two aspects are difficult to measure, we focus on the latter aiming to explain euro area price differentials caused by heterogeneous living standards and business cycle conditions across member states.[19] Following Crucini et al. (2005), we regress the monthly country- and product-specific inflation rates $\pi_{c,i,t}$ on national GDP per capita:

$$\pi_{c,i,t} = \alpha + \beta_{i,c} GDPC_{c,t} + \varepsilon_{c,i,t}, \tag{4}$$

[19]The related literature can be divided into studies that explain price differentials within the euro area using Phillips curve-type regressions (Honohan and Lane, 2003, Angeloni and Ehrmann, 2007, Lagoa, 2017) and in papers analysing deviations from the law-of-one-price using micro price data (Crucini et al., 2005, Lipsey and Swedenborg, 2010, Fischer, 2012, Crucini and Yilmazkuday, 2014). For an earlier overview of the topic, see Deutsche Bundesbank (2009). Our approach is inspired by these studies, although it is not our aim to fully explain price differentials by testing and adding different explanatory variables. Instead, we try to estimate the (unobservable) impact of the different QA procedures conditional on income differentials across euro area countries.

where $GDPC_{c,t}$ is the year-on-year growth rate of national GDP per capita (linearly interpolated from quarterly to monthly figures), c represents a euro area country and i a quality-adjusted product according to the narrow or broad definition. In this regression, we allow for the possibility that income growth affects the prices of each product group differently in each country. Note that we do not include country- and time-fixed effects as these would essentially remove the unobserved impact of country-specific QA practices. We interpret the residuals of this regression as the annual inflation rates net of income differentials.[20] To rule out that our estimates are affected by the Covid-19 pandemic, we split the estimation sample into a pre-Covid period from 2016:01 to 2020:02 and a Covid period from 2020:03 to 2021:09. The resulting estimates for the impact of quality adjustment on the euro area HICP are summarised in Table 2.

Over the period 2017 to 2020, we observe an average increase of 1.5% for headline inflation and 1.0% for core inflation using the aggregate series as published by Eurostat. Note that aggregating these rates ourselves by combining the available disaggregate inflation series at the COICOP-5 level results in some rounding differences (row "Own aggregation"). This is due to the fact that HICP sub-indices are published with only one decimal point or, in a very few cases, are not published for confidentiality reasons.[21]

Regarding the potential impact of heterogeneous QA practices, the second and third rows of Table 5 give the upper and lower bounds of the inflation rates adjusting the price index of the narrowly defined quality-adjusted products. Similarly, the fourth and fifth rows give the limits of the products defined more broadly. Computing the difference between these bounds gives us a range, which we interpret as an estimate of the impact of quality adjustment on euro area inflation. According to our approximation, for the period 2017:01-2020:02, this estimate varies between $\pm$ 0.2 and 0.6 p.p. for headline inflation and between $\pm$ 0.3 and 0.8 p.p. for core inflation. Controlling for the impact of income differentials between countries, the impact of quality adjustment is reduced by up to $\pm$ 0.2 p.p. for headline inflation and $\pm$ 0.1 to 0.3 p.p. for core inflation.

For the Covid period, the results shown in the bottom panel of Table 2 give a fairly similar estimate of the impact of heterogeneous QA methods on inflation without controlling for income

[20] Alternatively, we could have included country-specific income effects and fixed effects by interpreting the contribution of the latter as the impact of quality adjustment net of income effects.

[21] As the HICP is a chain-linked price index, simply averaging the sub-indices would be incorrect. Hence, we first unchain the sub-indices, compute the weighted average and rechain them again (see Eurostat, 2024).

differentials. However, taking income changes into account does not actually lower this estimate, suggesting that our simple regression approach is not able to adequately capture all the different economic and statistical effects of the pandemic, such as lockdown measures and imputed prices.

Finally, it is important to note that our regression results may themselves be biased by the impact of quality adjustment in different member states. If the relationship between income growth and "true" inflation is indeed positive, but if the QA practice introduces a bias, the observed correlation will be lowered or estimated with the wrong sign. With this in mind, plotting our estimate over time in Figures A.4 and A.5 in the appendix suggests that for the pre-Covid period, without controlling for income differentials, the impact of quality adjustment on inflation tends to be negative. This implies that inflation would have been lower if QA practices had been more harmonised across countries. However, controlling for income differentials yields a small positive impact of quality adjustment. These conflicting results point to the limitations of this simple approximation of the impact of quality adjustment. Overall, the unadjusted estimates provide an upper bound on the potential impact of heterogeneous QA methods on inflation differentials across euro area member states. Controlling for income differences should come closer to the true impact, but we cannot rule out that inflation differentials are caused by additional statistical factors.[22] A more precise estimate can only be obtained by applying a harmonised quality adjustment to a harmonised dataset, which we will do in the next section.

[22] Differences in the measurement of inflation across euro area NSIs may arise from differences in the sampling of products, the definition of elementary products, the treatment of sales, the use of auxiliary data sources such as scanner or web-scraped data, and the index formula used for aggregation.

Table 5: The impact of quality adjustment on the euro area HICP, 2017-2021

2017:01-2020:02

	unadjusted		net of income changes	
Inflation:	Headline	Core	Headline	Core
Official rates	1.49	1.03		
Own aggregation	1.46	0.96		
Narrowly defined products:				
Minimum rate	1.32	0.77	1.45	0.96
Maximum rate	1.55	1.09	1.54	1.08
Broadly defined products:				
Minimum rate	1.11	0.47	1.40	0.89
Maximum rate	1.68	1.28	1.62	1.19
Gfk products:				
Minimum rate	1.34	0.79	1.47	0.98
Maximum rate	1.55	1.08	1.53	1.06
Range (Max. - min. rate):				
Narrow definition	0.23	0.32	0.09	0.12
Broad definition	0.57	0.81	0.22	0.30
Gfk products	0.21	0.29	0.06	0.08

2020:03-2021:09

	unadjusted		net of income changes	
Inflation:	Headline	Core	Headline	Core
Official rates	0.93	0.86		
Own aggregation	0.91	0.81		
Narrowly defined products:				
Minimum rate	0.81	0.67	0.84	0.71
Maximum rate	1.02	0.97	1.01	0.95
Broadly defined products:				
Minimum rate	0.59	0.36	0.68	0.49
Maximum rate	1.23	1.27	1.18	1.20
Gfk products:				
Minimum rate	0.81	0.67	0.84	0.71
Maximum rate	1.03	0.98	1.00	0.94
Range (Max. - min. rate):				
Narrow definition	0.21	0.30	0.17	0.24
Broad definition	0.64	0.91	0.50	0.71
Gfk products	0.22	0.31	0.16	0.23

Note: *Official rates* refers to the average euro area HICP published by Eurostat, *own aggregation* gives the average euro area inflation rates aggregated from disaggregate national inflation rates. The *minimum rates* and *maximum rates* denote the lowest and highest inflation rates of adjusting products affected by quality adjustment narrowly and broadly. *Range* gives the difference between the maximum and minimum rates.

4.2 Estimating the impact of quality adjustment on euro area inflation using scanner data

4.2.1 Deriving scanner data-based price indices following a harmonised QA approach

Scanner data provide a straightforward basis for assessing price developments, since they reflect actual purchases by consumers. We use micro-level transaction data from the GfK's Point-of-Sales (POS) retailer panel.[23] Our sample covers semi-durable and durable products, primarily in the consumer and home electronics sectors, from January 2017 to May 2021. An overview of the available product categories and the COICOP 5-digit categories to which they are mapped is provided in Table 6.[24]

For each retailer, sales are reported for a given product and month. Information is available at a granular product level, i.e. products are defined by a product ID that is unique across countries. In order to obtain a consistent period and product sample across countries, we restrict our analysis to the five largest euro area economies (Germany, France, Italy, Spain, and the Netherlands).

From the scanner data, we derive price indices as follows. First, we compute the average price $p_{i,t}$ of a given product i in a given month t defined as:

$$p_{i,t} = \frac{total\_sales_{i,t}}{total\_units_{i,t}}, \tag{5}$$

where $total\_sales_{i,t}$ is the total expenditure (in euros) on a given product in month t and $total\_units_{i,t}$ denotes the number of units of product i purchased in month t. In this way, we obtain a sample of unit value observations for each product and month. In each period, we drop outliers below and above the 1st and 99th percentiles of the price distribution within a given product category.

Second, we run weighted Time-Product Dummy (TPD) regressions at the product category level. This method, proposed by Diewert (2005), is widely used in official price statistics to

[23] A more detailed description of the GfK's POS dataset can be found in Beck and Jaravel (2021).

[24] Data for smartphones are only available until December 2020 and data for headphones are missing in the Netherlands in April and May 2021. We fill these data gaps by using the latest available observations. Simply omitting the data would not change the results.

Table 6: Matching HICP COICOP-5 subcomponents and GfK product categories

COICOP-5	COICOP-5 Name	GfK Product Categories
05311	Refrigerators, freezers and fridge-freezers	Cooling/refrigerators, freezers
05312	Washing machines, dishwashers or the like	Dishwashers, tumble dryers, washing machines
05313	Cookers	Cooking, microwave
05314	Room heaters and air conditioners	Air conditioner, air treatment
05315	Vacuum cleaners and other cleaning equipment	Vacuum cleaners
05321	Food processing appliances	Foodprep
05322	Coffee machines, tea makers and similar appliances	Hot beverage makers
05323	Irons	Irons
05324	Toasters and grills	Toasters
08202	Mobile phone without contract	Phablets, smartphones
09111	Equipment for the reception, recording and reproduction of sound	(Audio home systems), loudspeakers, mini/bluetooth speakers, flat screen
09119	Other equipment for the reception, recording and reproduction of sound	Corewear, headphones, headsets
09121	Cameras	Camcorder, digicam
09131	Personal computers	Desktop PC, media tables, mobile PC
09132	Accessories for information processing equipment	Keying devices, (mfd printer), monitors, (printers)

Note: GfK product categories are available from January 2017 to May 2021. Product categories in brackets are dropped because the available sample period is too short. If more than one product group is assigned to a given COICOP-5 component, the series are aggregated with an unweighted average.

construct price indices from scanner or web-scraped data (de Haan et al., 2021; Eurostat, 2022). It is one of the so-called "multilateral" price index methods that avoid the occurrence of chain drift[25], and it provides an efficient approach to implementing a harmonised quality adjustment across countries. Specifically, for each month $t = 0, \dots, T$ and product $i = 1, \dots, N$, we fit the following equation:

$$\ln p_{i,t} = \beta^0 + \sum_{\tau=1}^{T} \delta^\tau d_{i,t}^\tau + \sum_{j=1}^{N-1} \gamma^j D_i^j + \varepsilon_{i,t}, \tag{6}$$

where $D_{i,t}^j$ represents a product dummy that takes the value 1 if $i = j$ (as identified by its unique product ID) and 0 otherwise, and $d_{i,t}^\tau$ denotes a time dummy that takes the value 1 if $t = \tau$ and 0 otherwise. Weights are given by the total expenditure, $total\_sales_{i,t}$, for a given product. As in official price statistics, this increases the price effect of bestsellers compared to less frequently

[25] See Eurostat (2022) and Diewert and Fox (2022). An alternative solution to the problem of chain drift is to compute and chain monthly year-on-year price changes (see, for example, Bajari et al., 2023). However, since we focus on the euro area, we follow the TPD approach recommended by Eurostat (2022).

purchased products.

Finally, for each month $t = 0, ..., T$, we estimate a price index from the exponential of the coefficient on the respective time dummy, such that:

$$I_{TPD}^{0,t} = 100 \times \exp\left(\hat{\delta^t}\right). \tag{7}$$

To mimic the real-time compilation of scanner data-based price indices, we follow Ivancic et al. (2011) and estimate Equation (6) on the basis of a rolling window of 13 months, covering at least one full year of scanner data. For example, the first estimation window will cover periods 1 to 13 (providing a price index of equal length), the second estimation window will cover periods 2 to 14, and so on. The linking of this sequence of 13-period price indices is done in the sense of a mean splice. By linking subsequent index values to the existing one, a non-revisable price index is obtained:

$$I_{TPD}^{0,t} = \prod_{k=t-\lambda}^{t-1} \left(I_{TPD}^{0,k} \times I_{[t-w+1,t]}^{k,t}\right)^{\frac{1}{\lambda}}, \tag{8}$$

where w is the window size (13 months) and λ is an overlapping linking period, which we set to 13 months. This rolling window approach has the advantage that it also captures changes in consumer preferences for products over time. In addition, to rule out the possibility that compositional effects are driving our results, we use a quantity-weighted, but not quality-adjusted, price index method instead of the TPD method. Specifically, we compute a monthly *unit value price index* for each product category under consideration. For this, we calculate the ratio of total sales to total units purchased in the respective product category.

4.2.2 Comparison with official price indices

Figure 3 plots our resulting scanner data-based price indices against the official HICP price indices for a selection of product categories (mobile phones, PCs, and washing machines/dishwashers).[26] Obviously, price trends as measured by the HICP (first column of Figure 3) are heterogenous across countries. For mobile phones, the official price indices show a downward trend in all coun-

[26] Appendix A.3 plots the corresponding figures for all product categories in our sample; they show similar patterns across all categories.

tries, but the extent of the decline varies. For PCs, prices show a broad-based downward trend until 2020, after which prices increase in Italy while they continue to fall in the other countries. At the end of the sample period, prices also show an upward trend for Germany. The results for washing machines and dishwashers also suggest clear differences in price dynamics between countries: While we observe an upward price trend in the Netherlands, the price dynamics for the other countries tend to be flat or downward.

In contrast, our scanner data-based price indices, derived from a harmonised TPD approach to adjust for quality changes (second column of Figure 3), show a fairly symmetrical pattern: in general, quality-adjusted product prices are falling, and at a similar rate across countries. Finally, for most categories, non-quality-adjusted prices (right column of Figure 3) are increasing rather than decreasing as expected, in some cases significantly so. While the non-adjusted price indices for product categories tend to move together across countries, there are outliers for individual countries in some product categories. Also, the dispersion is generally much greater than the one observed for the TPD price indices.

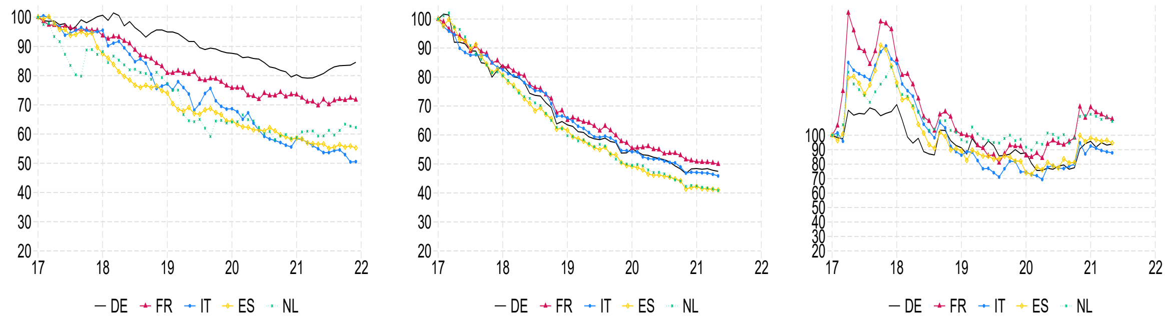
Based on our scanner data-based price indices, what are the implications for cross-country price dispersion? For this purpose, we take the minimum and the maximum inflation rates for each COICOP group and compute a (Big-5) euro area aggregate using country weights. The resulting ranges are shown in Figure 4. The inflation differences are larger than 10 p.p. for the official country-specific inflation rates, while they are typically at around 4 p.p. for the TPD price indices. Multiplied by the corresponding HICP weights, this gives a range of 0.1 p.p. in terms of headline inflation caused by non-harmonised quality adjustment methods. Assuming that the reduction in inflation differences also applies to product categories that are in the broad set of products likely to be affected by quality changes but for which we do not have scanner data, the effect on headline inflation increases to 0.5 p.p. Our results therefore suggest that a large part of the inflation differences between the Big-5 countries and product groups for which we have data is caused by the use of non-harmonised quality adjustment methods by NSIs.

Turning to the implications for aggregate inflation, Figure 5 shows the resulting price dynamics by country, when aggregating either the official or the scanner data-based price indices for the 15 products in our sample. The panels show striking differences in the calculated figures. Throughout the sample period and for all countries, the official inflation numbers are in most cases much higher than those based on scanner data. This suggests that official price indices

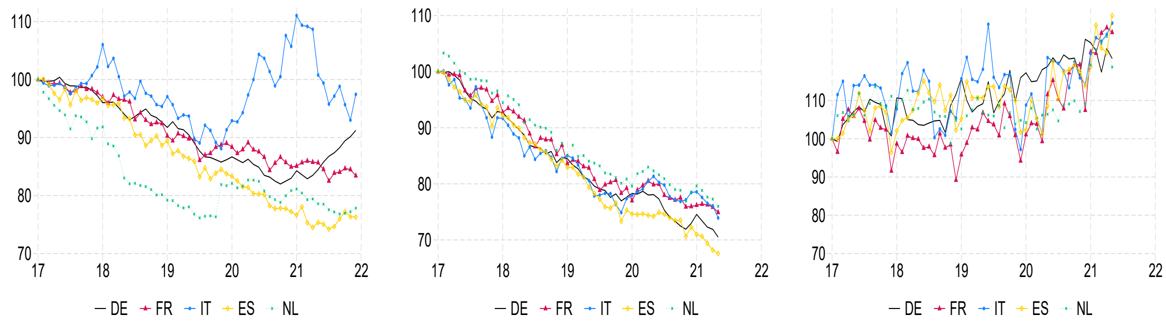
Figure 3: Official HICP vs. scanner data-based price indices for selected product categories

HICP | TPD - harmonised QA | Unit values - no QA

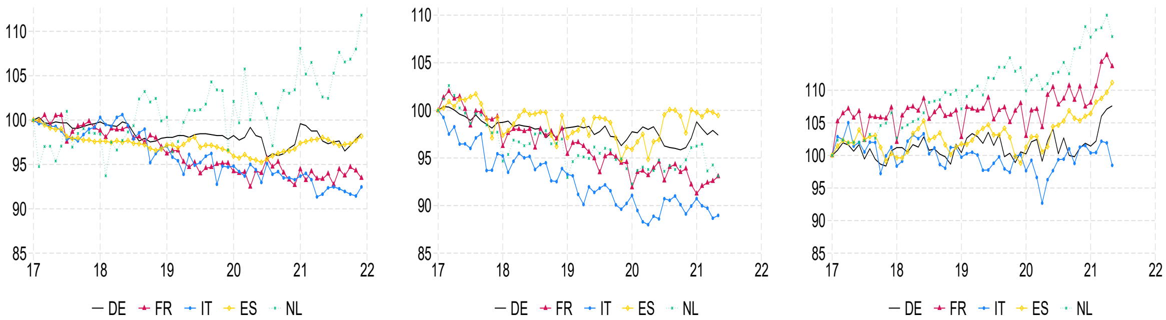
ECOICOP 08202: Mobile phone without contract



ECOICOP 09131: PCs

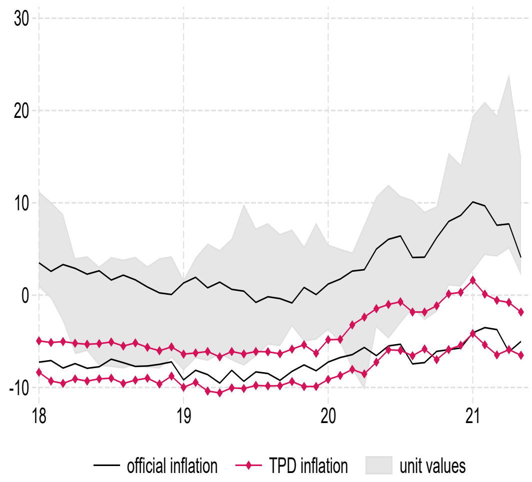


ECOICOP 05312: Washing machines, dishwashers or the like



Note: The figure shows price indices for three COICOP 5-digit components (mobile phones, personal computers, and washing machines/dishwashers) for the period 2017:01-2021:05. The figures in the left column are the official HICP indices and the figures in the second column are scanner data-based price indices applying a harmonised quality adjustment procedure (TPD method) across countries. The right-hand column shows unadjusted turnover-weighted unit values based on scanner data. All series are normalised to January 2017=100. Missing Gfk data for smartphones in 2021 are replaced by the last available observations from December 2020.

Figure 4: Cross-country dispersion of official and scanner data-based price indices

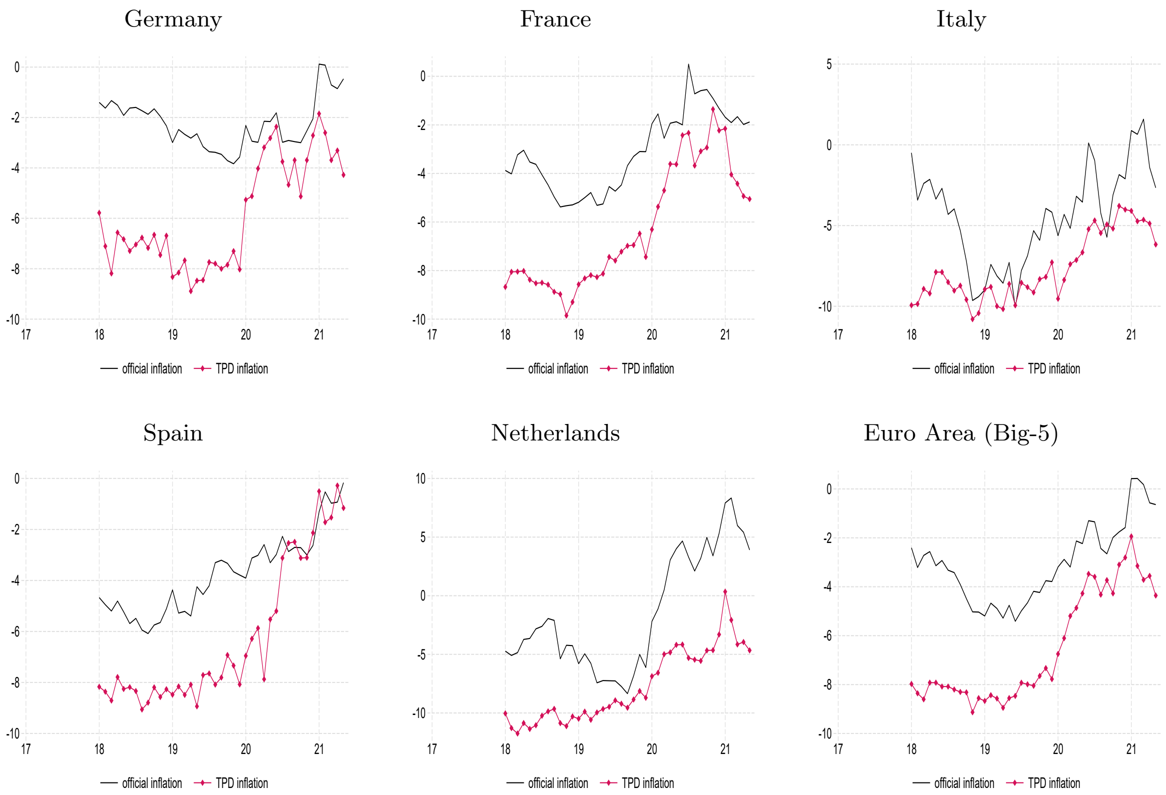


Note: The black solid lines show the maximum and minimum official HICP inflation rates for the Big-5 euro area countries, the red dotted lines show the corresponding ranges of the quality-adjusted scanner data-based inflation rates, and the grey shaded area shows the ranges using only sales-weighted unit values. Euro area rates are calculated as averages using country weights. Period: 2018:01-2021:05.

significantly overestimate actual inflation, at least for the products under consideration. On average, the absolute inflation differences range from 2.6 p.p. for Spain to 6.2 p.p. for the Netherlands. For the euro area, the average difference is 3.5 p.p. If this difference is multiplied with the HICP weight of those product groups that are typically adjusted for quality changes, the approximate bias for euro area headline inflation is +0.1 p.p. using the narrow set of products and +0.3 p.p. using the broad set of products. Note that this estimate represents a lower bound, as statistical institutes are likely to adjust a larger share of the consumption basket for quality changes. If we assume that the estimated difference of 3.5 p.p. applies to about 27% of the HICP, as reported by Statistics Sweden, we arrive at an estimated bias of 0.9 p.p. for euro area inflation.

Finally, it is important to note that our results do not depend on the time period and the method of quality adjustment we use. For a sub-sample of our data, i.e. for washing machines, we estimate hedonic regressions that adjust for changes in product quality using product characteristics. Figure 6 plots the quality-adjusted price indices using the TPD approach and compares them with the price indices obtained from a hedonic regression and with the corresponding HICP component "washing machines". The resulting quality-adjusted price indices derived from scanner data are very similar whether TPD or hedonic regressions are used.[27] In contrast, the official HICP indices vary considerably across countries.[28]

Figure 5: Comparison of official and scanner data-based inflation rates

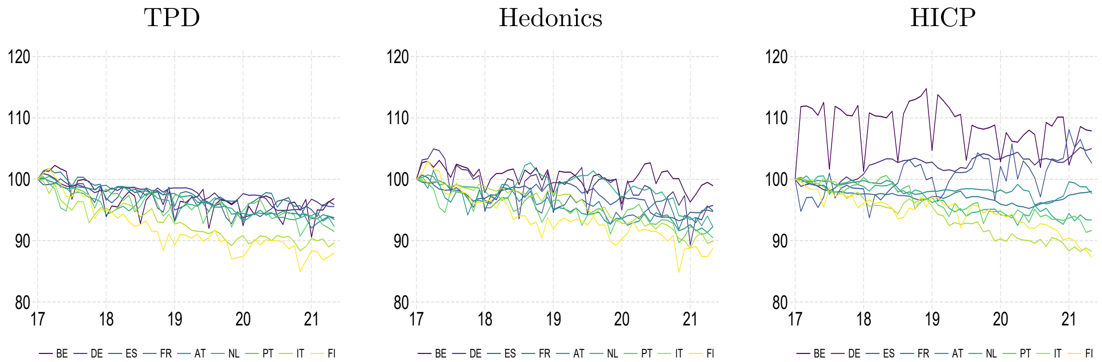


Note: The figures compare implied inflation rates obtained from aggregating the price indices of the 15 product groups in our scanner data sample (see Table 6). Period: 2018:01-2021:05.

[27] One of the important caveats of the hedonic regression approach is its dependence on the choice of variables and the modelling strategy. Nevertheless, we obtain very similar results for different versions of the hedonic regressions. Appendix A.4 provides more details on our case study for washing machines.

[28] An alternative approach to computing quality-adjusted prices is provided by Pakes (2003) and Erickson and Pakes (2011), who run hedonic regressions and estimate price relatives directly. These authors find that the resulting quality-adjusted price indices are generally significantly negative, while official numbers are not. Furthermore, they show that the results of quality adjustment are generally not affected by the inclusion or exclusion of a particular variable. For the sake of simplicity, we focus on the TPD approach recommended by Eurostat (2022), which provides a straightforward way to perform a harmonised (indirect) quality adjustment of prices across countries.

Figure 6: Quality-adjusted price indices for washing machines using TPD and Hedonics



Note: The figure shows the quality-adjusted price indices (weighted by turnover) derived from TPD and hedonic regressions and the HICP series "05.3.1.2 Washing machines, dryers and dishwashers" for the years 2017-2021, indexed to January 2017=100. The hedonic regression refers to time-dummy hedonics using the baseline specification + `energy` + `smart` + `noise` + `spin`.

5 Conclusion

In this paper, we have tried to shed some light on the impact of quality adjustment on consumer price inflation in Germany and the euro area. Based on micro and macro price data, we have documented several stylised facts.

First, for Germany, we find that quality adjustment applies to a wide range of goods and services but on average price adjustments due to quality changes reduce headline inflation by only 0.06 p.p., which is offset by an increase due to quantity adjustments (e.g. smaller package size) of the same amount. This small effect may seem surprising, but it should be borne in mind that we lack data for a number of products that are typically adjusted for quality changes. Therefore, this estimate should be considered as a lower bound.

Second, we have provided an approximation of the range of euro area inflation that could be caused by heterogeneous QA practices across member countries. According to our estimates using official HICP data, the range of headline inflation could be overestimated by $\pm$ 0.2 p.p. and core inflation by $\pm$ 0.6 p.p., taking into account income differences across countries. Applying a harmonised quality adjustment to a scanner dataset of 15 product categories leads to very similar results. The range of cross-country inflation rates for the available product categories is reduced from around 10 p.p. to around 4 p.p. Multiplied by the corresponding HICP weight of 1.5%, this gives a range of 0.1 p.p. in terms of headline inflation caused by non-harmonised quality adjustment methods. Assuming that the reduction in inflation differences also applies to product categories that are likely to be affected by quality changes but for which we do not have scanner data, the effect on headline inflation increases to 0.5 p.p.

Third, the use of non-harmonised QA methods or the lack of quality adjustment of some product groups in some countries also leads to a bias in the euro area inflation rate. For the period 2017-2021, we find that the quality-adjusted inflation rate based on scanner data is on average around 3.5 p.p. lower than the official inflation rate for the same set of products. Multiplied by the corresponding HICP weight, this implies a measurement bias of +0.3 p.p. for headline inflation, if a similar bias is assumed for typical quality-adjusted products.

Turning to the implications for policymakers, we find that heterogeneous QA procedures across euro area member states are a source of non-negligible measurement bias affecting euro area inflation. Our estimate of the impact of heterogeneous QA procedures on euro area inflation is similar in magnitude to the measurement bias in the HICP due to substitution effect or the absence of owner-occupied housing (ECB, 2021). As this bias is not constant over time, it poses a double problem for policymakers: not only does it lead to an overestimation of euro area inflation, but it also contributes to larger inflation differentials between countries. This creates difficulties in terms of communication, but also in terms of measuring the stance of monetary policy.

Overall, our findings would support the call for further harmonisation of QA methods across member states. In addition, more efforts should be made to quantify both the magnitude and the direction of the impact of quality adjustment on euro area inflation with greater precision, as is regularly done, for example, by Statistics Sweden (2019).

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Appendix

A.1 The impact of quality adjustment on the German CPI

Description of German CPI micro data

The German CPI micro dataset contains more than 77 million observations for the period 2010:01-2020:12. The database is provided by the Research Data Centres (RDC) of the Federal Statistical Office and the statistical offices of the Federal States and is available for research purposes.[29] Most prices are collected decentrally by the federal states. For individual price information, the database contains flag indicators on sales, replacements and imputation of the individual price (e.g. carry forward in case of a missing price) as well as information on quality and quantity adjustments. The lowest level of product category with weight information is the so-called COICOP-10 level (e.g. "01.1.1.1.01100 - Rice"); after excluding imputed prices and aggregated price measures, our underlying dataset contains 716 product categories at the COICOP-10 level. The product ID in the dataset is based on a combination of five variables (region, store ID, COICOP-10 number, survey ID and product variant). Due to the regular revision of the survey ID with each new CPI base year, the dataset contains a statistical break in 2015:01; therefore, all statistics are calculated separately for each sub-sample (base year 2010: 2010:01-2014:12 and base year 2015: 2015:01-2020:12).

Inflation measures derived from micro price data

Table A.1: Official CPI inflation vs. micro price inflation

HICP component	π_t^{adj}	π_t^{raw}	π_t^{quan}	π_t^{qual}
Total	0.84	0.84	0.83	0.84
Unprocessed food	0.84	0.81	0.83	0.81
Processed food	0.64	0.63	0.56	0.62
Energy	0.99	0.99	0.99	0.99
NEIG	0.28	0.35	0.29	0.36
Services	0.22	0.18	0.18	0.18

Note: The table shows the correlation coefficients between the official inflation rates as reported by the German Federal Statistical Office and the four different rates calculated from the micro price dataset from 2015:01 to 2020:12. π_t^{adj}: micro price inflation adjusted for quality and quantity changes; π_t^{raw}: micro price inflation without any adjustments; π_t^{quan}: micro price inflation adjusted for quantity changes; π_t^{qual}: micro price inflation adjusted for quality changes. NEIG: non-energy industrial goods.

[29] See "Verbraucherpreisindex für Deutschland", EVAS 61111, 2010 - 2020, DOI: https://doi.org/10.21242/61111.2010.00.00.3.1.0 to https://doi.org/10.21242/61111.2020.00.00.3.1.0.

Figure A.1: Official inflation rates and micro price inflation in Germany

Note: The figure shows year-on-year inflation rates for Germany for both headline inflation and five sub-components. π_t^{adj}: micro price inflation adjusted for quality and quantity changes (based on "adjusted price" variable); π_t^{raw}: micro price inflation without any adjustments (based on "raw price" variable); π_t^{HICP}: official CPI inflation.

Figure A.2: Unadjusted and quality-adjusted micro price inflation in Germany

Note: The figure shows year-on-year inflation rates for Germany for both headline inflation and five sub-components. The black solid line shows the inflation rates derived from the quality-adjusted prices and the red line plots the inflation rate derived from unadjusted prices.

Figure A.3: Unadjusted and quantity-adjusted micro price inflation in Germany

Note: The figure shows year-on-year rates for Germany for both headline inflation and five sub-components. The black solid line shows the inflation rates derived from the quantity-adjusted prices and the red line plots the inflation rate derived from unadjusted prices.

A.2 Estimating the impact of quality adjustment in euro area inflation based on typical quality-adjusted products

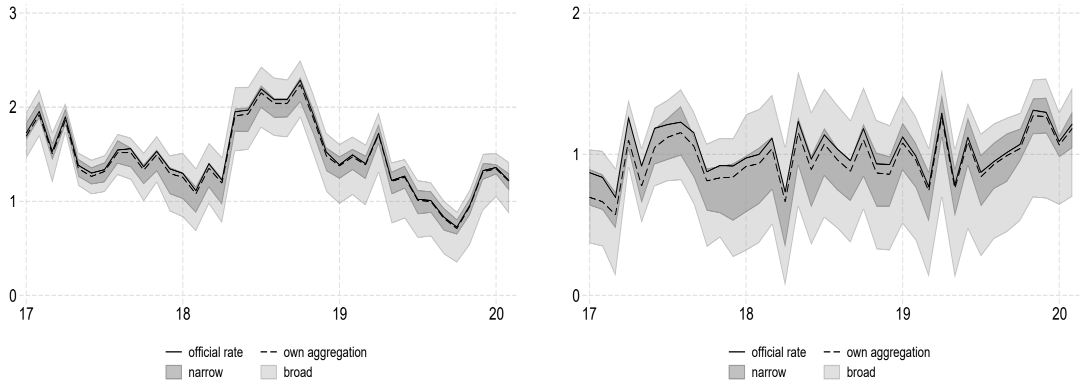
Table A.2: Defining a list of typical quality-adjusted products

COICOP-5		EA Weight in ‰	DEFINITION NARROW	BROAD	GFK
08201	Landline telephones	0.2	1	1	0
08202	Mobile phone without contract	3.48	1	1	1
09111	Equip. for the reception, recording & reproduction of sound	0.59	1	1	1
09112	Equip. for the reception, recording & reproduction of sound & vision	2.71	1	1	0
09113	Portable TV sets, sound & vision devices	0.07	1	1	0
09119	Other equip. for the reception, recording & reproduction of sound & picture	0.35	1	1	1
09121	Cameras	0.64	1	1	1
09122	Accessories and parts for photographic & cinematographic equip.	0.09	1	1	0
09123	Optical equipment	0.04	1	1	0
09131	Personal computers	3.45	1	1	1
09132	Accessories for information processing equip.	0.76	1	1	1
09133	Software	0.38	1	1	0
09141	Pre-recorded recording media	1.24	1	1	0
09142	Unrecorded recording media	0.02	1	1	0
09149	Other recording media	0.48	1	1	0
05311	Refrigerators, freezers & fridge-freezers	1.49	0	1	1
05312	Washing machines, dishwashers or the like	2.22	0	1	1
05313	Cookers	1.06	0	1	1
05314	Room heaters and air conditioners	1.11	0	1	1
05315	Vacuum cleaners & other cleaning equip.	0.64	0	1	1
05319	Other major household appliances nec	0.03	0	1	0
05321	Food processing appliances	0.81	0	1	1
05322	Coffee machines, tea makers & similar appl.	0.58	0	1	1
05323	Irons	0.29	0	1	1
05324	Toasters and grills	0.11	0	1	1
05329	Other small electric household appliances	0.36	0	1	0
06110	Pharmaceutical products	11.5	0	1	0
06121	Pregnancy tests, condoms or the like	0.34	0	1	0
06129	Other medical products nec	0.66	0	1	0
06131	Glasses and contact lenses	4.78	0	1	0
06132	Hearing aids	0.87	0	1	0
06139	Other therapeutic appliances & equip.	1.33	0	1	0
07111	New passenger cars	27.41	0	1	0
07112	Used passenger cars	10.57	0	1	0
07120	Motorcycles	1.99	0	1	0
07130	Bicycles	1.09	0	1	0
09211	Campers, caravans or other trailers	1.52	0	1	0
09213	Boats, outboard motors & equip. for boats	0.77	0	1	0
09221	Musical instruments	0.53	0	1	0
Total	**NARROW**	**14.50**	**15**	**0**	**0**
Total	**BROAD**	**86.56**	**0**	**39**	**0**
Total	**GFK**	**17.58**	**0**	**0**	**15**

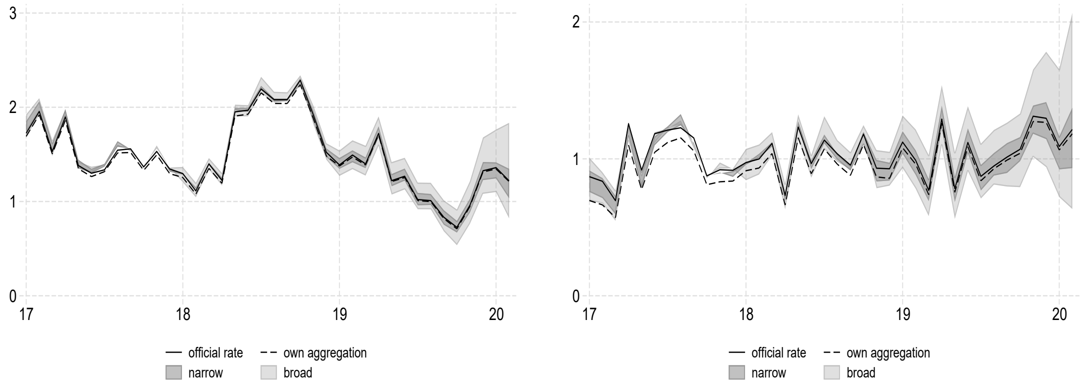
Figure A.4: The impact of quality adjustment over time: pre-Covid

HICP | HICP excluding energy & food

Without income adjustment



With income adjustment

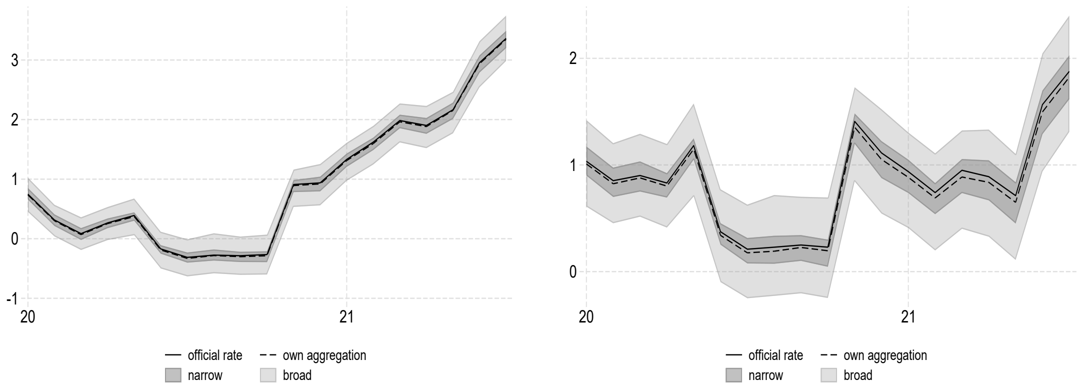


Note: The figure shows the annual rate of euro area headline and core inflation as published by Eurostat ("official rate"), and aggregated from the disaggregate COICOP-5 series ("own aggregation"). "Narrow" and "broad" denote the inflation rates using the lowest and highest inflation rates by country and product group assumed to be affected by quality changes.

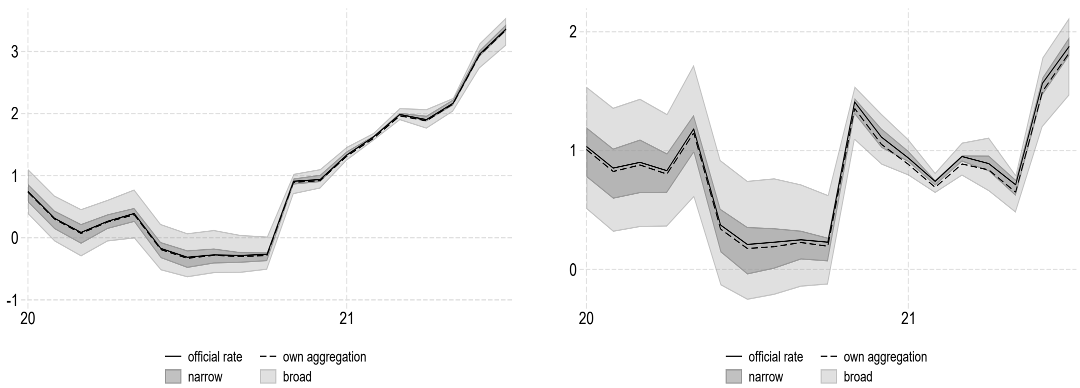
Figure A.5: The impact of quality adjustment over time: Covid period

HICP | HICP excluding energy & food

Without income adjustment



With income adjustment



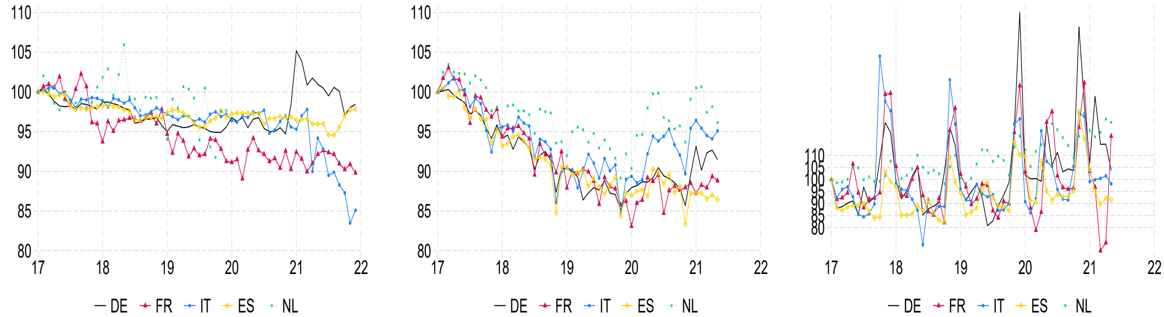
Note: The figure shows the annual rate of euro area headline and core inflation as published by Eurostat ("official rate"), and aggregated from the disaggregate COICOP-5 series ("own aggregation"). "Narrow" and "broad" denote the inflation rates using the lowest and highest inflation rates by country and product group assumed to be affected by quality changes.

A.3 HICP vs. scanner data-based price indices

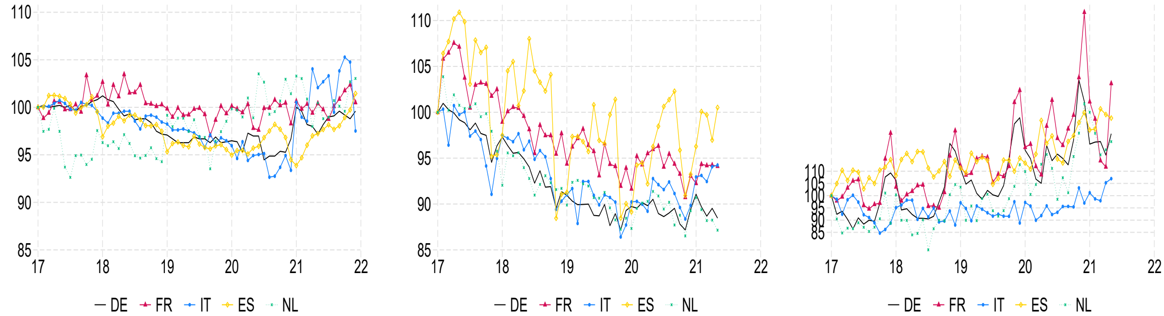
Figure A.6: HICP vs. scanner data-based price indices (I)

HICP | TPD - harmonised QA | Unit values - no QA

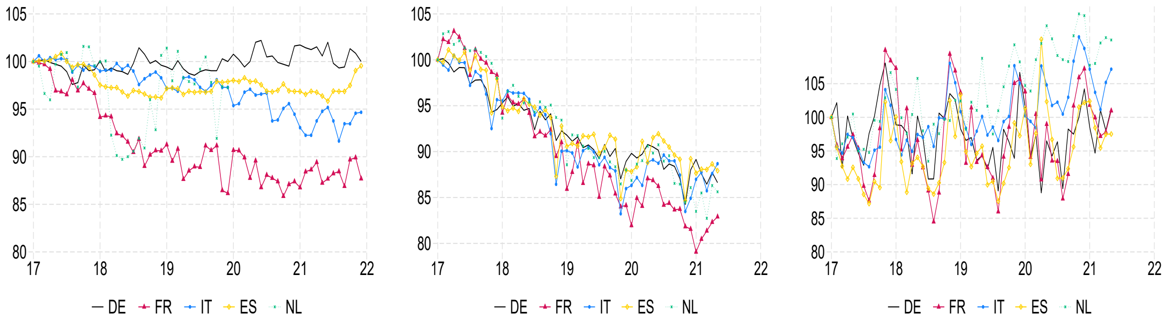
ECOICOP 05321: Food processing appliances



ECOICOP 05322: Coffee machines, tea makers and similar appliances



ECOICOP 05323: Irons

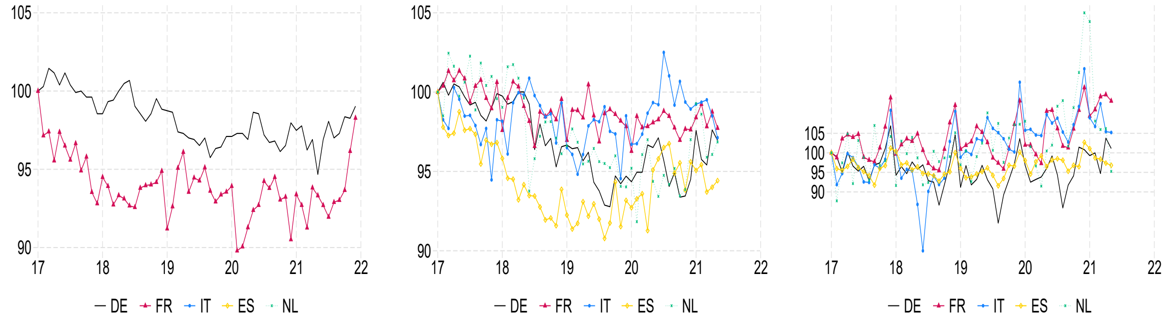


Note: The figures in the left column are the official HICP indices and the figures in the second column are scanner data-based price indices applying a harmonised quality adjustment procedure (Time-Product Dummy (TPD) method) across countries. The right-hand column shows unadjusted turnover-weighted unit values based on scanner data. All series are normalised so that January 2017=100.

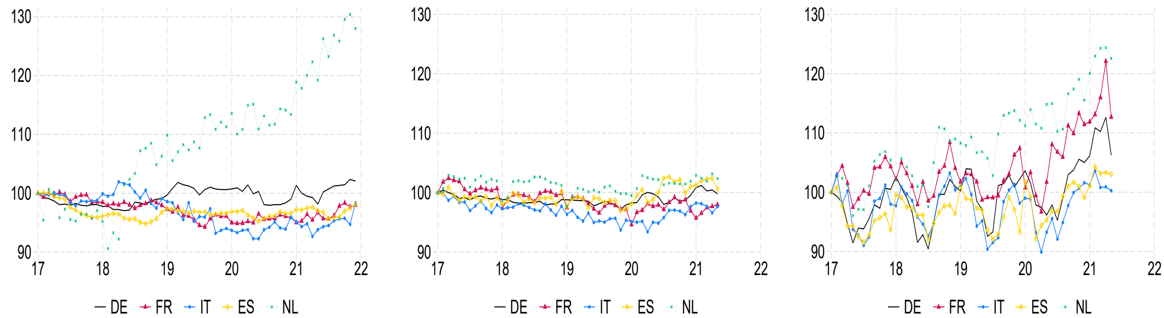
Figure A.7: HICP vs. scanner data-based price indices (II)

HICP | TPD - harmonised QA | Unit values - no QA

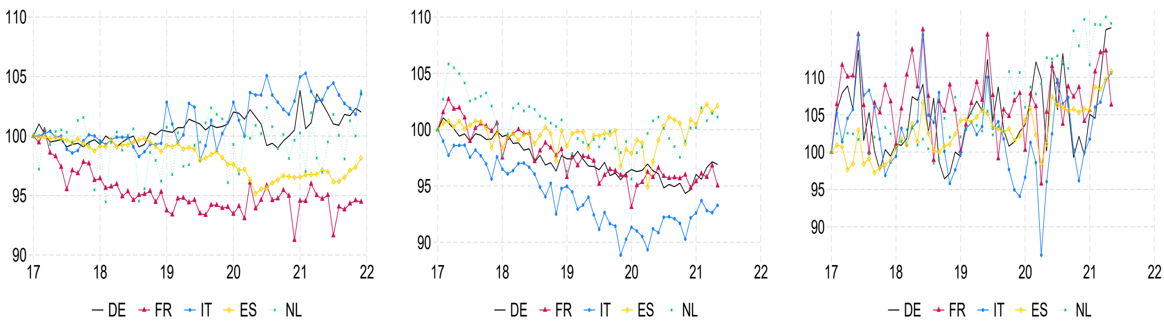
ECOICOP 05324: Toasters and grills



ECOICOP 05311: Refrigerators, freezers and fridge-freezers



ECOICOP 05313: Cookers

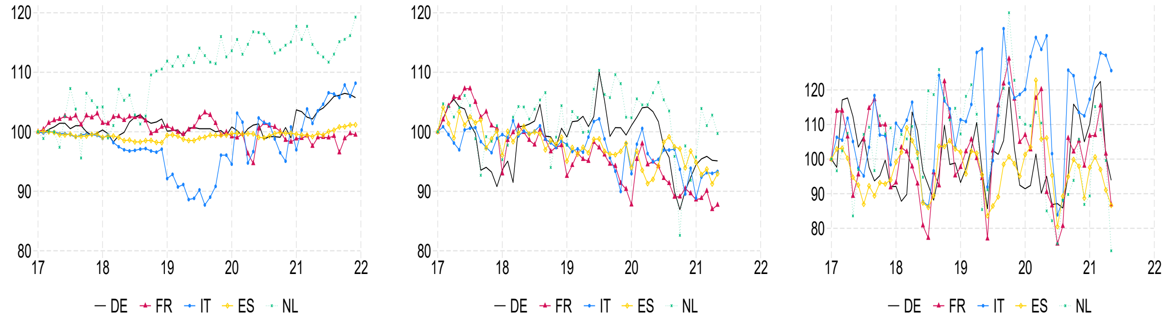


Note: The figures in the left column are the official HICP indices and the figures in the second column are scanner data-based price indices applying a harmonised quality adjustment procedure (Time-Product Dummy (TPD) method) across countries. The right-hand column shows unadjusted turnover-weighted unit values based on scanner data. All series are normalised so that January 2017=100.

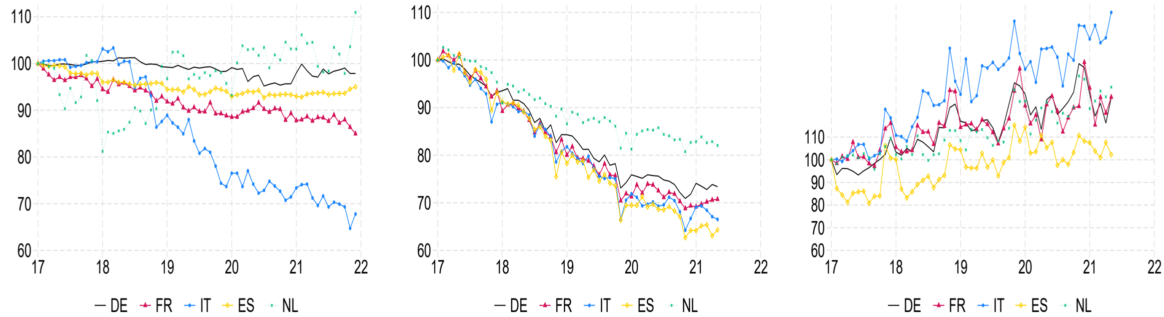
Figure A.8: HICP vs. scanner data-based price indices (III)

HICP | TPD - harmonised QA | Unit values - no QA

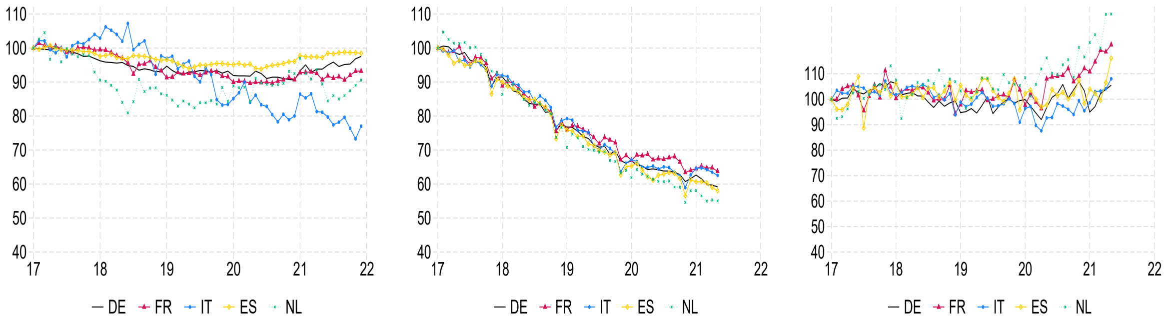
ECOICOP 05314: Room heaters and air conditioners



ECOICOP 05315: Vacuum cleaners and other cleaning equipment



ECOICOP 09111: Equipment for the reception, recording and reproduction of sound

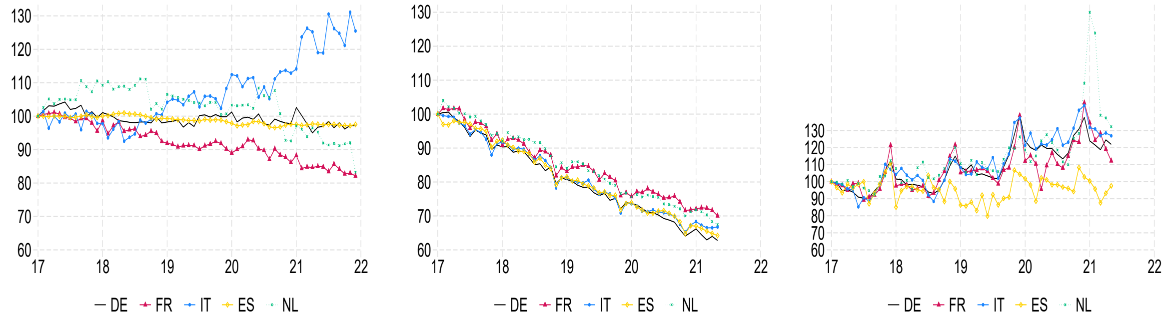


Note: The figures in the left column are the official HICP indices and the figures in the second column are scanner data-based price indices applying a harmonised quality adjustment procedure (Time-Product Dummy (TPD) method) across countries. The right-hand column shows unadjusted turnover-weighted unit values based on scanner data. All series are normalised so that January 2017=100.

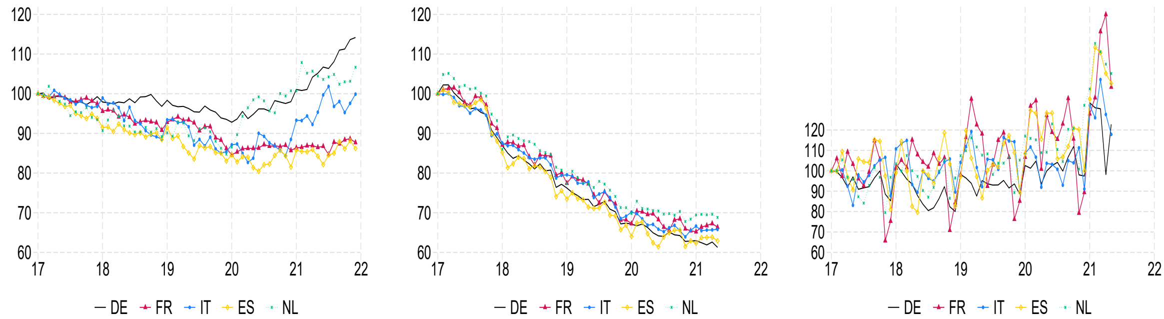
Figure A.9: HICP vs. scanner data-based price indices (IV)

HICP | TPD - harmonised QA | Unit values - no QA

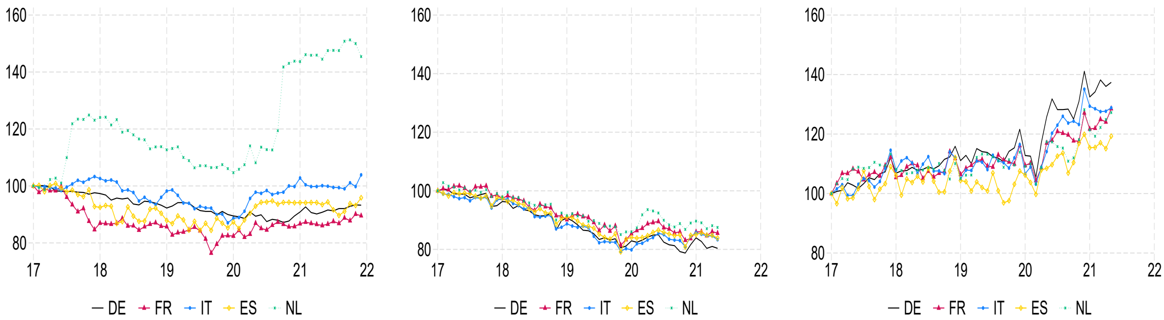
ECOICOP 09119: Other equipment for the reception, recording and reproduction of sound and pricture



ECOICOP 09121: Cameras



ECOICOP 09132: Accessories for information processing equipment



Note: The figures in the left column are the official HICP indices and the figures in the second column are scanner data-based price indices applying a harmonised quality adjustment procedure (Time-Product Dummy (TPD) method) across countries. The right-hand column shows unadjusted turnover-weighted unit values based on scanner data. All series are normalised so that January 2017=100.

A.4 Estimating the impact of quality adjustment based on scanner data for washing machines

To illustrate the potential impact of different QA methods on price measurement, we use a scanner dataset for washing machines from the GfK Point-of-Sales (POS) panel, as described in Section 4.2. Our sample covers ten euro area countries for two separate periods, 2000:01-2005:12 and 2017:01-2021:05:[30] Austria, Belgium, Finland (from 2003), France, Germany, Greece (until 2005), Italy, the Netherlands, Portugal and Spain. The frequency of the first sample is bimonthly, while the second sample covers monthly data. In addition to prices and volumes (sales) of washing machines, several physical model characteristics are included, such as load capacity, spin speed and construction type. For the more recent period, the dataset also includes information on energy efficiency, noise level, spinning efficiency and whether the washing machine is equipped with Smart Connect features. Table A.3 provides a description of the variables.

To set the scene for analysing the potential impact of different QA methods, consider the following scenario. The GfK POS panel covers the population of washing machines available to consumers, along with their prices, volumes and features. Each NSI then samples from this population in some way to represent washing machines in their national CPI. Based on the samples, price indices are calculated using the nationally available data (e.g. sales information or price quotations only) and specific methodological choices, in particular on QA procedures. At all stages of the process there can and will be differences in compilation practices between statistical offices, either because of differences in available data or because of differences in methodological choices. We restrict our analysis here to the narrow field of quality adjustment.

To this end, we compute different scanner data-based price indices for each of the ten euro area countries in our sample. For this purpose, we use three prominent approaches that are used to varying degrees in official price statistics and that can be considered to cover the range

[30] The GfK dataset for the first period was also used by Fischer (2012), who examined washing machine prices in euro area countries to test for price convergence after the introduction of the euro. Similarly, several studies have examined price convergence in individual euro area markets. See, for example, Goldberg and Verboven (2001, 2005) and Brenkers and Verboven (2006), who take a detailed look at the European car market. Interestingly, these papers find a clear tendency towards price convergence until the introduction of the euro, while Dvir and Strasser (2018) show that car prices do not converge further after 2003. More recently, Duch-Brown et al. (2020) also use a GfK dataset (for portable computers) to analyse the impact of online market integration on consumer prices.

Table A.3: Variable description of GfK dataset

Variable	Type	Variable description	Sample 2000-05	Sample 2017-21
`model`	categorical	Identifier of washing machine model	X	X
`country`	categorical	Country (local market)	X	X
`brand`	categorical	Brand's name of a given washing machine model	X	X
`lnprice`	numeric	(Log) average price of a given model (incl. value-added tax)	X	X
`turnover`	numeric	Transaction value (average price × quantity) of a given model	X	X
`construction`	categorical	Construction type (base: freestanding / built in or under / unknown)	X	X
`revpermin`	numeric	Spinning speed (revolutions per minute)	X	X
`loadingkg`	numeric	Load capacity in kg	X	X
`loadingdir`	categorical	Loading direction (base: frontloading / toploading / unknown)	X	X
`autoxdry`	categorical	Degree of automation and presence of drying function (base: fully automatic, no dryer / semi-automatic, no dryer / wash dryer / unknown)	X	X
`energy`	categorical	Energy efficiency according to the EU energy label from A+ + + (best) to G (worst)		X
`smart`	categorical	Equipment with any smart connect functions, e.g. smart check/diagnosis, smart app control, voice control		X
`noise`	numeric	Noise level in decibel		X
`spin`	categorical	Spin efficiency from A (best) to G (worst)		X

Source: GfK Point-of-Sales (POS) Panel.

from "best practice procedures" to "no quality adjustment".[31] These three approaches are then compared with official HICP data.

First, we estimate a *Time-Dummy Hedonics* (TDH) regression, which represents an "explicit" quality adjustment based on observable product characteristics. To do this, we run a hedonic price regression to obtain a quality-adjusted washing machine price per time period. The semi-log regression equation shown below is estimated for each country based on pooled data over all periods $t = 0, \ldots, T$:

$$\ln p_k = \beta_0 + \sum_{t=1}^{T} \delta^t d_k^t + \sum_{j=1}^{p} \beta_j z_{kj} + \varepsilon_k, \tag{9}$$

where p_k denotes the price of washing machine model k in a given country, the time dummy variable d_k^t takes the value 1 if the observation of washing machine k is from period t and 0 otherwise, and z_{kj} is the j-th product characteristic of model k. The vector of product

[31] See IMF (2020), Chapter 6 on quality adjustment and Chapter 10 on price indices in the context of transaction (scanner) data.

characteristics for the first sample 2000-2005 closely follows Fischer (2012) and consists of five variables, namely the load capacity in kg, the spin speed, the degree of automation and the presence of a drying function, the loading direction, the construction type and brand-specific dummies.[32] For the second sample, four additional variables (energy efficiency, noise level, Smart Connect features and spin efficiency) are added. Equation (9) is estimated by weighted least squares, where observations are weighted by their corresponding expenditure share to properly represent the local market structure. The quality-adjusted price index, I_t, can be derived directly from the exponential of the coefficient on the time dummy:

$$I^{0:t}_{TDH} = 100 \times \exp(\hat{\delta}^t). \tag{10}$$

Second, we perform an "implicit" quality adjustment using a *Time-Product Dummy* (TPD) regression, which is also used in Section 4.2. Here, quality adjustment is performed by controlling for differences in the price level of washing machine models k identified by the combination of brand and specific model. The hedonic regression equation can be simplified as follows:

$$\ln p_k = \beta_0 + \sum_{t=1}^{T} \delta^t d^t_k + \sum_{k=1}^{K-1} \gamma_k D_k + \varepsilon_k, \tag{11}$$

where D_k is a dummy variable equal to 1 if the price refers to model k and 0 otherwise. Again, a quality-adjusted price index can be derived from the exponential of the coefficient on the time dummy such that:

$$I^{0:t}_{TPD} = 100 \times \exp(\hat{\delta}^t), \tag{12}$$

Finally, we also consider a price index method that does not include any quality adjustment. For this purpose, we compute a *Unit Value* (UV) price index such that:

$$I^{0:t}_{UV} = \frac{\sum_{k=1}^{K^t} p^t_k \times q^t_k}{\sum_{k=1}^{K^t} q^t_k} \Bigg/ \frac{\sum_{k=1}^{K^0} p^0_k \times q^0_k}{\sum_{k=1}^{K^0} q^0_k}, \tag{13}$$

where q^t_k (q^0_k) denotes the sales of the k-th model in period t (0).

[32]We differ from Fischer (2012) by estimating the hedonic regression for each country separately, allowing shadow prices to vary across countries, and weighting each observation by its expenditure share rather than by the number of sales, as is common practice in index compilation. Moreover, we focus on gross prices including the value-added tax rate (VAT), as the HICP also includes VAT charges.

There are some caveats to the comparison of these three scanner data-based price index methods with official HICP data. First, the comparison is limited by the unavailability of official data at a more disaggregated level. The best candidate for comparison, "05.3.1.2 Clothes washing machines, clothes drying machines and dish washing machines", is only available from December 2016, as shown in Figure A.10. The closest match for the period before is the HICP subindex "05.3 Household appliances", which mainly covers large household appliances.[33] However, given that the subindex "05.3.1.2" accounts for about a quarter of the higher-level index "05.3 Household appliances", we argue that the overall trend of the latter should also reflect the price development of washing machines.[34] Second, even for the more recent sample, there is no official price index just for washing machines, which are grouped together with dryers and dishwashers. However, as noted by Fischer (2012), cross-country price variations for washing machines are expected to be similar to those for dryers and dishwashers. Third, metadata on sampling and quality adjustment at the national level are limited. Returning to the ideal scenario, it should be possible to replicate the official HICP data with the right choice of subset of observations and using different methodologies.

Figure A.11 shows the scanner data-based price indices and the cumulative rate of change from 2001 to 2005, together with the HICP counterpart "05.3 Household appliances". The resulting cumulative rates of change are consistently negative when the same hedonic quality adjustment is applied across countries. Compared to the unadjusted case of the *Unit Value* approach, the range of the hedonic measures is also smaller, with a range between -3% and -29% compared to +7% and -24% in the unadjusted case. Compared to the quality-adjusted price indices based on scanner data, the cumulated rates of the HICP subindex "Household appliances" differ less in terms of range (from 6% to -8%), but more in terms of the sign of the overall price trend, with five out of ten countries showing a positive increase over time. It should also be noted that all three methods do not provide a seasonal pattern for washing machine prices as in the case of the official HICP figures for some countries (Belgium and Greece).

Figure A.12 compares the scanner data-based price indices and the cumulative rate of change for the later period from 2017 together with the more disaggregated HICP series "05.3.1.2 Clothes

[33] According to the euro area HICP weighting scheme in 2017, the HICP "05.3 Household appliances" consists of three sub-indices: "05.3.1 Major household appliances whether electric or not" (71%), "05.3.2 Small electric household appliances" (21%), and "05.3.3 Repair of household appliances" (8%).

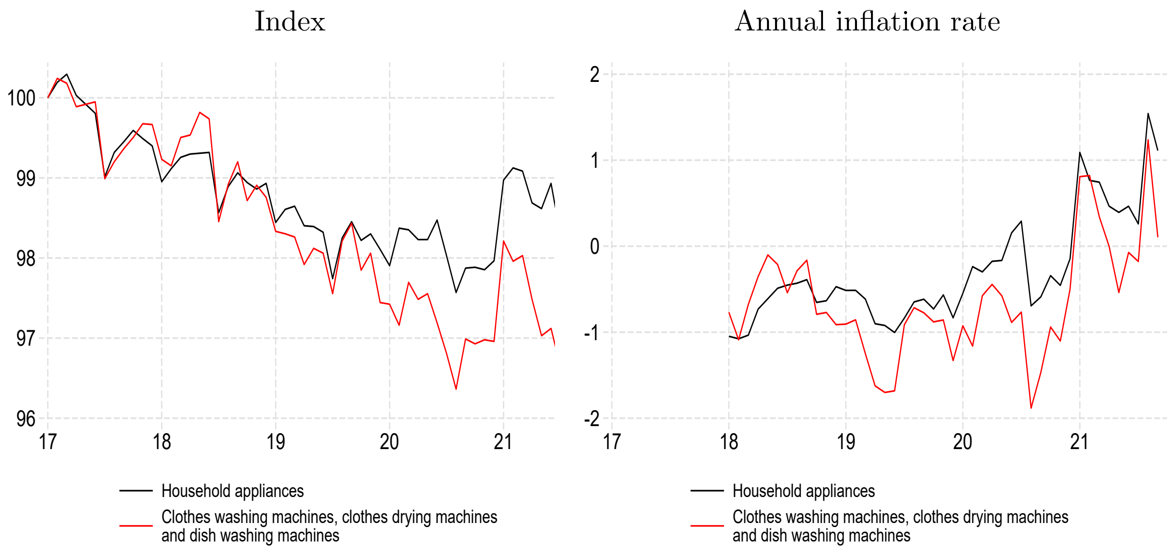
[34] A strong comovement between the two series can be observed with the start of the more disaggregate series in December 2016, as shown in Figure A.10.

washing machines, clothes drying machines and dish washing machines". Contrary to the first period, the unadjusted case of a *Unit Value* price index now signals a strong price increase over time for all countries considered. This could be related to the fact that this index method is unable to control for changes in the composition of the basket of washing machines, with consumers switching to more sophisticated but also more expensive products over time, the so-called *Unit Value* bias. In contrast, the resulting cumulative rates of change are consistently negative when applying the same hedonic quality adjustment across countries, as derived from the *Time-Dummy Hedonics* and *Time-Product Dummy* methods. Compared with the HICP subindex, the latter again signals mixed price trends across countries over the 2017-2021 period. Figure A.13 also shows different specifications of the *Time-Dummy Hedonics* method for the period 2017-2021. It shows the sensitivity of the regression specification, with diverging price trends according to the baseline estimate (i.e. without controlling for newer model features such as energy efficiency and smart control). The resulting price trend thus depends not only on the method, but also on the choice of variables.

Regarding the ideal scenario described above, we could not perfectly reproduce the price changes as shown by the HICP subindex, mainly due to limited information on QA methods as well as the unavailability of a more disaggregated HICP benchmark for washing machines. Therefore, discrepancies between the two series should not be interpreted solely as the impact of quality adjustment.[35] Nevertheless, when comparing our scanner data-based price indices and the official HICP sub-index, a strong pattern emerges, namely consistently declining price trends across countries. This also calls into question the QA procedures applied to the specific product "washing machines" in some of the euro area countries considered. Moreover, the crucial role of the choice of QA methods for the resulting price trend is also consistent with the micro-price findings of Conflitti et al. (2022) for Austria and Italy.

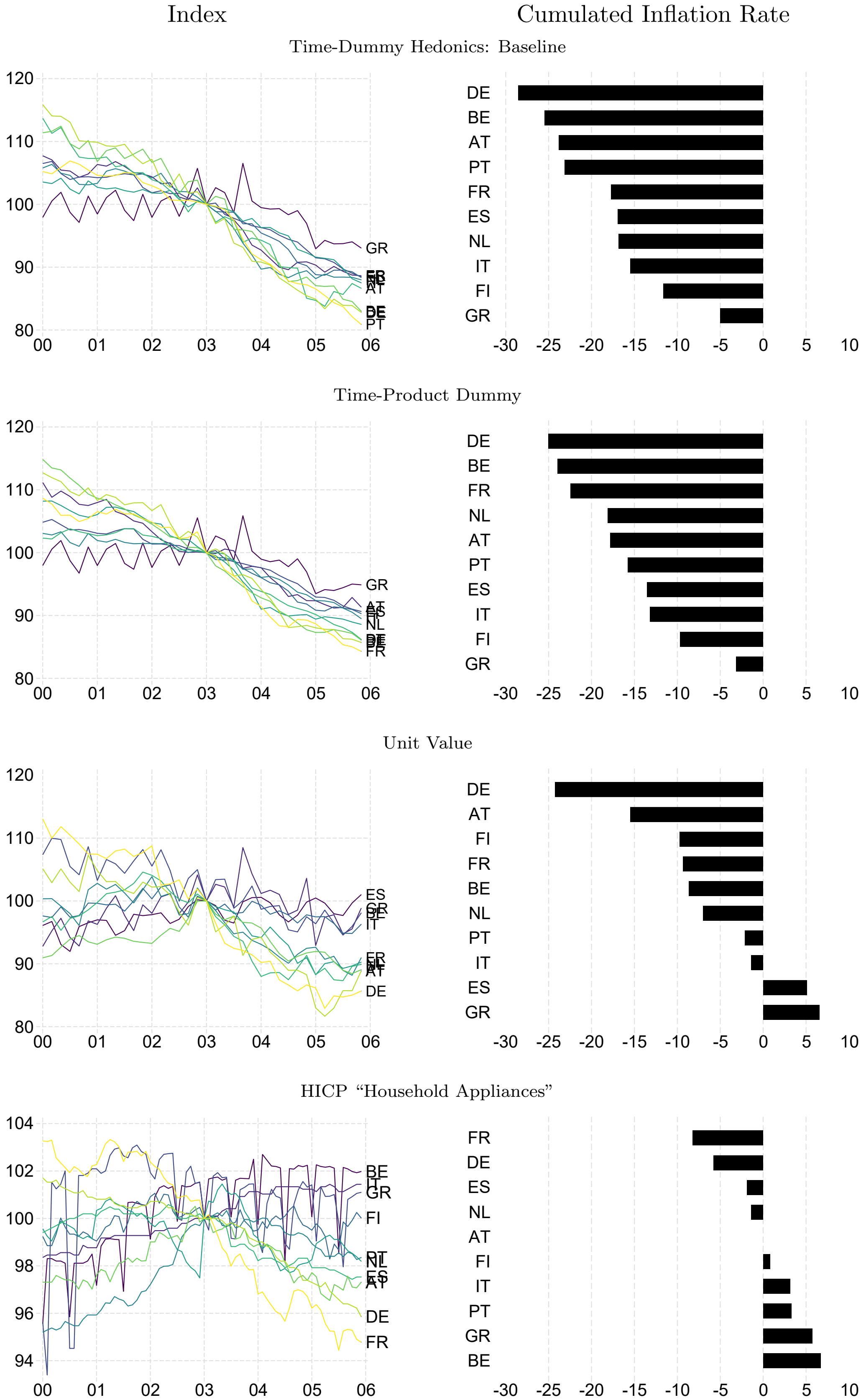
[35] As shown by Henn et al. (2019) for German package holidays, different data sources (transaction prices vs. offer prices) may also play a role.

Figure A.10: HICP on Household Appliances



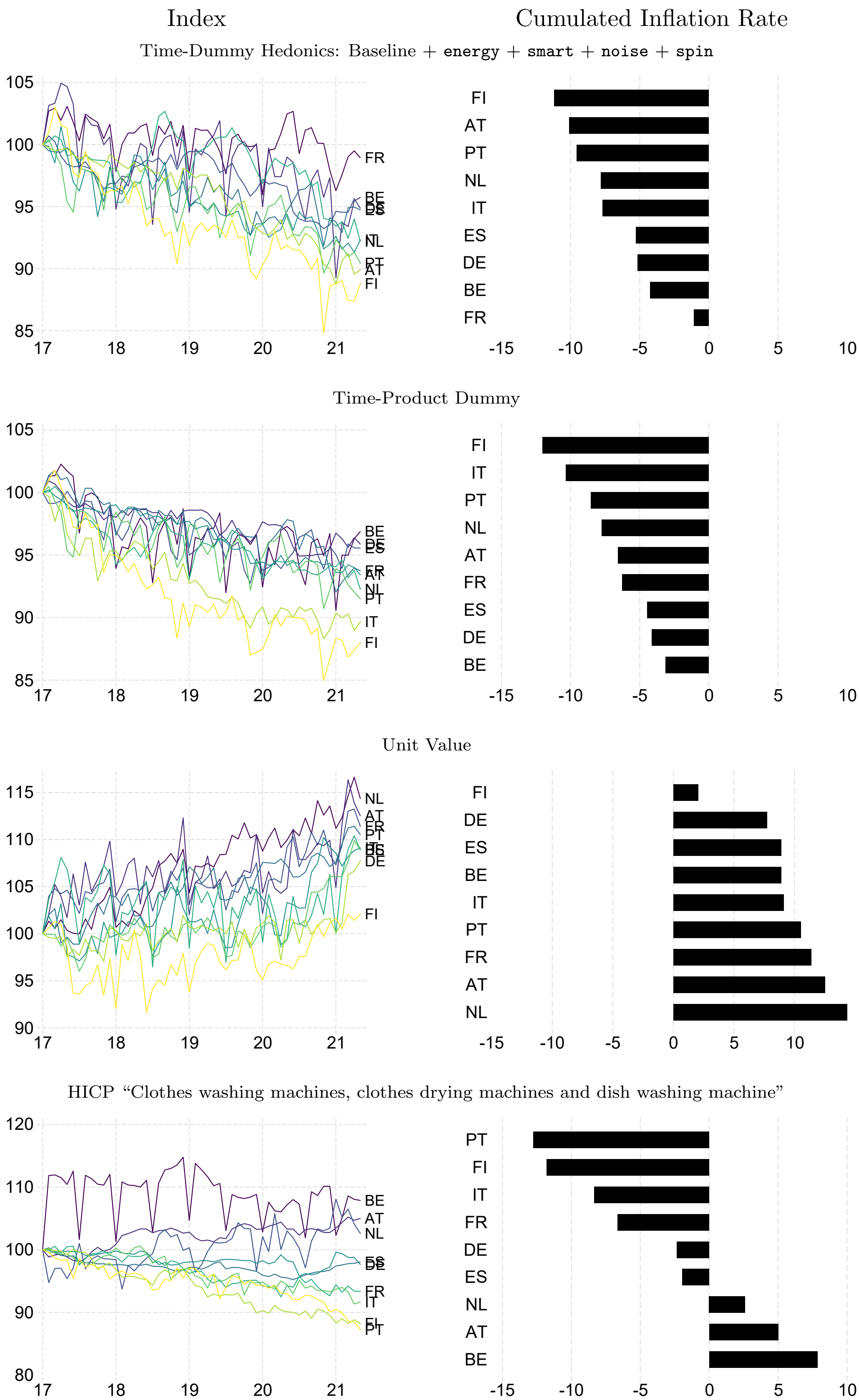
Note: The figure shows the HICP subindices "05.3 - Household Appliances" and "05.3.1.2 Clothes washing machines, clothes drying machines and dish washing machines". Price indices adjusted to January 2017=100. Annual inflation rates are correlated by 0.8.

Figure A.11: Scanner data-based price indices for washing machines vs. HICP, 2000-2005



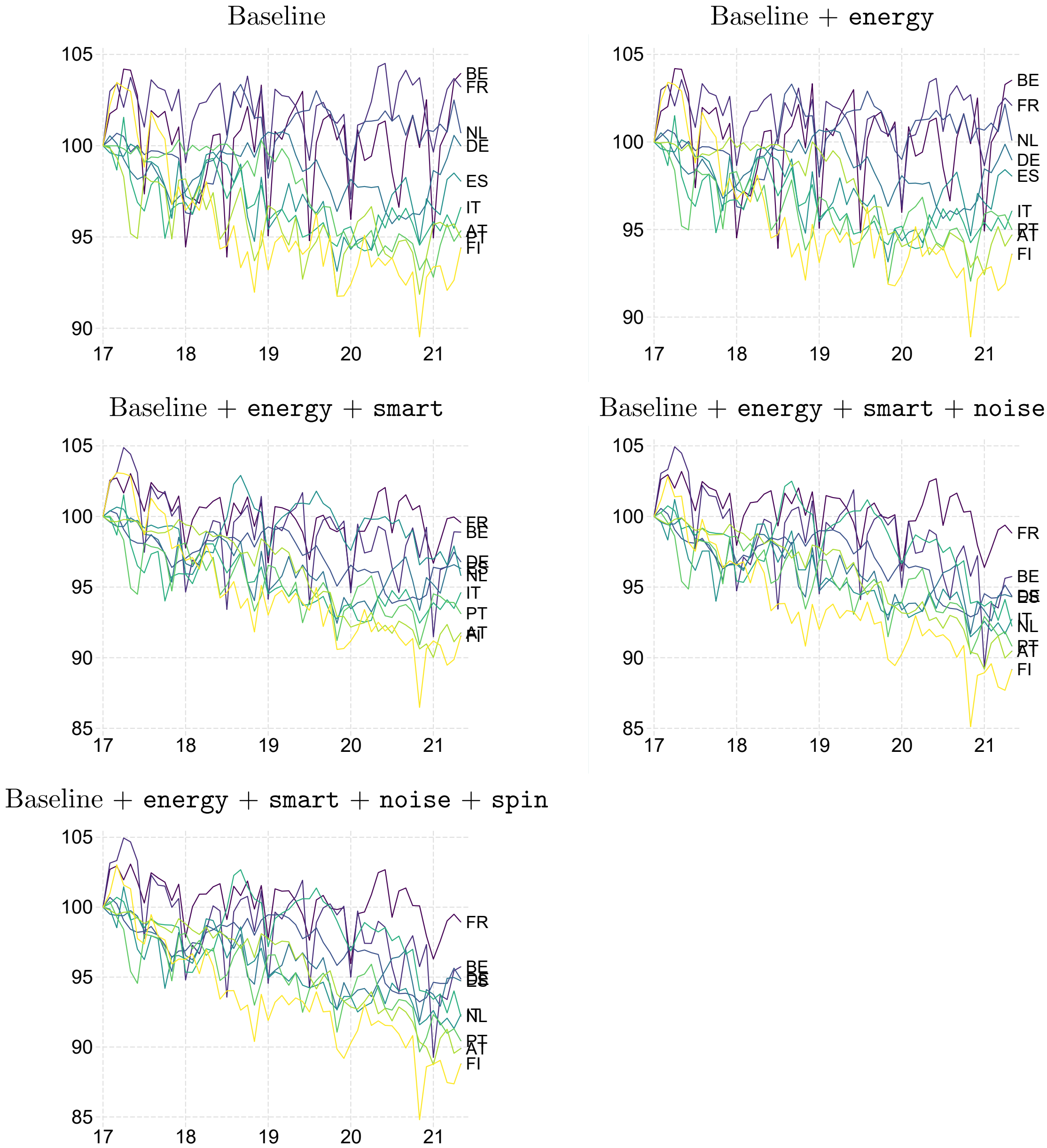
Note: The figure shows the three scanner data-based price indices (weighted by turnover) and the HICP series “05.3 - Household Appliances” for the years 2000-2005, indexed to January 2003=100, as well as cumulated inflation rates between 2001:01 and 2005:12. Data for Finland are only available from January 2003 onwards.

Figure A.12: Scanner data-based price indices for washing machines vs. HICP, 2017-2021



Note: The figure shows the three scanner data-based price indices (weighted by turnover) and the HICP series “05.3.1.2 Clothes washing machines, clothes drying machines and dish washing machines” for the years 2017-2021, indexed to January 2017=100, as well as cumulated inflation rates between 2017:01 and 2021:05.

Figure A.13: Alternative hedonic price indices for washing machines vs. HICP, 2017-2021



Note: The figure shows various specifications of the time-dummy hedonics regression of washing machine prices for the years 2017-2021, indexed to January 2017=100, as well as cumulated inflation rates between 2017:01 and 2021:05. The figures underlying the graphs are obtained by estimating equation (9) of the main text. The R-squared values of the regressions performed are in the range [0.80, 0.90] for "Baseline", [0.80, 0.90] for "Baseline + energy", [0.81, 0.92] for "Baseline + energy + smart", [0.84, 0.93] for "Baseline + energy + smart + noise" and [0.84, 0.93] for "Baseline + energy + smart + noise + spin".

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