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Research Report

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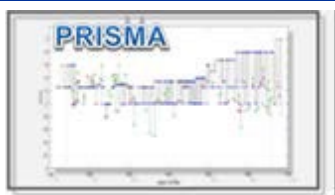
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Occasional Paper Series

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E-commerce and price setting: evidence from Europe



No 320

Price-setting Microdata Analysis Network (PRISMA)

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

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

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

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

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

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

No 322, "Micro price heterogeneity and optimal inflation"

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

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

No 325, "Inflation heterogeneity at the household level"

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Abstract

E-commerce has become more prevalent throughout Europe in the last decade. The coronavirus (COVID-19) pandemic accelerated this trend, particularly in the retail sector. This paper focuses on the implications of increasing business-to-consumer e-commerce for prices and inflation in the euro area. It highlights three key results. First, whether online prices and inflation are higher or lower than their offline counterparts depends on the distribution model, the sector and the country. Moreover, properly selected online prices track official inflation indices even in real time. Second, the effect of e-commerce on inflation appears to be transient and differs between countries. However, as the penetration of some markets is still low, these transitory effects will likely persist at the euro area level for several years. Third, online prices change more frequently than offline prices. This might lead to greater price flexibility overall as online trade gains market share in a growing number of sectors.

Keywords: e-commerce, price rigidity, inflation, consumer prices, microdata

JEL codes: D4, E31, L11

1 Introduction

Electronic commerce (e-commerce) has become more prevalent throughout Europe. The coronavirus (COVID-19) pandemic accelerated this trend, particularly in the retail sector.¹ This paper focuses on the implications of increasing business-to-consumer e-commerce on inflation in the euro area.

Online shopping changes the structure of the retail market in three important ways:

1. **First, it lowers, prima facie, consumer search costs and thus simplifies price comparison.** However, this might be offset by an increased ability to segment customers via personalised marketing and pricing, which might eliminate the notion of a market price, and thus reduce overall price transparency.
2. **Second, fully digitalised and centralised supply chain and customer relationship management reduce the cost of differentiating and adjusting prices.** Furthermore, the mere existence of a new (online) channel might by itself represent a new dimension of price differentiation.
3. **Third, the online channel has attracted new players whose marketing, logistics and invoicing is specifically tailored to online retailing.** These new players are often more efficient than the incumbents. Increased competition, together with efficiency gains, may initially result in downward pressure on prices.

1.1 New market – new questions

What are the implications of widespread online shopping for central banks? Many important questions arise. Does e-commerce change inflation determination? Is there an effect on price dispersion and inflation heterogeneity across households?² And, last not least, are these phenomena transitory or will they stay with us in the future?

This paper highlights three key results:

1. **Whether online prices and inflation are higher or lower than their offline counterparts depends on the distribution model, the sector and the country.** Convergence between online and offline segments seems to have

¹ See Work stream on digitalisation (2021). Dedola et al. (2023) note three main technological advancements that facilitate the growth of e-commerce: efficient information collection, automated information processing, and largely cost-free information exchange.

² See Kiss and Strasser (2022) for a general discussion of inflation heterogeneity across households.

progressed further in some, more mature, markets. Moreover, it is possible to select online prices so as to track official inflation indices, including in real time.

2. **The effect of e-commerce on inflation appears to be transient and differs between countries.** However, as the penetration of some markets is still low, these transitory effects will likely persist at the euro area level for several years.
3. **Online prices change more frequently than offline prices.** Overall, this may lead to greater price flexibility, as online trade gains market share in a growing number of sectors.

Our data place a spotlight on important areas of e-commerce in Europe, but the picture is far from complete. This paper provides indicative evidence for a rapidly evolving market, rather than definite conclusions. It draws on diverse and complementary data sources, including consumer price index (CPI) microdata for Germany, which includes information on online trade, web-scraped data for Poland, which can be compared with the Polish CPI microdata analogue, and household-level scanner data on online and offline fast-moving consumer goods (FMCG) purchases in France, Spain and the United Kingdom, collected by GfK and Kantar. The latter dataset has the key advantage that both prices and quantities sold are included.³

Based on these diverse and complementary sets of microdata, in this paper we assess questions related to price levels, price changes (“reset prices”) and inflation. The remainder of the introduction describes the current state of e-commerce in Europe and the data available for analysing it. Section 2 studies prices and their cross-sectional distribution. It looks for differences between the online and the offline markets in terms of price levels and price dispersion, and examines whether these differences are persistent or whether there is evidence of convergence between the two channels. Section 3 discusses the implications of e-commerce for aggregate inflation. It compares online and offline inflation and studies the persistence of the differential. Section 4 looks at the underlying price changes in more detail. As the question of whether online prices are more flexible than offline prices is key, this section explores how often and how much online prices change. Section 5 contains a brief conclusion.

³ See the PRISMA Online Appendix for a description of the various datasets.

1.2 The state of e-commerce in Europe

Within the business-to-consumer market segment, e-commerce initially spread primarily in the retail market for small consumer durables and semi-durables.

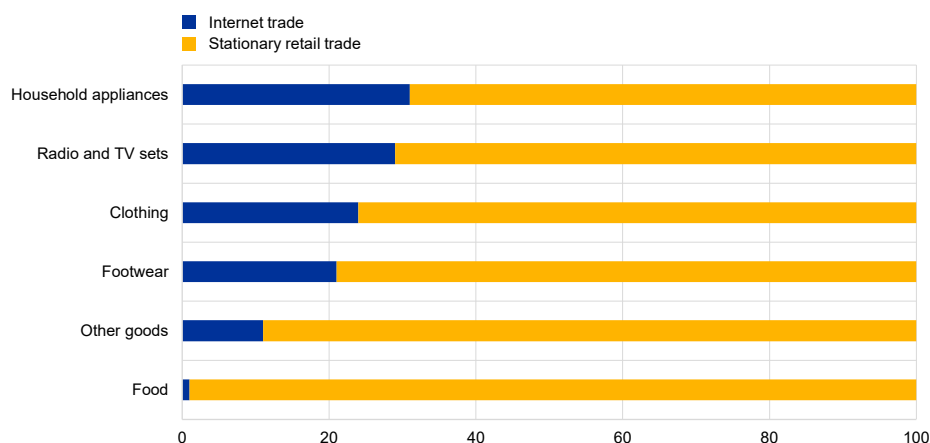
1.2.1 Market shares in selected countries and markets

In 2015, the latest CPI base year, internet trade in Germany made up roughly 11% of the relevant consumer expenditures.⁴ In the German CPI, the dataset with the most comprehensive information available for the euro area, about one-third of products are weighted by outlet type, one of these being “internet trade”. The share of internet trade varies markedly between sub-categories, ranging from 31% for household appliances to just 1% for food (Chart 1).

Chart 1

Weight of internet trade in the German CPI (selected product groups)

(percentages)



Source: Destatis (2019).

Note: Refers to products in the German CPI, for which a weighting scheme by outlet type is applied (about one-third of private consumption).

The diffusion of e-commerce in goods markets followed a similar course in most European countries, starting with small consumer durables and not spreading into food retail until much later. The diffusion in the market for services is at least as heterogeneous. Travel-related sectors such as accommodation and transportation switched to online retailing rapidly, whereas most of the service sector remains largely offline.

Focusing on a specific market for which we have very detailed microdata, the market for FMCG provides an interesting case for the study of the evolution of e-commerce. FMCG include grocery and items related to personal care, hobbies

⁴ Destatis applies an explicit outlet-type weighting to about one-third of private consumption in the German CPI (see Sandhop, 2012, and Destatis, 2019). Note that the Destatis “internet trade” outlet type also captures the “mail order” distribution channel. The share of the “mail order” channel is expected to be rather small, also in comparison to previous base years (2005 and 2010), with Destatis changing its external communication for this outlet type from “internet trade/mail order” to “internet trade” starting with the base year 2015 (see Destatis, 2019).

and household maintenance. FMCG retailers have faced little online competition until recently. France and the United Kingdom are among the countries with the largest online grocery retail penetration. In these countries, the online channel won up to 10% of the FMCG market in 2018. In most other European countries, however, online FMCG is still a niche market, as shown, for example, by the German CPI data in Chart 1. However, this situation is unlikely to continue (partly because of structural change caused by the COVID-19 pandemic). Table 1 shows that, as far back as 2018, South Korean consumers were purchasing almost one-fifth of FMCG online. The right-hand columns of this table also show that the online channel is more prevalent outside of the groceries segment.

Table 1
Online FMCG retail market share by country (%)

	Online sales 2018 (% of FMCG sales)	Groceries consumer survey (% of shoppers)	Personal care consumer survey (% of shoppers)
United Kingdom	7	43	37
Sweden		34	36
Spain	2	32	31
Finland		25	29
France	5	24	28
Netherlands	4	22	31
Denmark	2	21	22
Italy	1	20	30
Germany	2	19	28
Poland	1	15	33
Belgium		12	24
United States	4		
South Korea	19		
World (avg.)	5		

Sources: Online sales from GfK/Kantar, Intage and United States Commerce Department for 2018 (Roger, 2019). Consumer shares based on a PostNord/Nepa survey of about 1,000 people per country in the second quarter of 2019 (PostNord, 2019).

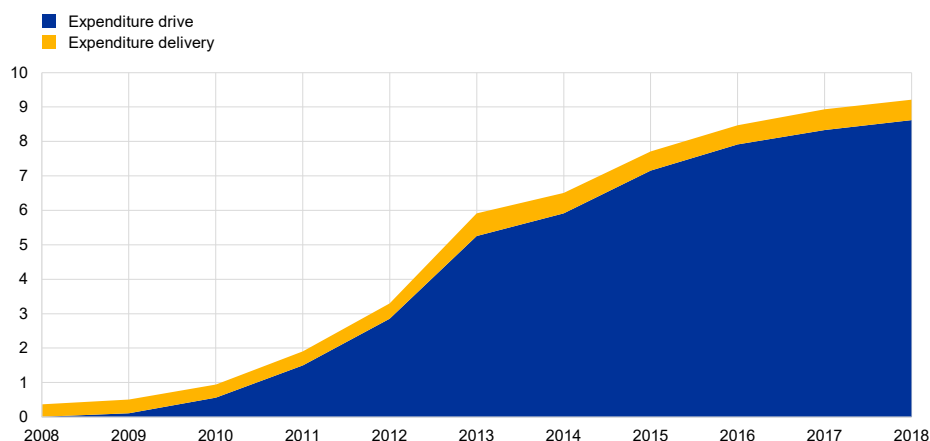
1.2.2 Distribution model

The specific structure of e-commerce differs between market segments and countries. Overall, home delivery of orders dominates. In grocery retailing (which does not include fresh meals), however, online pre-ordering combined with collection by customers (“click and collect”) has gained ground in some countries. The store collects the items, and the customer simply picks up the purchased bundle.

Chart 2

Expenditure share of all reported FMCG transactions (France)

(expenditure share of total transactions in household panel, percentages)



Source: GfK/Kantar household panel.

In France, until 2018, very few online FMCG purchases are delivered, whereas more than 90% are picked up by customers in-store (Chart 2). In some countries, most notably France, the customer convenience in terms of click and collect has been further refined, with the “drive-through” format providing special facilities for easy shopping collection.

The cost structures of delivery and click and collect are different. Whereas both involve a fixed cost for setting up the facilities, home delivery involves a considerably larger variable cost component than click and collect, due to the cost of shipping (and of handling returns).

1.2.3 Product assortment and market penetration

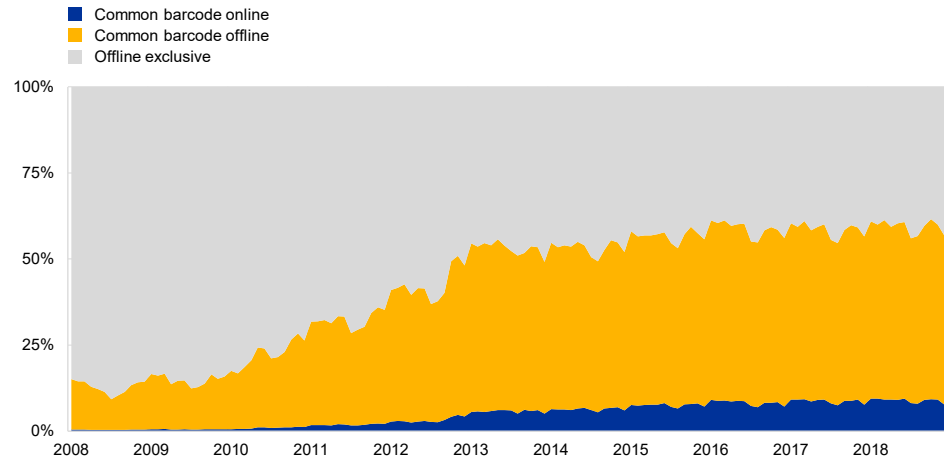
One reason for the slow adoption of online grocery shopping by consumers may be the incomplete assortment available online. Even in France and the United Kingdom, it seems that in 2018, a (competitive) online offer was available for only half of households' FMCG expenditure at most. In the case of France⁵, this is indicated by the yellow area in Chart 3, which shows the share of total household expenditure on products that at least one panellist purchased online. For more than five years, the share of expenditure on products not purchased online by any panellist has been stable, at around 40%. The low take-up by households of online product offers might indicate slow adoption of this new channel. It is more likely, however, that many FMCG offered online are not competitively priced once delivery charges are included, or are not available at all.

⁵ Further results for Spain and the UK are reported by Strasser and Wittekopf (2022).

Chart 3

Market shares in online FMCG over time (France)

(expenditure share of total transactions, percentages)



Source: Strasser and Wittekopf (2022) based on GfK/Kantar household panel.

Note: Restricted to the food, non-alcoholic and alcoholic beverages, household maintenance, hobbies/pet food and personal care categories.

Online and offline prices can be compared only for those product categories with some prevalence in both channels, to avoid the comparison being dominated by a few niche products with limited market shares. Even then, the share of e-commerce varies considerably across product categories. The German CPI micro database allows us to distinguish online prices from offline prices within roughly 290 narrow product categories for the period 2015-19. Here, the product definition follows the narrowest product category available (e.g. “women’s sport shoes”).⁶ These product categories correspond to about 16% of total expenditures in the CPI. The online and offline products in the German CPI are sampled in a representative way by focusing on top-seller products, which underlines the relevance of these products from a consumer’s perspective.

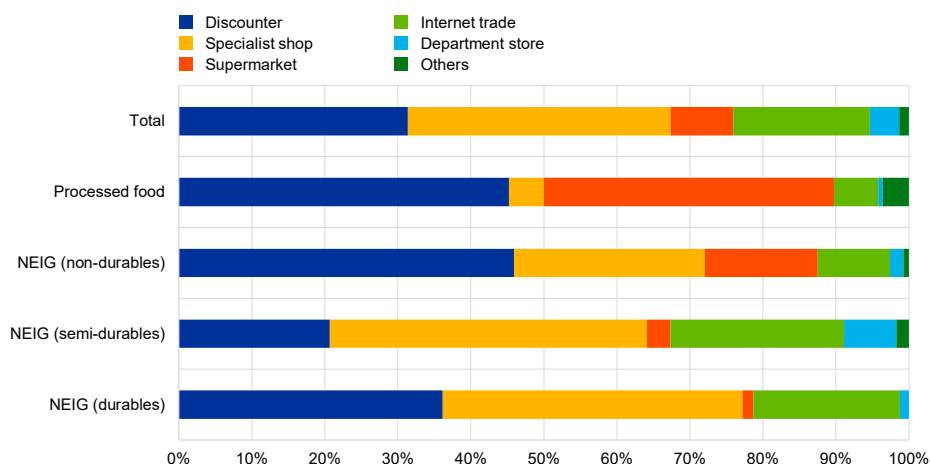
⁶ We identify online products in the German CPI micro database as prices collected for the “internet trade” outlet type, whereas offline products correspond to prices collected for the remaining stationary outlet types. Like Gorodnichenko et al. (2018), we cannot match online with offline micro prices, since the dataset does not contain a common product identifier such as a barcode, as is the case with scanner or web-scraped data.

Chart 4

Share of outlet types by purpose of consumption in the German CPI

Expenditure share in base year 2015, only for products collected in both online/offline stores

(percentages)



Source: Bundesbank staff calculations based on German CPI microdata.

Notes: "Total" refers to the four "processed food" and "NEIG" product categories. "Discounter" includes specialist markets. "Supermarket" includes consumer markets. "Other" includes other retail trade and service companies.

The e-commerce basket is clearly dominated by more durable goods. Chart 4 shows, for these product groups in the German CPI, the distribution of outlet types by four major product categories. In Germany, the share of internet trade is smallest for perishables and largest for semi-durables and durables.

Accordingly, e-commerce flourishes in categories with a large share of specialist shops and struggles in categories dominated by supermarkets and discounters. Products in the "durable non-energy industrial goods (NEIG)" category mostly include household appliances, furniture, and electronics; the major outlet types are specialist shops (41%) and discounters (36%). Semi-durable NEIG mainly include clothing and footwear, but also recreational products, and are mainly attributable to specialist shops (43%). For both durables and semi-durables, the share of internet trade is considerable, adding up to 20% and 24%, respectively. Non-durable NEIG include articles such as personal care items, stationery, plants/flowers and pharmaceutical products. Here, the highest share is assigned to discounters (46%), whereas the share of internet trade is only about 10%.

Food items in the online basket covered by the CPI dataset capture only a narrow sub-set of food consumption. First, the CPI data cover only very few products in the "unprocessed food" category.⁷ Second, within "processed food", the items sampled both online and offline are mainly frozen food and alcoholic beverages. Discounters (45%) and supermarkets (40%) clearly dominate, while internet trade makes up only about 6%.⁸

⁷ Due to the small number of products (fewer than four), we have dropped the "unprocessed food" and "recreational services" product categories from our analysis. The online channel for food also contains frozen food home delivery services.

⁸ Likewise, based on the GfK/Kantar household panel shown in Table 1, only 1.5% of FMCG were sold in online stores in 2018.

2 Prices: levels and dispersion

The rise of online retailing raises the question of whether efficiency gains in disseminating and changing information dominate the new personalised pricing opportunities. In this vein, this section examines whether the online price level differs from its offline counterpart, and whether online prices are more, or less, dispersed.⁹

2.1 Online and offline price levels

The existing evidence on online price levels is mixed, as the characteristics of the online market change over time and depend fundamentally on the distribution model. In this section, we place the existing results for specific product types (e.g. top brands), retailer type (e.g. multi-chain retailers), and country (most often the United States) in a broader perspective.

For many sectors, the research reveals only minor differences between online and offline prices. Cavallo (2017), for example, compares the online and offline prices of multi-channel retailers for the same product in ten countries. On average, 72% of the prices are identical, ranging from 42% in Brazil to 91% in Canada and the United Kingdom. For the only euro area country in his study (Germany), he reports a share of 74% identical prices at five retailers.¹⁰

Multi-channel retailers in Germany, in around 2015, were offering the same product online at 2% cheaper, on average, than offline (Cavallo, 2017). If we focus specifically on online prices in Germany that differ from their offline counterparts, then these are, on average, 8% lower. This substantial discount is also reflected in the fact that only one of seven non-identical prices is higher online.

⁹ This section closely follows Strasser and Wittekopf (2022).

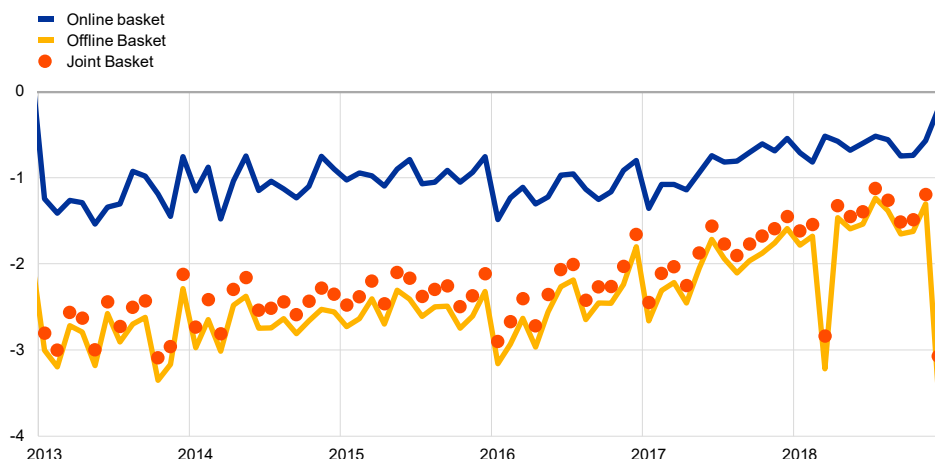
¹⁰ The numbers for Germany in this and the following paragraph are taken from Table 3 in Cavallo (2017). The study covers ten countries (Argentina, Australia, Brazil, Canada, China, Germany, Japan, South Africa, United Kingdom and United States) and six sectors (food, clothing, household, drugstore, electronics, and office). Unfortunately, neither Cavallo (2017), nor the corresponding online appendix specify the sectors of the five German retailers in the sample.

Chart 5

Offline-online price level difference for groceries baskets

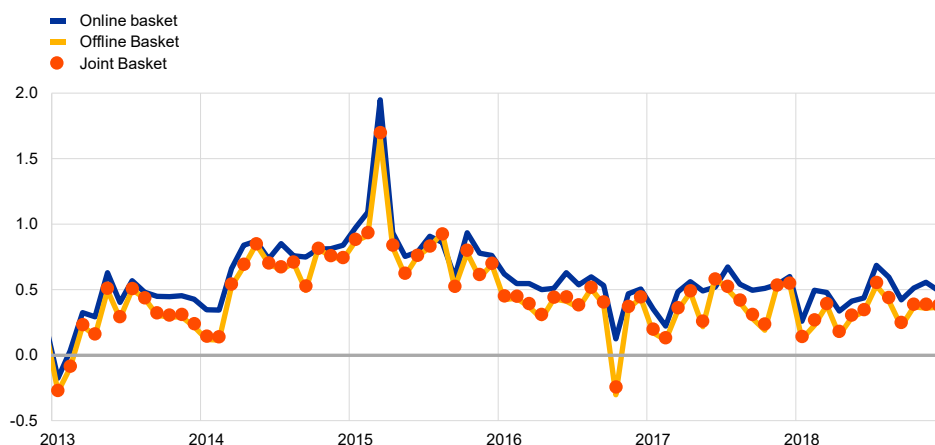
a) United Kingdom

(percentages)



b) France

(percentages)



Source: Strasser and Wittekopf (2022) based on GfK/Kantar household panel.

Notes: Percentage excess offline relative to online price level for various baskets. The "joint basket" weights prices according to the overall purchases of the panellists, the "offline basket" according to their offline purchases, and the "online basket" according to their online purchases.

Groceries tend to be more expensive online if delivered to the home. For a sample of ten countries worldwide, Cavallo (2017) reports that groceries purchased online are, on average, 1% more expensive. Only one-third of food products are cheaper online. We confirm this observation for the United Kingdom with microdata from the GfK/Kantar household panel. The blue line in panel a) of Chart 5 shows the price difference for products that UK households did purchase online, i.e. prices weighted by the share of online expenditure of the respective product. For a long period of time that included 2015, online FMCG prices were about 1% higher. Only in recent years has the price gap narrowed somewhat. A higher online price for FMCG is not a general result that holds across different countries, however, as the following section shows.

2.1.1 The role of the online distribution model

Online pricing differs between the various distribution models, in particular between click and collect/drive-through and home delivery. As described in the introduction, the French online FMCG market is dominated by the drive-through format, i.e. with consumers picking up products themselves. Panel b) of Chart 5 shows that this has a profound effect on prices: online FMCG prices in France are, in fact, lower than offline prices for each of the three baskets shown in the chart (about 0.4% lower, on average, in 2018).

Many online prices include a service component: home delivery. This not only makes online prices more expensive (as shown in panel b) of Chart 5, for example, for the United Kingdom), but – as described in Section 1.2.1 – also implies a different cost structure. A considerable part of the difference between online and offline prices might therefore not be a peculiarity of the online market, but simply a reflection of the additional cost of the delivery service.

Overall, in a mature online FMCG market with home delivery, as in the case of the United Kingdom, online prices tend to be higher, whereas with click and collect, as in the case of France, they tend to be lower than offline prices. Both countries in Chart 5 show signs of price convergence between online and offline price levels. In France – without home delivery – the overall online discount has declined, possibly because introductory pricing to advertise the new distribution model has ended. In the United Kingdom – with more home delivery – the online price premium has halved in the past five years, which might reflect economies of scale in the delivery network, but also the loss of the premium status of home delivery.

2.1.2 The role of basket composition

The online consumer basket is dominated by products that are relatively cheaper online, consistent with bargain hunting. In France, the products purchased online are those with the largest discount relative to offline products (panel b) of Chart 5). However, even when a home delivery service makes shopping online more expensive than shopping offline, for example in the United Kingdom, shoppers still select products that are relatively cheaper online. In recent years, online shoppers in the United Kingdom have paid a surcharge of only 0.5% on what they paid offline, in exchange for the convenience of home delivery. Had they moved all their purchases online, the price premium would have been 1.5%. This shows that online and offline prices are linked by a non-negligible level of arbitrage.

2.2 Price dispersion

In frictionless markets with uniform shipping costs, a product sells at a unique price at a given point in time. In real-world markets, frictions may lead to price dispersion. On the consumer side, incomplete information and transaction costs

inhibit arbitrage. On the retailer side, menu costs and other forms of price stickiness slow down price adjustment.

By simplifying price comparisons, e-commerce may reduce information frictions, but the new possibilities of segmenting the market further and of personalising prices might increase them. The (technological) feasibility in e-commerce of changing prices incessantly entails lower menu costs and thereby favours more flexible and quicker price adjustment. Prima facie, this reduces market frictions, but its effect on price dispersion is ambiguous. On the one hand, lower menu costs speed up the pass-through of cost shocks and responses to competitor price changes. On the other, frequent price adjustments may reduce price transparency by confusing consumers. Furthermore, the short period of validity of price information restricts its usefulness for arbitrage to brief time windows and allows segmenting of the customer base according to search intensity and patience. Taken together, the informational benefits of e-commerce (Overby and Forman 2015) work against the effect of personalised pricing (Aparicio et al. 2021). The net effect on price dispersion of lower menu costs in e-commerce is ambiguous and warrants an empirical investigation.

Table 2
Selected studies on online price dispersion

	Country	Products	Retailers	Results
Overby and Forman (2015)	United States	Used vehicles	Business-to-business (wholesale) market	E-commerce reduced regional price dispersion
Gorodnichenko and Talavera (2017)	United States, Canada	Software, electronics, computer parts, cameras	Online-only and multi-channel retailers (online price comparison site)	Substantial online price dispersion, but smaller than offline
Gorodnichenko et al. (2018)	United States, United Kingdom	Broad coverage of categories (incl. furniture, garden equipment, etc.)	Online-only and multi-channel retailers (online price comparison site)	Online price dispersion similar or larger than offline
Cavallo (2018a)	United States	Broad coverage (Billion Price Project)	Multi-channel retailers + Amazon	Largely uniform pricing online, even higher if in competition with Amazon
Ater and Rigbi (2023)	Israel	FMCG	Five offline supermarket chains	Legally mandated online publication of offline prices reduced price dispersion within chains
Aparicio et al. (2021)	United States	FMCG	Online grocery retailers	Online pricing less uniform than offline

Online price transparency without the option of personalised pricing increases uniform pricing. With the available data, it is not possible to control for personalised pricing within online stores. But it is possible to study how online information affects offline pricing. Ater and Rigbi (2023) look at how the requirement for Israeli supermarket chains to post their prices online has affected prices and price dispersion. They find a decrease in prices of more than 4%, hinting at increased

competition. Price differences at the product level, however, decreased very little.¹¹ However, prices converged considerably within chains, pushing retailers closer to uniform pricing.¹²

In the United States, in many product categories, online prices tend to be more dispersed than offline prices. Studies on price dispersion have so far focused on the United States (Table 2). Most of these studies report that online prices are equally or more dispersed than offline prices (Aparicio et al., 2021, Gorodnichenko et al., 2018). One exception may be consumer electronics, for which Gorodnichenko and Talavera (2017) report a lower dispersion online than offline. For FMCG, Aparicio et al. (2021) report that 78% of offline price pairs are identical, whereas only 66% of online prices are (right-hand columns of Table 3).

Table 3
Price dispersion within retailers

	France (2018)		Spain (2018)		United Kingdom (2018)		United States	
	Online	Offline	Online	Offline	Online	Offline	Online	Offline
Identical prices (%)	75	71	91	90	87	85	n.a.	n.a.
Rounded prices (%)	79	76	91	91	89	87	66	78
Price diff. (avg., %)	1.8	2.2	1.3	1.0	2.7	2.9	5.2	3.4
Price diff. (med., %)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Price pairs (avg., tsd.)	3	3	0.06	0.06	44	44	5	40

Sources: Columns 2-7 are taken from Strasser and Wittekopf (2022) and columns 8 and 9 from Aparicio et al. (2021).
Notes: Price dispersion in columns 2-7 across two-digit postal regions (outward code region in the United Kingdom) within a given distribution channel (online vs offline) and retailer during 2018. See Strasser and Wittekopf (2022) for details.

In many European countries, even FMCG prices are less dispersed online than offline. In France and the United Kingdom, the prices charged by the same retailer for the same FMCG, identified by its barcode, are more homogeneous online than offline (Strasser and Wittekopf, 2022). The third row of Table 3 shows that, in these two countries, the online price dispersion is respectively 0.4 percentage points and 0.2 percentage points lower than offline. In terms of identical prices, reported in the first row of Table 3, Spain also shows more online homogeneity. The share of identical prices in these three countries is 1 percentage point to 4 percentage points larger online than offline.

For many FMCG products, online and offline prices each show little dispersion. The median price difference, reported in the fourth row of Table 3, is zero in all four countries, including the United States.

More generally, both offline and online FMCG prices in Europe appear less dispersed than in the United States. In Table 3, this applies to all except French offline prices. In Europe, unlike in the United States, at the current time, the

¹¹ Retailers compete on the price of entire baskets. They may deviate in the prices of individual products from those charged by competitors in either direction over time. Messner, Rumler and Strasser (2023) show that even in a higher-price country multi-national retailers charge lower prices for specific products than in their stores in a neighbouring lower-price country.

¹² Cavallo (2018a) makes similar observations for the offline prices of products that are also available on Amazon.

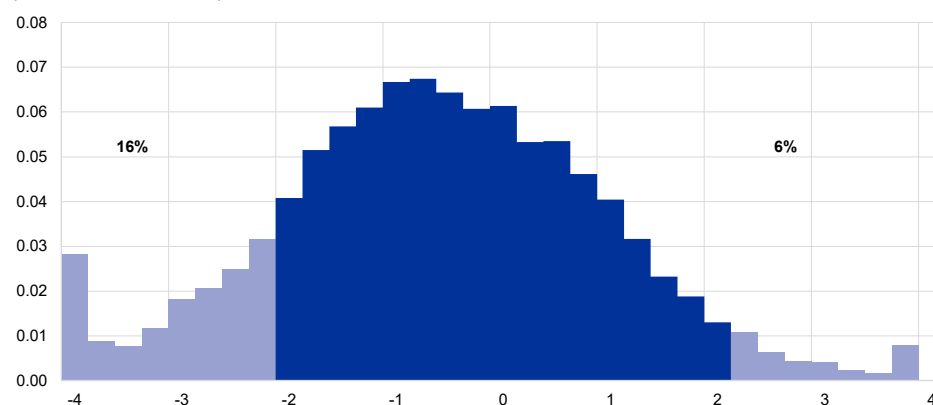
informational benefits of e-commerce in supermarket goods appear to dominate the effect of personalised pricing.

Chart 6

Distribution of mean differences between offline and online prices (France)

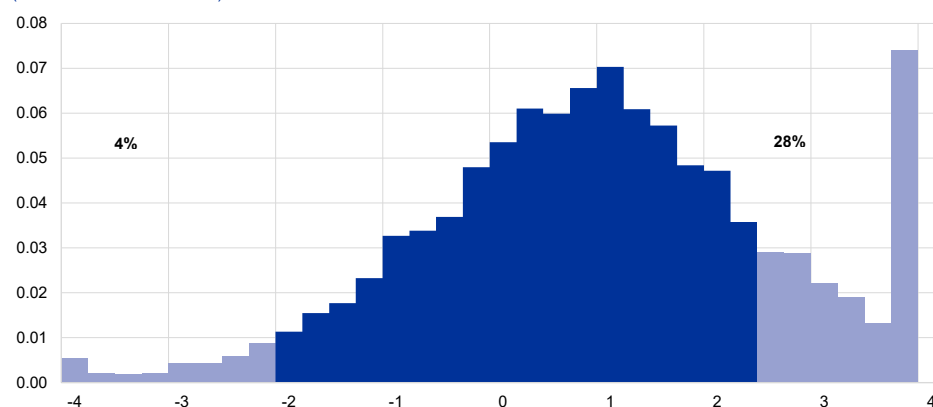
a) Retailer A

(t-statistic of mean difference)



b) Retailer B

(t-statistic of mean difference)



Source: Strasser and Wittekopf (2022) based on GfK/Kantar household panel.

Notes: Distribution of the value of the t-statistics from testing the mean difference between the offline price and the online price against the null hypothesis of no difference. Based on products present in the database for at least ten months. Transaction prices during sample period 2015-18. t-statistics exceeding 4 in absolute value reported at 4 or -4. Examples for two retailers with both online and offline distribution channels.

Within a given retailer, the online-offline price difference often goes in either direction. Chart 6 shows the distribution of the statistic from testing the hypothesis of, on average, identical online and offline prices by barcode. Both multi-channel retailers taken as examples charge, on average, substantially different prices online and offline for about one-fourth of their respective assortments. As the chart shows, within a given retailer, some prices are higher online, while others are higher offline.

Retailers follow different pricing strategies, resulting in some charging higher and others lower online prices. Strikingly, even the retailers in direct competition with each other, shown in Chart 6, differ in terms of how they price products online and offline. One of them charges higher prices online, on average, whereas the other tends to charge higher prices offline, on average. This suggests that the characteristics of the retailer, which might include the relative service level, for

example the convenience of delivery and collection options, in the online versus the offline channel, will determine the relative price more than the channel as such.¹³

Online transparency may limit offline price dispersion. Jo et al. (2019) report that, in Japan, online competition has reduced price differences between cities.¹⁴ Importantly, this finding applies only to goods subject to intense online competition and mirrors the different results for electronics in the literature review in Table 2. This cross-channel effect may also become increasingly evident in the European FMCG market. Evidence for the United Kingdom in Strasser and Wittekopf (2022), for example, hints at a trend towards more uniform pricing, both online and offline.

Overall, the trend towards lower price dispersion might increase the responsiveness of price levels to common aggregate shocks but decrease it with respect to local shocks. On the one hand, by increasing price synchronisation, uniform pricing at the retailer level means that, after a common aggregate shock, each retailer adjusts its prices nationwide in a uniform manner, rather than making staggered regional adjustments. As more uniform pricing seems to be pervasive across retailers, this trend towards more uniform prices *within* retailers might affect aggregate price indices. On the other hand, uniform pricing may hinder price adjustments in response to local conditions across jurisdictions within countries.

¹³ Ignoring such differences in service levels, the contemporaneous existence of the two mirror-inverted pricing models of Retailer A and Retailer B suggests that strategic complementarity at the product level is weak.

¹⁴ As this reduction could be due to more uniform pricing within each retailer with price differences between retailers unchanged, this observation does not establish an increase in strategic complementarity.

3 Inflation differentials

As e-commerce does not cover all parts of the economy, any currently available online inflation statistic reflects only a fraction of the official CPI.

Moreover, micro price data for online/offline comparisons are not readily available. This explains the limited number of studies of online inflation undertaken to date.

Moreover, sector-specific differences may emerge in relation to co-movements of online and offline inflation. For example, in more volatile sectors, such as unprocessed food, common shocks might result in more synchronised pass-through across online and offline retailers. In addition, product variety may differ across sectors. For example, NEIG are typically more heterogeneous than many grocery items and usually exhibit a higher number of product varieties, which complicates comparison between the online/offline channels.

3.1 Inflation based on household panel data

Online and offline inflation rates tend to be similar. An early illustration of this pattern has been provided by Cavallo (2013), showing that online prices allow for the approximation of both the level and dynamics of aggregate inflation – and even the detection of mismeasurement in the official numbers, as in the prominent example of Argentina. These early results are based on offer prices, i.e. prices scraped from websites. This section shows that this pattern describes grocery inflation in Europe well, but not the dynamics of NEIG inflation.

Table 4**Studies comparing online and offline inflation**

	Countries	Products	Retailers	Results
Cavallo (2013)	Five South American countries	FMCG	Supermarket chains	Online inflation mirrors level and dynamics of official inflation (except in Argentina)
Cavallo and Rigobon (2016)	Argentina, Brazil, South Africa, United Kingdom, Germany, Japan, euro area, United States	Broad coverage	Multi-channel retailers	Online inflation tends to anticipate offline CPI inflation
Goolsbee and Klenow (2018)	United States	Apparel, FMCG, recreation	n.a.	Online inflation lower than CPI inflation
Aparicio and Bertolotto (2020)	Australia, Canada, France, Germany, Greece, Ireland, Italy, Netherlands, United Kingdom, United States	PriceStats	-	Online price indices anticipate changes in official inflation one month in advance
Cavallo (2018b)	31 countries	Broad coverage	Multi-channel retailers	Inflation rates not correlated with overall frequency or size of price changes, but with frequency and size of price increases relative to price decreases
Cavallo (2018a)	United States	Broad coverage (Billion Price Project)	Multi-channel retailers + Amazon	Prices more sensitive to aggregate shocks (gas prices, exchange rate)

In Europe, online and offline FMCG inflation rates are closely aligned, once the online market is sufficiently mature. Chart 7 shows that, in recent years, for both France and the United Kingdom, online and offline inflation rates have become almost identical, on average.¹⁵ Even the (compared with France) larger inflation differences in the United Kingdom of up to 1 percentage point in either direction are modest compared with the overall time variation in UK inflation.

¹⁵ For the joint online-offline basket in France, for example, the online and offline annual inflation rates averaged -1.46% and -1.49% in the period 2015-18. These series are based on actual transactions and thus reflect the prices that households pay.

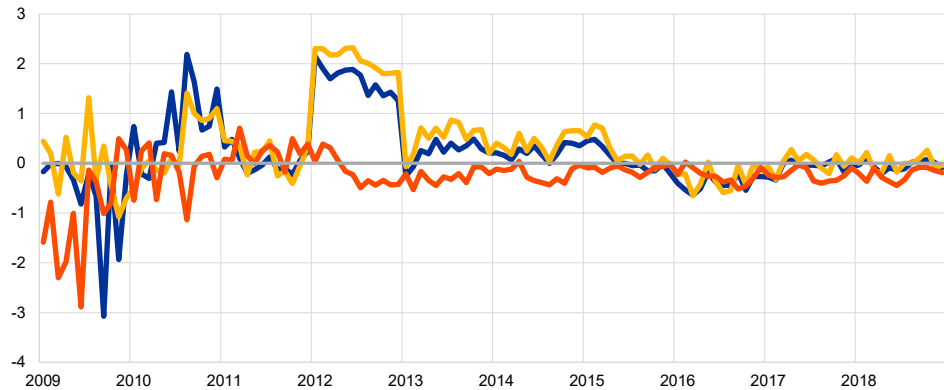
Chart 7

Difference between online and offline inflation

a) France

(differences of Laspeyres indices in percentage points, p.a.)

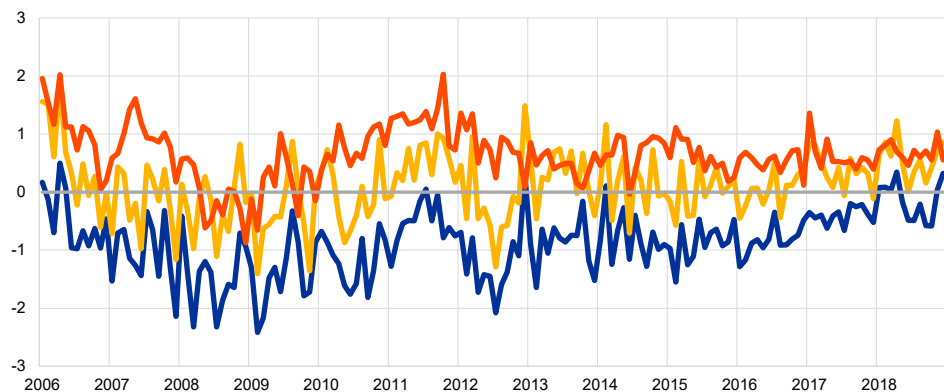
- Online basket: offline minus online inflation
- Offline basket: offline minus online inflation
- Offline basket inflation minus online basket inflation (at offline prices)



b) United Kingdom

(differences of Laspeyres indices in percentage points, p.a.)

- Online basket: offline minus online inflation
- Offline basket: offline minus online inflation
- Offline basket inflation minus online basket inflation (at offline prices)



Source: Strasser and Wittekopf (2022) based on GfK/Kantar household panel.

Notes: Year-on-year Laspeyres inflation index, calculated at monthly frequency. Excluding transactions in products without a proper global trade item number (GTIN). The baskets are as explained in the notes to Chart 6.

Online and offline inflation rates may differ while markets are still developing.

High fixed costs (combined with lower volumes) or temporary marketing discounts at early stages of market development may lead to temporarily higher online inflation as the market matures. In France, the inflation gap closed in around 2015. Before this, offline inflation had tended to be slightly higher than online inflation. In the United Kingdom, where online retail is more clearly differentiated from offline retail due to the delivery service, the inflation difference remains more volatile than in France. However, even here, the difference based on the online basket (blue line in Chart 7)

gradually approached zero and became similar to the difference based on the offline basket (yellow line).¹⁶

3.2 Inflation based on CPI online microdata

The German CPI microdata show that the inflation rate of online products is more volatile than that of offline products, while average inflation differentials are heterogeneous across sectors. Chart 8 shows the online and offline annual inflation rates by product category. The rates of online prices fluctuate more strongly in most sectors and are significantly higher, on average, for processed food and semi-durable products, as measured by the cumulative inflation rate over time.¹⁷ By the same token, the average inflation of non-durables is similar online and offline, while the online inflation of durables is lower, on average.

Online and offline inflation rates co-move strongly for processed food, but not for industrial goods. The annual rates of change for online and offline products in the food sector show a high correlation of 0.6. For industrial goods, contemporaneous correlations are rather small or even negative, although overall inflation trends tend to be more similar. For example, for both online and offline semi-durables, inflation rates decreased during 2017/2018, before increasing again from early 2019.

Overall, the online channel pushed up overall inflation slightly in Germany during the period under consideration, and added noise to the general price level. Nevertheless, the different inflation dynamics may also be partly driven by a different sample composition, since the dataset does not allow for the comparison of prices at the item level between the two channels.

¹⁶ Goolsbee and Klenow (2018) report lower online inflation in the United States in all categories except drugs and medical supplies. Overall, and in the food and beverage category in particular, their online inflation rate is on average 1.2 percentage points per year lower than the CPI. One reason for this finding may be their broad coverage of product categories, for many of which the online market was still rapidly emerging during the sample period 2014-17.

¹⁷ For processed food, the annual cumulative rate of change from 2015 to 2019 is 5.1% for online products and 3.3% for offline products. For semi-durables, the cumulative rate of change is 7.7% for online products and -0.4% for offline products.

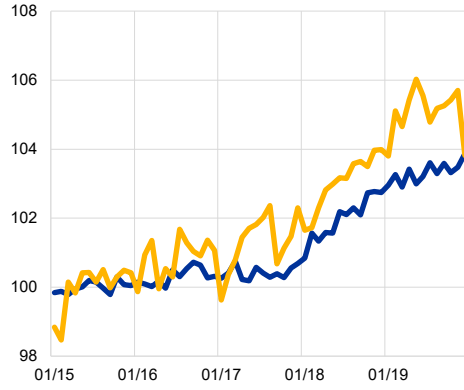
Chart 8

Online and offline inflation derived from German CPI microdata

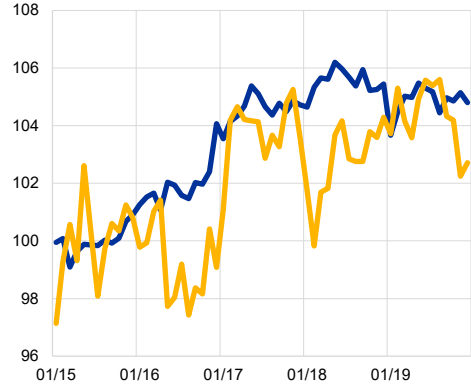
a) Index

(2015 = 100)

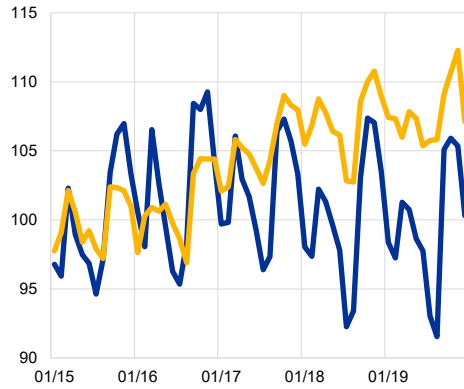
■ Processed Food Offline
■ Processed Food Online



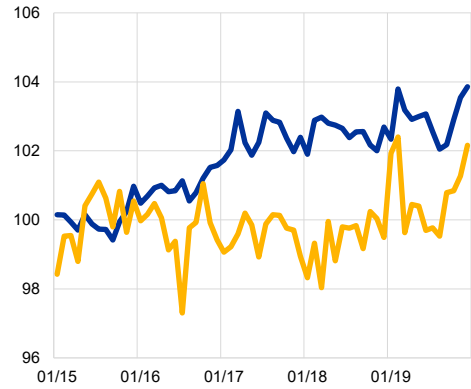
■ NEIG (non-durables) Offline
■ NEIG (non-durables) Online



■ NEIG (semi-durables) Offline
■ NEIG (semi-durables) Online



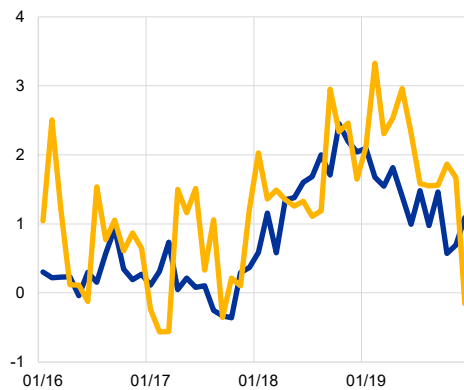
■ NEIG (durables) Offline
■ NEIG (durables) Online



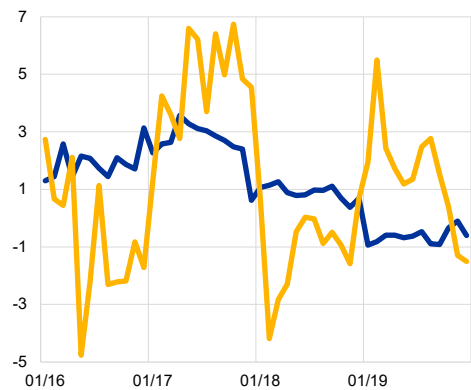
b) Year-by-year

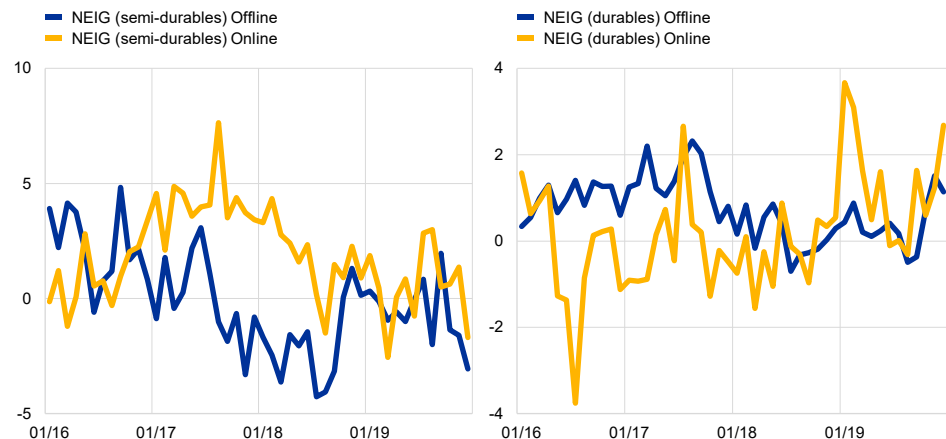
(year-on-year percentage changes)

■ Processed Food Offline
■ Processed Food Online



■ NEIG (non-durables) Offline
■ NEIG (non-durables) Online





Source: Bundesbank staff calculations based on German CPI microdata.
 Notes: "Online" denotes the "internet trade" outlet type and "offline" all remaining stationary outlet types. The statistics are derived at the level of 270 online/offline products (COICOP ten-digit level) which are consistently available from 2015M1 onwards. The average price by product is aggregated to a given product category and channel using the corresponding 2015 expenditure and outlet-type weights. The correlation coefficient between online and offline annual rates is 0.59 for processed food, 0.19 for non-durables, -0.07 for semi-durables and -0.02 for durables.

3.3 Inflation based on web-scraped prices and nowcasting the official CPI

Nowcasts based on online prices processed in real time tend to anticipate official inflation. Aparicio and Bertolotto (2020) and Cavallo and Rigobon (2016) document this for a large set of countries. Macias et al. (2023) show this for web-scraped food prices in Poland.

This and the next section explain in detail the procedure and caveats for inflation nowcasting with online prices. Until recently, online food retail has been a niche market, and even now its market share is small compared with its offline counterpart.

We compare web-scraped prices from 22 Polish stores with the prices at bricks-and-mortar stores collected for the Polish CPI. The focus is again on FMCG product categories (food and non-alcoholic beverages, personal care), with the addition of clothing, footwear, pharmaceutical products and restaurants.¹⁸ The offline database covers the period from January 2000 to December 2018, and contains over 66.4 million prices for 4,180 various products, each collected in 300 to 500 points of sale.¹⁹ Ensuring the comparability of prices between these two sources, we select approximately 360 million quotations of online prices for 2.4

¹⁸ Prices in online stores are collected by Narodowy Bank Polski via web-scraping techniques. The individual prices quoted in physical stores across Poland are taken from the CPI database by Statistics Poland. The CPI database and its respective weighting scheme has been used in the calculations.

¹⁹ The analysis is carried out for several COICOP groups, namely food and non-alcoholic beverages (CP01), clothing (CP03.1), footwear (CP03.2), pharmaceutical products (CP06.1.1), restaurants, cafés and the like (CP11.1.1), and other appliances, articles and products for personal care (CP12.1.3). Different excerpts from the database are used for different analyses, e.g. for food inflation tracking and nowcasting a selection of eight stores is used, whereas for the price stickiness analysis below, the full sample is employed.

million products from 22 stores²⁰ and approximately 34 million prices for 1,532 products from the Statistics Poland database.

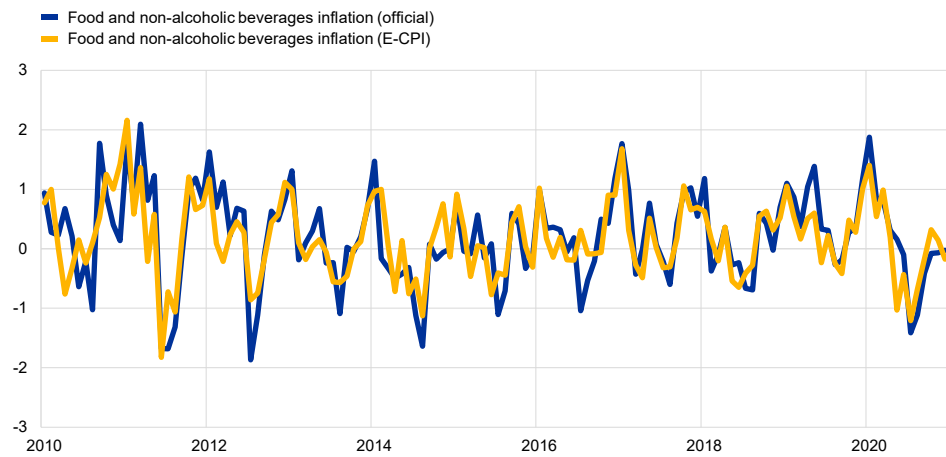
The accurate classification of products and application of the official product weighting scheme are prerequisites for the replication of aggregate CPI data with web-scraped data. Box 2 shows that naively using all available food prices and disregarding the official weighting scheme returns an index which barely resembles the official CPI. For example, monthly online food inflation does not reflect the strong seasonal pattern observed in the official data.

Chart 9

Comparison of official CPI and online prices

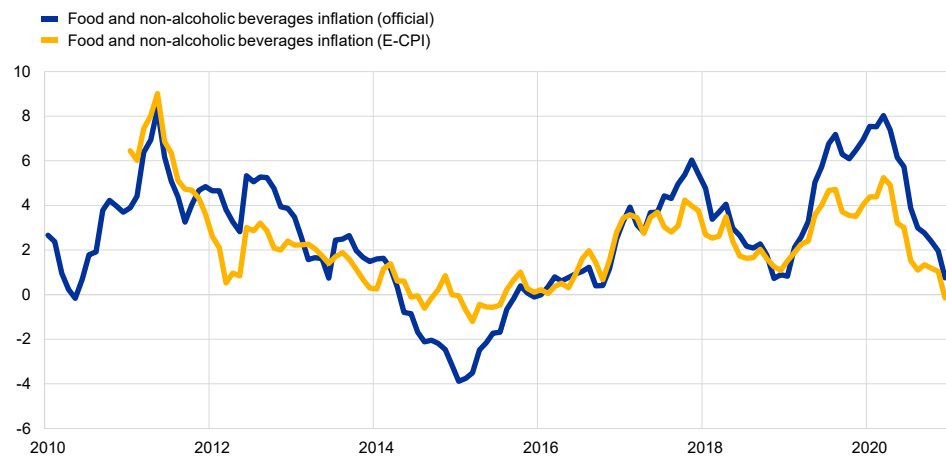
a) Month-on-month

(percentages, based on official product selection and aggregation)



b) Year-on-year

(percentages, based on official product selection and aggregation)



Sources: Statistics Poland, NBP and NBP calculations.

²⁰ The data used in the analysis differ in the time range. However, the calculated statistics are not sensitive to the time range and are thus a good indicator of the differences in the pricing mechanisms between offline and online stores.

Prices from Polish offline and online stores generally maintain similar

tendencies. Once we classify products carefully and apply comparable basket weights to both online and offline prices, Polish online and offline inflation are closely related. The web-scraped prices thus resemble our findings based on the household panels of France and the United Kingdom in the previous subsection. Chart 9 compares the monthly and annual rates of change in the official CPI for food and non-alcoholic beverages (blue line) with its counterpart based on online prices (i.e., E-CPI, yellow line). The short-term price dynamics in offline and online stores are very similar (panel a). Over longer horizons, for example for the yearly inflation measure shown in the panel b), some differences remain. The annual online index – being based on a much larger dataset – is less volatile than aggregate CPI inflation.

Despite the high correlation between online and offline inflation, evidence on the usefulness of online prices for forecasting inflation remains scarce.

One exception is Aparicio and Bertolotto (2020), who use scraped data from July 2008 to September 2016 for ten advanced economies to show that online prices help with the forecasting of headline inflation in the short term, particularly when considering parsimonious models.

Online prices are useful for nowcasting monthly food inflation, even in emerging economies where the e-commerce markets are not fully developed.

Box 1 follows the methodological approach of Aparicio and Bertolotto (2020) and complements their analysis in several aspects.

Box 1

Nowcasting food inflation with online prices²¹

We employ an extensive dataset of online food and non-alcoholic beverages prices, gathered automatically from the webpages of major online retailers in Poland since 2009. Next, we establish a real-time nowcasting experiment using popular, simple, univariate approaches (Table A). We perform recursive estimation on the sample spanning the period December 1999 to December 2016 and assess the quality of the nowcasts for the evaluation period January 2017-December 2020 using the mean forecasting error (MFE) and the root mean squared forecasting error (RMSFE). Moreover, we compare the accuracy of the nowcasts with the Diebold and Mariano (1995) test.²²

Online prices are extremely useful in food inflation nowcasting. Table B presents the outcomes of our analysis. The results indicate that incorporating information on online prices, even into simple model-based frameworks, delivers a substantial increase in the nowcast accuracy of food inflation with respect to most competing approaches. Specifically, we report that our recursively optimised model (EC^{SX}) outperforms the random walk models as well as the best Seasonal Auto-Regressive Moving Average (SARMA) model by a wide margin (approximately 34-44% in terms of RMSFE), a change statistically significant at the 1% level, while maintaining a very low bias. Moreover, this framework also beats the judgemental nowcast, with the difference in accuracy significant at the 10% level. We also show that approximating food inflation in the nowcast by the pure change in

²¹ This section is based on Macias P. et al. (2023). See also Section 3.2 of Henkel et al. (2023) for an analysis of this dataset in the context of the COVID-19 pandemic.

²² In this section we report only the results for CPI food and non-alcoholic beverages inflation. Macias et al. (2023) report the results of the nowcasting competition for a larger number of highly disaggregated food inflation components.

online prices (EC^{RT}), at least when the data are properly treated, provides a reduction in the RMSFE of 29-39% by comparison with traditional benchmarks. This result should encourage forecasting practitioners at central banks, as it shows that, after only several months of data collection, online prices can successfully be used to adjust the nowcast before reliance on model-based approaches becomes possible. It also demonstrates that online and offline prices develop in a fairly similar way. As regards model combinations, our results provide a conclusion that contradicts the consensus established in the literature. We report that combining nowcasts from all possible models with equal weights delivers inferior results. However, this outcome is driven by our very rigorous selection of the best performing model.

Table A
Models entering the nowcasting competition

Abbreviation	Short description of the model
EC^{SX}	The best Seasonal Auto-Regressive Moving Average with exogenous factors (SARMAX) model with online prices treated as an exogenous variable. The best specification is chosen using the RMSFE criterion calculated on a pseudo-validation set. In total, 256 models varying in the lag structure are considered.
EC^{RT}	The pure, real-time nowcast of the change in online prices calculated with readily available online prices. To mimic the methodology by the statistical office, only prices from the first half of the month are considered.
$EC^{SX'}$	The EC^{SX} model estimated on a dataset with products selected and classified according to simple dictionary rules.
$EC^{RT'}$	The EC^{RT} model estimated on a dataset with products selected and classified according to simple dictionary rules.
RW	A simple random walk model for the monthly inflation.
AO	The Atkeson and Ohanian (2001) random walk model adjusted by a seasonal factor to account for seasonal patterns.
BS	The best SARMA model without online prices. The best specification is chosen using the RMSFE criterion calculated on a pseudo-validation set. In total, 64 models varying in lag structure are considered.
JD	Nowcast prepared internally by an expert for in-house purposes.
BS^{MC}	The equal weight combination of nowcasts from all BS models.
EC^{MC}	The equal weight combination of nowcasts from all EC^{SX} models.

Source: Macias et al. (2023).

Note: Table A summarises the models entering the nowcasting competition in Macias et al. (2023).

Table B
RMSFE and MFE statistics of the competing models

		Frameworks with online prices				Traditional benchmarks			Judgemental nowcast	Forecast combinations	
		EC^{SX}	EC^{RT}	$EC^{SX'}$	$EC^{RT'}$	RW	AO	BS	JD	BS^{MC}	EC^{MC}
Whole sample	RMSFE	0.338	1.082	1.299**	1.400***	1.784***	1.528***	1.524***	1.144*	1.621***	1.181**
	MFE	0.018	-0.093	0.036	-0.117	0.042	0.118	0.111	0.021	0.134	0.025
COVID-19 period	RMSFE	0.340	1.332	1.446	1.504	1.567	1.575	1.902	0.965	2.048	1.411
	MFE	0.146	-0.078	0.238	-0.076	0.084	0.362	0.394	0.147	0.394	0.212

Source: Macias et al. (2023).

Notes: Table B reports the outcomes of the nowcasting exercise performed using recursive window estimation. Results are reported for food and non-alcoholic beverages inflation. Nowcast errors are calculated for the whole sample evaluation period (January 2017–December 2020) as well as the COVID-19 period (January 2020–December 2020). For each evaluation sample, RMSFE statistics for EC^{SX} are reported in levels, whereas for the competing models they are reported as ratios, with the value above (below) 1 indicating that the competing model produces on average less (more) accurate food inflation nowcasts than EC^{SX} . For the whole sample evaluation period a two-sided Diebold and Mariano (1995) test has been performed (for the COVID-19 period it has not been conducted due to the low number of observations). Asterisks correspond to the outcomes of this test, where *** denotes significance at the 1% level, ** denotes significance at the 5% level and * denotes significance at the 10% level. All MFE statistics are reported in levels (a negative value indicates that the nowcast is on average overestimated).

Online prices proved to be especially helpful in nowcasting food inflation during the COVID-19 pandemic. The nowcast precision of the EC^{SX} model presented in Box 1 is an improvement on the traditional approaches following the outbreak of the COVID-19. Specifically, models that rely heavily on the seasonality in

the series perform very poorly, in terms of both nowcast accuracy, measured by the RMSFE, and bias. Conversely, the EC^{SX} model remains as accurate as in the whole sample, although the bias also rises somewhat.

Employing a precise classification of products is of paramount importance for nowcast quality. Our experiments with data curation show that only human supervision of the classification process guarantees virtually perfect assignment of products into respective groups. Such classification accuracy is vital, and dispensing with this step is detrimental to nowcast quality. When an approximate method of product classification is considered (based on the dictionary approach), the RMSFE statistics for food and non-alcoholic beverages inflation rise by 30% to 40%, depending on the approach considered.

Box 2

Online and offline CPI food inflation with web-scraped prices

Prices from offline and online stores generally maintain similar tendencies. Consequently, there should be no notable difference in inflation rates. Having said that, there may be differences, in the short term, between the traditional price indices and those compiled based on data from online stores. Both monthly and annual rates of change in food and non-alcoholic beverages prices are the most comparable between the offline and online channels. However, for this to be true, the products should be carefully selected to reflect the official basket of goods developed by the statistical office. This is well exemplified in Chart A, which illustrates the comparison between the monthly and annual rates of change in the official consumer price index (CPI) for food and non-alcoholic beverages inflation (blue line) and its counterpart based on online prices (i.e., E-CPI, yellow line). Panels a and b clearly show that using information on the prices of all available food products and discarding the official weighting scheme provides a highly inaccurate approximation of the official CPI. For example, monthly online food inflation does not reflect the strong seasonal pattern observed in the official data. Moreover, the annual rate of change develops independently of the official measure. Meanwhile, relying on an approximate classification of products into respective groups along with the official weighting of products (panels c and d) reduces the discrepancy between the two measures of inflation, and the seasonal pattern is still ineffectively pinned down.

Once an accurate classification of products is employed, along with the official weighting of products, the tracking properties of online prices improve by a significant margin. Panel b) of Chart 9 in Section 3.3 shows that some discrepancies are still discernible for the yearly inflation measure. In the short term, offline and online stores have similar price dynamics, usually in the case of groups characterised by high price volatility (i.e. unprocessed food). We attribute this phenomenon to the fact that, in the presence of a common shock, competitive market retailers are forced to change the price in a coordinated manner. In the case of moderate price swings, individual differences between retailers become more important (i.e. different suppliers, contracts and pricing policies).²³

In contrast, non-energy industrial goods (NEIG)²⁴ are more heterogeneous and usually have numerous product varieties. As a result, it is far more difficult to track the prices of the same items

²³ See also Box 1 in Henkel et al. (2023) on heterogeneous pricing behaviour across outlet types in the German CPI during the COVID-19 pandemic.

²⁴ We present here the results for clothing, footwear, cosmetics, and pharmaceutical products.

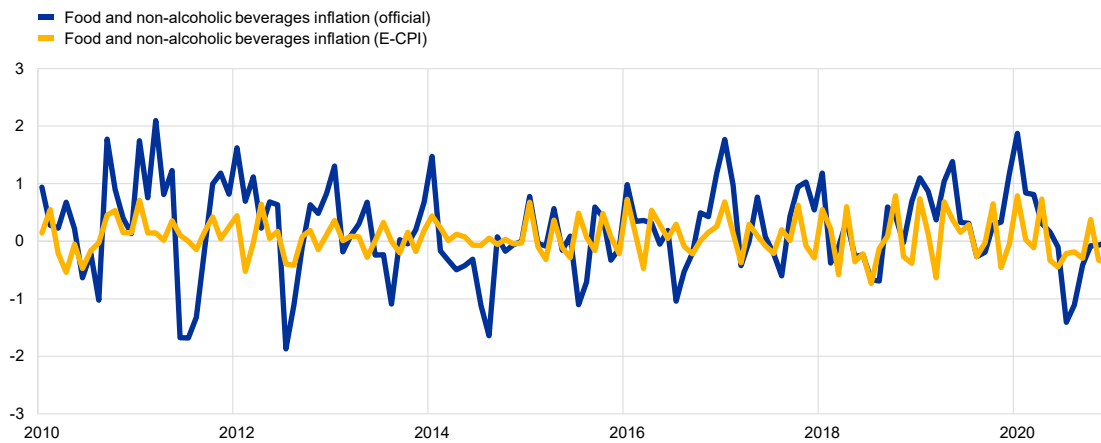
as the statistical office. Consequently, differences in price dynamics may emerge. Product varieties may also be more diverse across store types for NEIG, which affects estimates (e.g. a large chain store selling apparel offers different products from those of a small, local retailer, and may use specific price strategies).

Chart A

Comparison of the official CPI with online prices

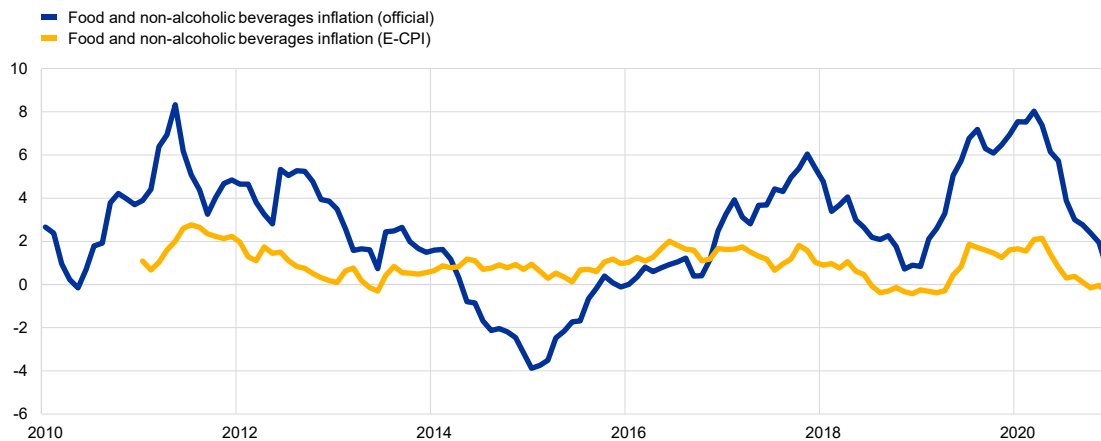
a) No product selection

(month-on-month, percentages)



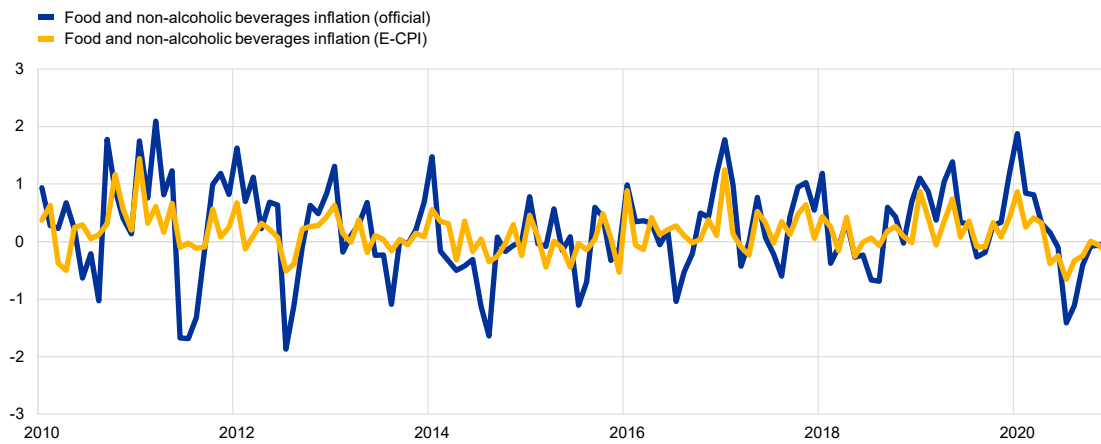
b) No product selection

(year-on-year, percentages)



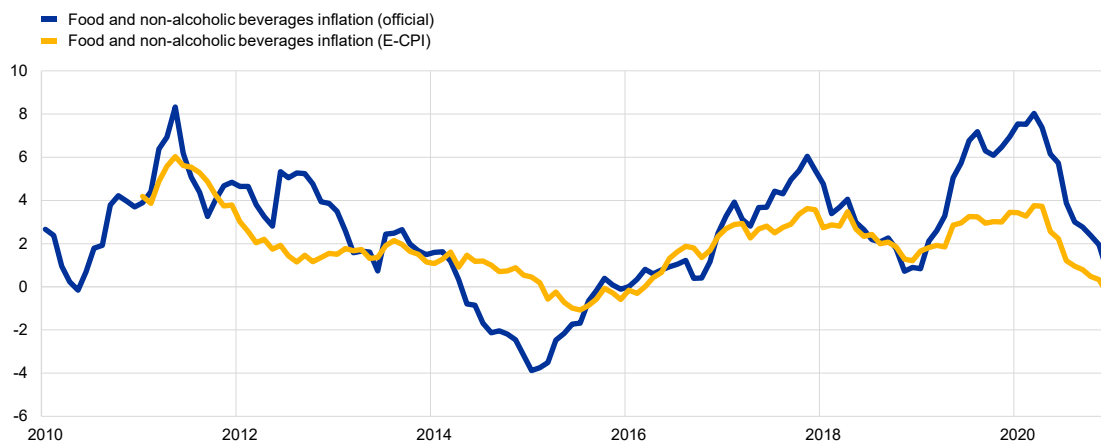
c) Simple selection and official aggregation

(month-on-month, percentages)



d) Simple selection and official aggregation

(year-on-year, percentages)



Sources: Statistics Poland, NBP and NBP calculations.

4 Price flexibility

The automated posting of prices and – potentially – automated responses to changes in competitor prices, inventory, demand and costs, suggest that online prices might respond faster to such developments. In other words, online prices might be more flexible than offline prices. This section compares price stickiness between bricks-and-mortar and online stores.

Studies on multi-channel retailers find no substantial difference between online and offline price flexibility. Both the frequency and the size of price changes are similar online and offline (e.g. Cavallo, 2017; Bonomo et al., 2020).

The prices of online retailers without an offline presence, however, tend to change more often than those of offline retailers. Most studies report a higher price change frequency online. However, whereas the frequency of these price changes is higher, they are similar in size to offline changes (Gorodnichenko et al., 2018) and dominated by small changes (Hillen and Fedoseeva, 2021). The next section shows, based on German CPI data, that in the euro area online prices also change more often than offline prices, but by smaller amounts.

Table 7
Studies on online price flexibility

	Countries	Products	Retailers	Results
Cavallo (2017)	10 countries (incl. Germany, United Kingdom)	Broad coverage	Multi-channel retailers	Frequency and size of price changes similar, but not synchronised
Cavallo (2018b)	31 countries	Broad coverage	Multi-channel retailers	Time averaging and price imputation in CPI and scanner data cause spurious smaller price changes and short durations
Cavallo (2018a)	United States	Broad coverage (Billion Price Project)	Multi-channel retailers + Amazon	Online competition raised frequency and size of price changes
Bonomo et al. (2020)	Israel	Food	Multi-product retailer	Frequency and size of price changes similar
Gorodnichenko et al. (2018)	United States, United Kingdom	Broad coverage of categories (incl. furniture, garden equipment, etc.)	Online-only and multi-channel retailers (online price comparison site)	Price change frequency online higher, size similar
Gorodnichenko and Talavera (2017)	United States, Canada	Software, electronics, tools, computer parts, photo	Online-only and multi-channel retailers (online price comparison site)	Online prices more flexible
Hillen and Fedoseeva (2021)	United States	Food	Amazon Fresh	Frequent, but mostly small price adjustments
Lünnemann and Wintz (2011)	France, Germany, Italy, United Kingdom, United States	Items typically sold over internet		Online prices not more flexible overall, but more flexible in Germany

Price changes seem to occur online and offline almost simultaneously. The contemporaneous correlation between FMCG offline and online prices is well above 60% in both France and the United Kingdom. The high correlation might explain the

smaller price changes in FMCG shown later in this section, as online prices, despite their frequent changes, mimic some of the more inertial adjustment of offline prices. In the United Kingdom, any price change in one channel is reflected in the other almost instantaneously. Chart 10 shows a correlation of less than 30%, at a time offset of only two months. Despite referring to the cross-correlation for the entire FMCG market, the pattern in Chart 10 is in line with the evidence of Ater and Rigbi (2023) that information transparency tends to synchronise price changes within a chain, which then, in turn, reduces contemporaneous price dispersion. In France, shown in the panel a), the decay is slower, suggesting that some price changes (e.g. sales) persist for longer in one channel than in the other.

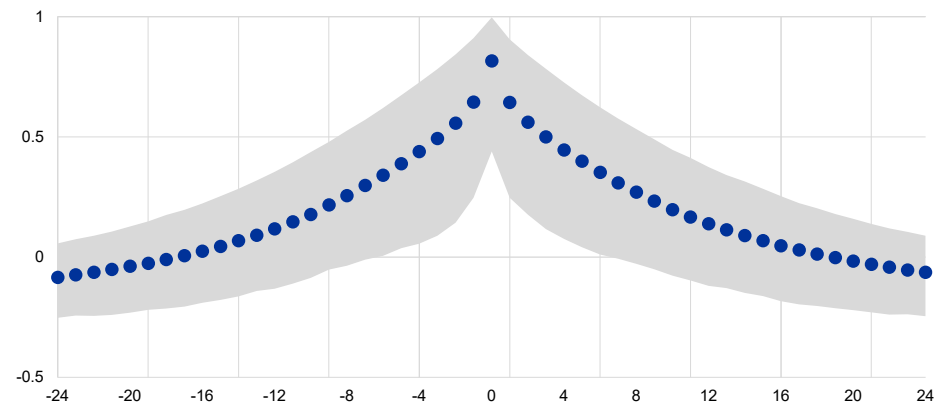
For the FMCG products in our sample, there is no lead-lag relationship between online and offline transaction prices. Chart 10 shows the cross-correlation function between online and offline prices. Both panels, a) for France and b) for the United Kingdom, are largely symmetric. This means that prices are not changed faster in either of the two channels, and, in particular, that online prices are not leading offline prices.

Chart 10

Lead-lag cross-correlation (common barcodes, 2013-18)

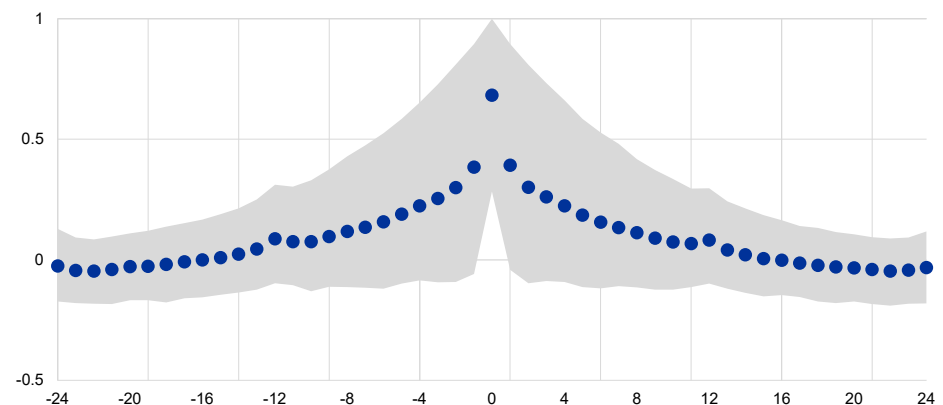
a) France

(offset in month online-offline, cross-correlation of price online and price offline)



b) United Kingdom

(offset in month online-offline, cross-correlation of price online and price offline)



Source: Strasser and Wittekopf (2022) based on GfK/Kantar household panel.

Notes: Averages of correlations of median prices calculated by product. Interdecile range shaded in grey. Only common barcodes which are in the sample every month from 2013 to 2018. Only barcode months with at least three offline and at least three online transactions.

4.1 Online price setting in Germany

This section²⁵ quantifies the degree of price rigidity of online versus offline prices in Germany. As described in Section 1.2, this analysis is based on German CPI microdata recently made available for research purposes and has been analysed in terms of relative price trends by Adam et al. (2022) and price setting in the euro area by Gautier et al. (2022).²⁶

²⁵ This section closely follows Wieland and Menz (2022).

²⁶ The dataset is provided by the Research Data Centre (RDC) of the Federal Statistical Office and statistical offices. See "Verbraucherpreisindex für Deutschland", EVAS 61111, 2010-19, DOI: <https://doi.org/10.21242/61111.2010.00.00.3.1.0> to <https://doi.org/10.21242/61111.2019.00.00.3.1.0>.

The frequency of price changes in Germany appears to be higher for online than offline products, also when controlling for the share of underlying sales.

On the basis of a product-by-product comparison, we find evidence of lower menu costs for online prices, with internet price quotes changing more often, but by less than offline price quotes. The feature of higher frequency of online price changes turns out to be quite stable throughout our five-year sample. Nevertheless, the monthly pattern of the frequency and size of price changes for internet stores is more volatile (non-seasonal) than for offline stores.

Breakdowns by outlet type and internet trade are rarely available within CPI microdata.

The German CPI micro dataset distinguishes between up to eight different outlet types (including, for example, discounters, supermarkets and internet trade). The weighting scheme by outlet type is applied to about one-third of the CPI basket at the lowest level of product definition, and mostly covers goods. These outlet-type weights are derived from various sources, such as official trade statistics and market research data on turnover distribution in the retail trade.²⁷

Our definition of online and offline stores is in line with the official weighting scheme of the German CPI.

As described in Section 1.2.3, we identify online products in the German CPI micro database as prices collected for the “internet trade” outlet type, whereas offline products correspond to prices collected for the remaining stationary outlet types. Accordingly, the analysis in this section is again based on roughly 290 product groups, for which prices were collected in both online and offline stores²⁸ during the years 2015-19.²⁹

In measuring nominal price rigidity, we follow the approach of Gautier et al. (2022) and compute price changes at the individual product item level for a given (regional) store.

This yields more than 500,000 unique online/offline product items over time, with online items representing one-fourth of observations. We then compute the share of individual price changes in the total number of price quotes for a given product (e.g. “women’s sport shoes”). To aggregate statistics by product category, we apply the German CPI weights as of 2015. Finally, like Gautier et al. (2022), we distinguish between price changes with and without sales and promotions. For this purpose, we use an indicator variable on sales in the database provided by the statistical office. Our baseline case covers all price changes, i.e. including sales.³⁰

²⁷ The lowest product definition in the German CPI is the COICOP (Classification of Individual Consumption According to Purpose) ten-digit level, e.g. “9.1.2.1.13100 - Digital Camera”. See Destatis (2021) for a detailed description of the underlying CPI methodology.

²⁸ Our German CPI micro dataset includes monthly observations in the period 2015-19, with roughly eight million price quotes per year covering more than 80% of the German CPI basket. As described in Section 1.2.3, the common online-offline product categories represent about 16% of the expenditure share of the German CPI.

²⁹ Given the peculiarities of price collection during the COVID-19 pandemic, we have excluded the pandemic year 2020 from the analysis. See also Box 1 in Henkel et al. (2023) for a discussion of price rigidity by outlet type based on German CPI microdata during the years 2020/2021.

³⁰ See Gautier et al. (2022) for more details on the computation of price rigidity measures. Note that we do not consider product substitutions (replacements) in our analysis.

4.1.1 Frequency of price changes

Nominal price rigidity appears to be lower for online than for offline NEIG. As shown in Table 8, the frequency of price changes is higher for online products across all three main categories of NEIG. This evidence is noteworthy for semi-durable goods (such as clothing and recreational items) as well as non-durable goods (such as personal care products and stationery). One exception is the “processed food” category, in which online products mainly include frozen food and alcoholic beverages. As shown in Chart 4, supermarkets make up 40% of this product category. With a relatively high share of sales, it makes a substantial contribution to the higher price flexibility of offline food products. The finding of generally lower online price rigidity still holds when we exclude price changes due to sales; when controlling for sales, both online and offline price flexibility measures are similar for “processed food”.

Online products are, on average, more expensive than offline products. Conversely, offline products have a higher share of sales than online products. With regard to the average price level, we find that, apart from the high-price category “NEIG – durables”, online products are, on average, more costly than their offline counterparts.³¹ The online/offline price ratio for “processed food” is the highest, at 2.3. This could point to both quantitative and qualitative differences between the online and offline products in our sample, although our database does not contain any product descriptions and therefore does not allow for the matching of individual product items between the two markets.³²

Table 8
Frequency of price changes, share of sales and average price

Period 2015-19

(percentages, unless otherwise indicated)

Product category	Frequency (including sales)		Frequency (excluding sales)		Percentage of sales		Average price (in EUR)	
	Online	Offline	Online	Offline	Online	Offline	Online	Offline
Processed food	5.6	8.9	4.1	4.2	1.2	3.6	10	4
NEIG (non-durables)	19.2	9.1	17.6	6.5	1.7	2.8	13	8
NEIG (semi-durables)	21.9	12.8	12.4	3.5	13.3	14.4	61	50
NEIG (durables)	19.4	12.7	16.8	9.2	2.9	5.5	511	920
Total	16.7	11.1	12.9	6.1	4.7	6.6	181	305

Source: Bundesbank staff calculations based on German CPI microdata.

Notes: “Total” refers to the four product categories of “processed food” and “NEIG”. The statistics are derived at the level of 288 online/offline products (COICOP ten-digit level) and aggregated to a given product category based on the corresponding 2015 expenditure share in the German CPI. The sample period covers 2015-19.

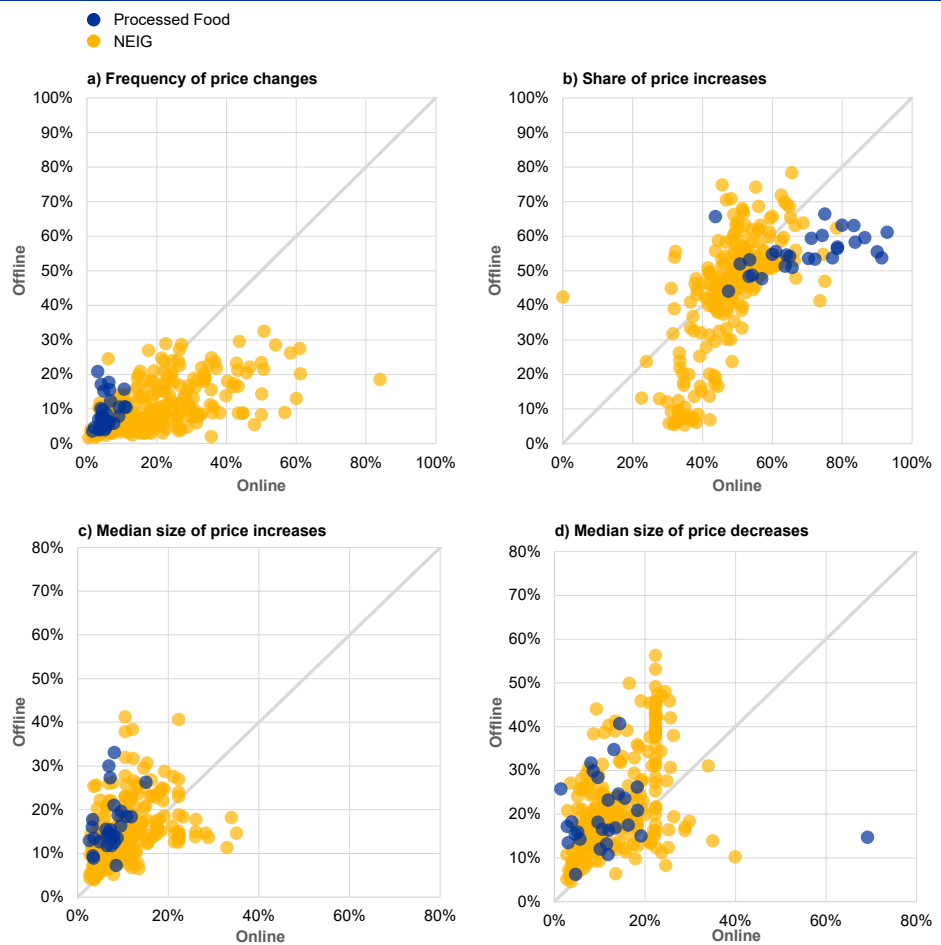
³¹ This is in line with Section 2.1, which finds that online FMCG delivered to the home are, on average, more expensive than offline products.

³² Note that delivery costs are not included in the online price, since this component enters the product category “08.1 – Postal and Parcel Services” in the German CPI separately. Concerning the quantity of a given product item, the German CPI database only indicates whether there has been a change over time, while the quantity of the product in the base period is unknown.

No clear-cut differences emerge between online and offline markets in terms of the share of price increases. Chart 11 shows the average frequency and share of price increases, as well as the median price increase and decrease for about 290 products in the period 2015-19. As indicated by the 45-degree line, we find only very few offline products with larger frequencies than their online counterparts, with the bulk of these products belonging to the “processed food” category (red dots in Chart 11). In the case of “processed food” alone, the share of price increases seems to be higher for online products.

Chart 11

Frequency and size of price changes in the German CPI



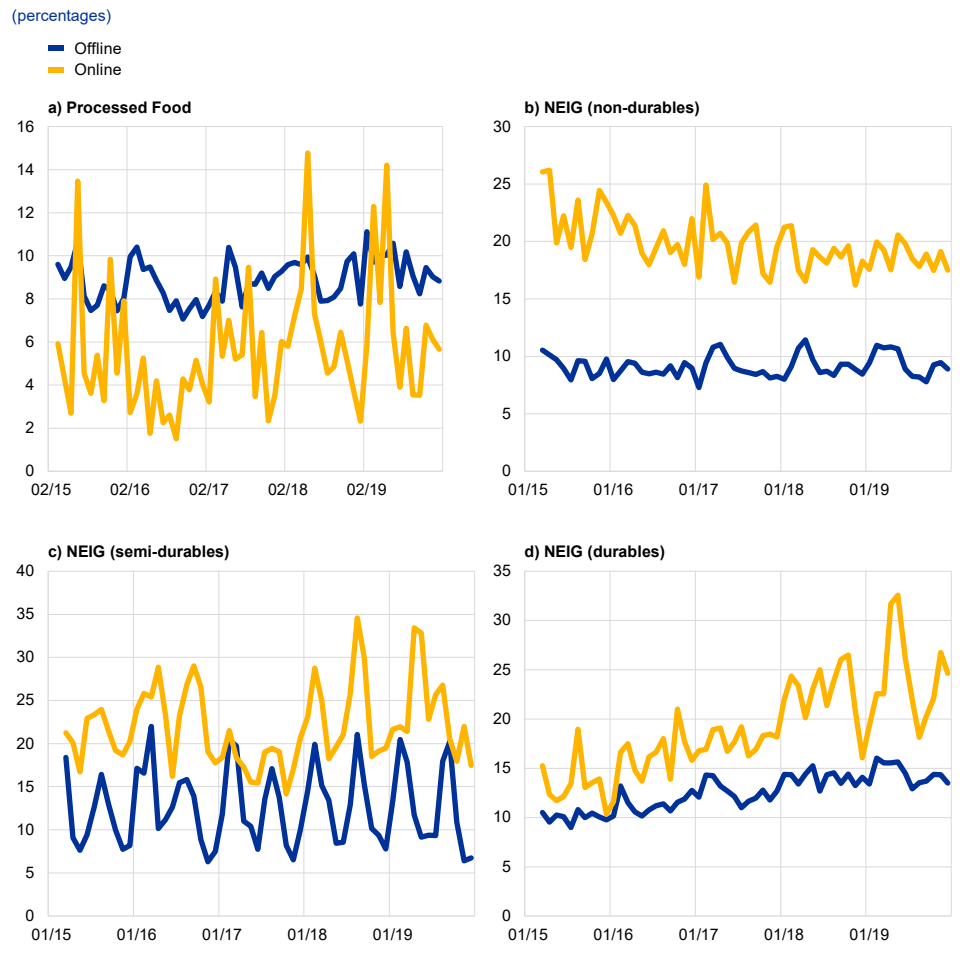
Source: Bundesbank staff calculations based on German CPI microdata.

Notes: The statistics are derived at the level of 288 online/offline products (COICOP ten-digit level) and aggregated to a given product category based on the corresponding 2015 expenditure share of the German CPI. The sample period covers 2015-19.

The frequency of price changes of online products has been consistently higher over time than those of offline products. Chart 12 shows the monthly frequency of price changes from February 2015 to December 2019 by the four main product categories. Throughout the sample, the difference between online and offline products is quite stable. One exception are online products in the “NEIG – durables” category, where the frequency has risen more dynamically than for their offline counterparts. Moreover, the frequency of price changes seems to be more volatile for online products, notably for the “processed food” and “NEIG – non-durables”

categories. The highest co-movement between online and offline products in terms of the seasonal pattern is found for “NEIG – semi-durables”, which latter contains seasonal items, such as clothing and footwear. This is reflected in Chart 12 by a higher share of price changes around the beginning and middle of the year for both online and offline products.

Chart 12
Frequency of price changes over time



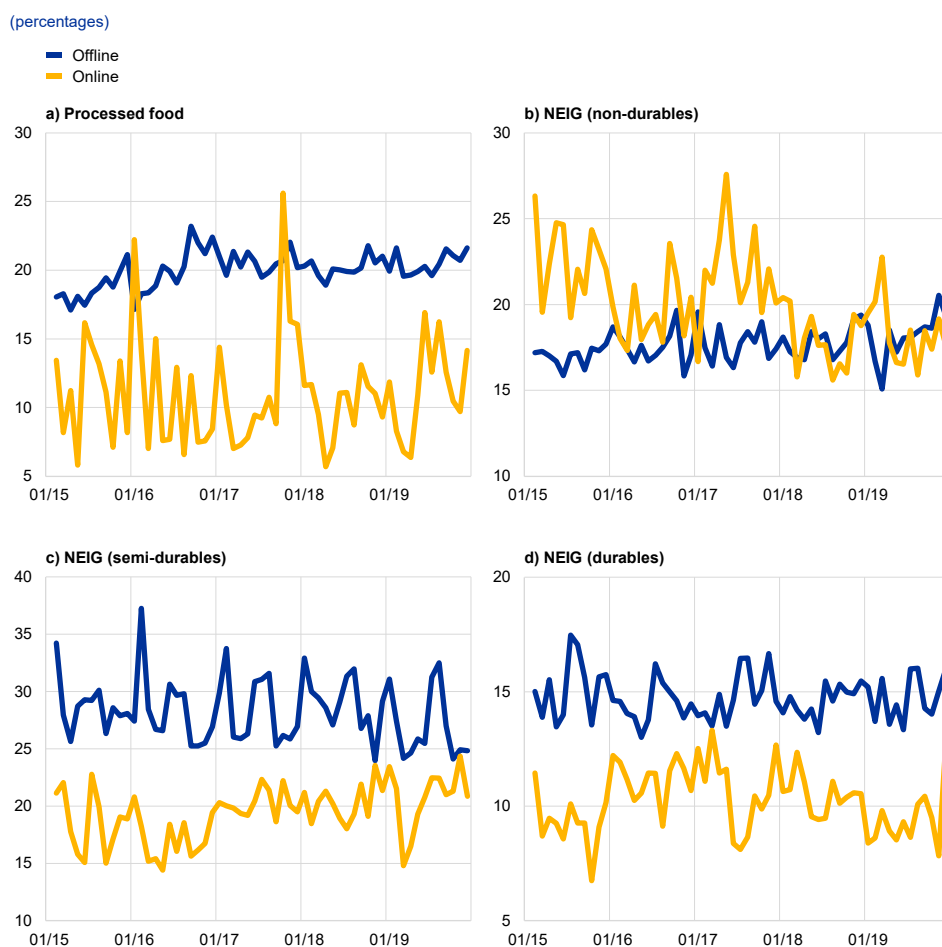
Source: Bundesbank staff calculations based on German CPI microdata.
Notes: The statistics are derived at the level of 288 online/offline products (COICOP ten-digit level) and aggregated to a given product category based on the corresponding 2015 expenditure share of the German CPI.

4.1.2 Size of price changes

The median size of price increases and decreases point to larger price changes for offline products. Panels c) and d) of Chart 11, which is based on the sample period 2015-19, reflect this: Most of the observations are above the 45-degree line, implying a higher magnitude of price cuts and increases in the offline market.

Chart 13

Average absolute size of price changes over time



Source: Bundesbank staff calculations based on German CPI microdata.

Notes: The statistics are derived at the level of 288 online/offline products (COICOP ten-digit level) and aggregated to a given product category based on the corresponding 2015 expenditure share of the German CPI.

Over time, price changes for online products have again been generally smaller, but appear more volatile than for offline products. As depicted in Chart 13, the average absolute price change is lower for online products in most product categories, with the difference between online and offline price changes being relatively stable over time. One exception is the lower-price category, “NEIG – non-durables”, where absolute online price changes are relatively high at the beginning of the sample and seem to converge to the level of offline price changes over time. This could reflect a convergence between online to offline price setting within this product category, assuming that internet trade for lower-price goods, such as personal care products and stationery, has increased since base year 2015.

The volatility in online products does not seem to be generally related to seasonality. One exception is semi-durables, which contain seasonal items, such as clothing and footwear. Here, large price cuts can be observed at the beginning and middle of the year for both online and offline products, contributing to a strong synchronisation between the two channels.

Overall, the higher frequency, together with smaller price adjustments, is consistent with lower menu costs for online markets. In online markets, prices change more often, but by less, than in offline markets.

4.2 Online price setting in Poland

This section quantifies the degree of price rigidity of online versus offline prices in Poland. As described in Section 3.3, this analysis is based on the prices of about two million products scraped from 22 online stores between 2010 and 2020 and on the prices of about 1,500 products recorded in the Polish CPI microdata.

The analysis shows that in Poland, also, prices of food, non-alcoholic beverages and pharmaceutical products, as well as products in restaurants, cafés and the like, have similar properties in offline and online stores. For NEIG, prices in online stores are less sticky, mainly due to a higher share of sales.³³

4.2.1 Frequency of price changes

In some product categories, namely groceries, pharmaceutical products and food services, the frequency of price changes in physical and online stores is similar. Around 28.6% of food prices change every month in the offline channel, compared with 27.7% in online stores (Chart 14). In particular, fruit and vegetable prices are most volatile, presumably because the supply of these goods is largely determined by weather conditions, while demand is relatively stable (Table 9). The frequency of offline and online price changes for pharmaceutical products is 22.6% and 25.9%, respectively. In turn, in the case of restaurants, cafés and the like, changes are recorded for 4.8% and 5.4% of all prices in physical and online stores.

However, the prices of clothing, footwear and other appliances change online considerably more often than offline (including articles and products for personal care). In the case of clothing and footwear, the frequency of online price changes is 15.3% and 28.1%, whereas the respective ratios for the offline channel are much lower, at 11.9% and 11.4%, respectively. Moreover, more than 44% of prices of other appliances change every month in online stores, compared with less than 20% in physical stores. The discrepancy between the frequency of price changes is due to a higher frequency of sales in the online channel than the offline channel. However, this outcome may be influenced by the sample bias, as online prices are recorded only in the stores of large retail chains, whereas Statistics Poland also collects data from smaller commercial establishments.

³³ Prices in online stores often change more than once a month. The statistics presented in this paper have been calculated for monthly frequencies. For online data, one price observed around the middle of the month was chosen to achieve comparability with the CPI data and to avoid problems related to different price collection frequencies.

Table 9

Frequency of price changes in offline and online stores across sectors (%)

COICOP	Group	Frequency of price					
		Change		Increase		Decrease	
		Offline	Online	Offline	Online	Offline	Online
CP01	Food and non-alcoholic beverages	28.6	27.7	15.8	15.1	12.7	12.6
CP0111	Bread and cereals	15.3	17.1	9.7	9.8	5.6	7.2
CP0112	Meat	31.9	24.3	18.6	13.6	13.3	10.7
CP0113	Fish and seafood	18.5	24.7	11.5	14.1	7.1	10.6
CP0114	Milk, cheese and eggs	23.6	25.7	13.7	14.3	9.9	11.3
CP0115	Oils and fats	29.9	29.9	17.1	16.9	12.8	12.9
CP0116	Fruits	56.4	55	26.3	28	30.1	27
CP0117	Vegetables	49.5	46.7	23	24.5	26.5	22.3
CP0118	Sugar, jam, honey, chocolate and confectionery	24.4	27.3	13.6	14.2	10.8	13.1
CP0119	Food products n.e.c.	18.5	21.7	11	12	7.5	9.7
CP012	Non-alcoholic beverages	21.6	23.8	12.4	13.2	9.2	10.7
CP031	Clothing	11.9	15.3	5.7	5.1	6.2	10.2
CP032	Footwear	11.4	28.1	5	8.8	6.4	19.3
CP0611	Pharmaceutical products	22.6	25.9	12.4	14.8	10.2	11.1
CP1111	Restaurants, cafés and the like	4.8	5.4	3.5	3.9	1.2	1.6
CP1213	Other appliances, articles and products for personal care	19.9	44.3	11.2	21	8.7	23.3

Sources: Statistics Poland, NBP and NBP calculations.

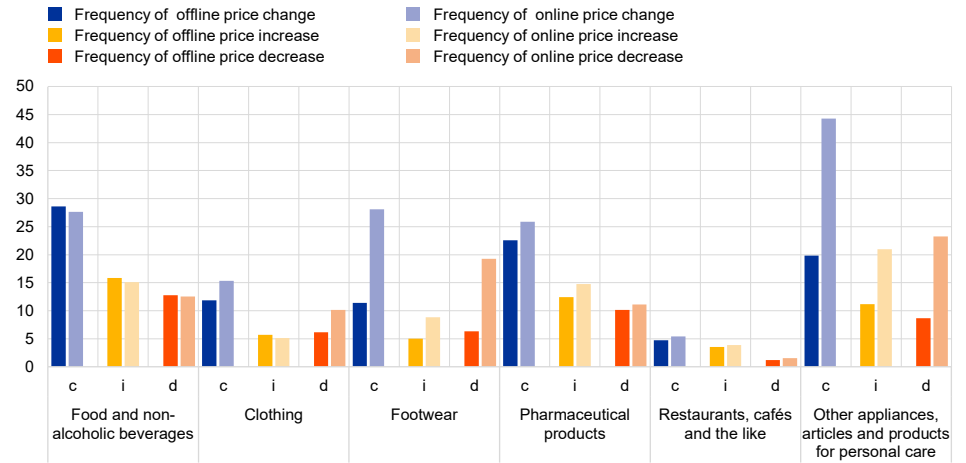
Notes: The statistics presented are calculated for different time ranges, dictated by data availability. For offline measures data from 2000-18 were used, for online food and non-alcoholic beverages prices data from 2010-20 were used, whereas for other categories data since 2017 were employed.

Differences in consumer search costs may also reduce the stickiness of online prices for most NEIG. Online shopping enables the consumer to check product prices very quickly, using price comparison websites. As a result, online stores selling big-ticket items (such as electronics) are exposed to greater price competition than traditional retailers. It may force them to change prices more often and apply various types of sales. In contrast, online grocery shopping is associated with the purchase of a whole basket of relatively inexpensive products. Therefore, it is far more time-consuming for households to compare the prices of the entire list of goods. The choice of a specific e-grocery store often results from the assortment a given store provides, additional costs and discounts related to delivery, or the prices of products perceived as necessities. Consequently, price comparison websites are far less popular in this market segment, as consumers usually visit the website of a specific store according to their preferences and choose multiple products before proceeding to transactions.

Chart 14

Frequency of price changes, increases, and decreases in physical and online stores

(percentages)



Sources: Statistics Poland and NBP calculations.
 Note: c denotes price change, i denotes price increase, d denotes price decrease.

4.2.2 Size of price changes

The average price change in physical and online stores for food, non-alcoholic beverages and food services is similar. The average price increase of grocery products is 11.2% in the offline channel, whereas for the online channel it is 17.2% (Chart 15). In the case of restaurants, cafés and the like, the average price increase is 20.8% and 19.9% in physical stores and online stores, respectively (Table 10). In turn, the average decrease is 10.7% and 15.4% for grocery products and food services in the offline channel, whereas the respective ratios for the online channel are 13.9% and 15.2%.

Table 10

Size of the average price increase and decrease in offline and online stores across sectors

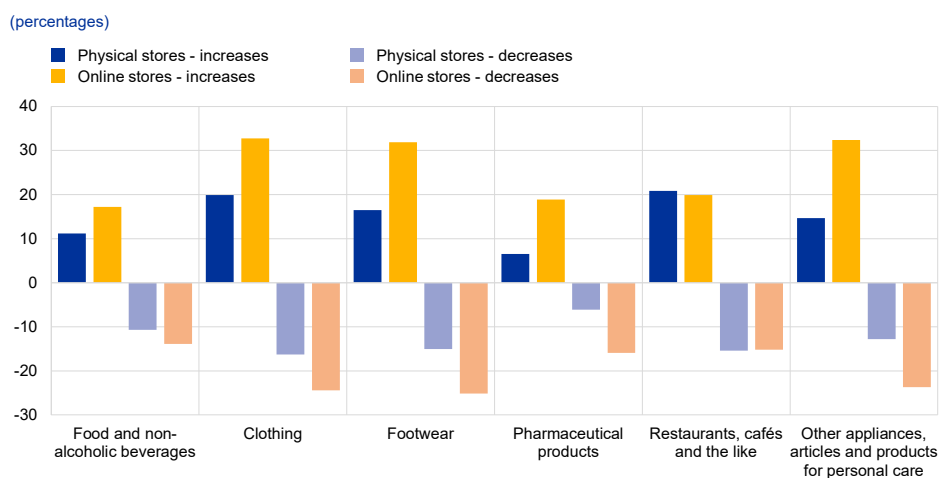
(percentages)

COICOP	Group	Size of price			
		Increase		Decrease	
		Offline	Online	Offline	Online
CP01	Food and non-alcoholic beverages	11.2	17.2	-10.7	-13.9
CP0111	Bread and cereals	10.8	15.6	-11.0	-13.7
CP0112	Meat	8.9	16.8	-9.2	-13.6
CP0113	Fish and seafood	10.0	18.4	-9.6	-14.9
CP0114	Milk, cheese, and eggs	8.8	14.5	-8.6	-12.4
CP0115	Oils and fats	9.1	14.0	-8.7	-11.7
CP0116	Fruits	18.0	24.3	-15.8	-17.5
CP0117	Vegetables	19.8	24.7	-16.7	-17.9
CP0118	Sugar, jam, honey, chocolate, and confectionery	9.8	15.2	-9.3	-12.5
CP0119	Food products n.e.c.	11.6	14.5	-10.8	-12.3
CP012	Non-alcoholic beverages	10.4	16.2	-9.9	-13.3
CP031	Clothing	19.9	32.7	-16.3	-24.4
CP032	Footwear	16.5	31.9	-15.0	-25.1
CP0611	Pharmaceutical products	6.5	18.8	-6.1	-16.0
CP1111	Restaurants, cafés, and the like	20.8	19.9	-15.4	-15.2
CP1213	Other appliances, articles and products for personal care	14.7	32.4	-12.8	-23.7

Sources: Statistics Poland, NBP and NBP calculations.

Notes: The statistics presented are calculated for different time ranges, dictated by data availability. For offline measures data from 2000-18 were used, for online food and non-alcoholic beverages prices data from 2010-20 were used, whereas for other categories, data since 2017 were employed.

However, the average (absolute) price change of NEIG in online stores is greater than in physical stores. Unlike in Germany, the increases and decreases in online prices range from a few percentage points greater to three times greater than increases and decreases in offline prices. Pharmaceutical products show the most notable difference. The average increase in online prices for these products is almost 19%, whereas for physical stores it is only 6.5%. Conversely, the decrease is 16% in online stores, compared with only just over 6% in offline stores.

Chart 15**Size of the average price increase and decrease in physical and online stores**

Sources: Statistics Poland, NBP and NBP calculations.

4.2.3 Sale prices

The frequency of sales is generally similar in the offline and online channel for food and non-alcoholic beverages and food services.³⁴ On average, around 6.8% and 7.0% of grocery products have sale prices in physical and online stores, respectively (Chart 16). Moreover, each month, about 8% of offline and online food prices change due to the introduction or end of a sale (Table 11). Given the overall frequency of price changes, this implies that 28.2% and 27.3% of all offline and online price changes in this group result from discounts. At the same time, the number of sale price decreases and post-sale price increases for grocery products is similar in the analysed channels. In turn, the percentage of sales for restaurants, cafés, and the like amounts only to 0.5% and 0.7% in the offline and online channels, respectively. In the case of pharmaceutical products, sales are not recorded in online stores. Under rules in place since January 2012, pharmacies in Poland are not permitted to use any discounts (including electronic newsletters) in their external marketing. Regarding physical pharmacies, our data show sales for 6.5% of pharmaceutical products. However, two caveats should be mentioned here. First, these statistics pertain to the period preceding the introduction of the promotions ban. Second, the Nakamura-Steinsson filter used for offline prices may incorrectly classify some price movements as sales.

³⁴ In this section, the data on offline and online prices differ in time range due to data availability. In the case of offline sales, we use data since 2000, whereas the online sales data start from February 2017 onwards, due to the lack of information on sales in the earlier period. For offline prices, the Nakamura-Steinsson filter is used to detect sales (Nakamura and Steinsson, 2008), whereas web-scraped information is used for online prices.

Table 11

Frequency of sale price occurrence and sale price changes, increases and decreases in offline and online stores across sectors

(percentages)

COICOP	Group	Frequency of sale price							
		Occurrence		Change		Increase		Decrease	
		Offline	Online	Offline	Online	Offline	Online	Offline	Online
CP01	Food and non-alcoholic beverages	6.8	7.0	8.1	8.0	4.0	3.9	4.1	4.1
CP0111	Bread and cereals	3.7	5.3	4.0	6.2	2.0	3.1	2.0	3.1
CP0112	Meat	7.4	5.7	9.0	6.1	4.5	3.0	4.5	3.1
CP0113	Fish and seafood	4.3	8.1	4.8	9.1	2.4	4.5	2.4	4.6
CP0114	Milk, cheese and eggs	6.5	7.7	7.3	9.0	3.7	4.5	3.7	4.5
CP0115	Oils and fats	7.6	8.7	8.8	10.2	4.4	5.1	4.4	5.2
CP0116	Fruits	11.2	7.3	14.6	9.6	7.0	4.5	7.6	5.1
CP0117	Vegetables	9.3	6.1	11.5	7.5	5.5	3.5	5.9	4.0
CP0118	Sugar, jam, honey, chocolate, and confectionery	6.2	10.3	7.1	10.6	3.6	5.2	3.6	5.4
CP0119	Food products n.e.c.	5.4	7.3	6.0	8.7	3.0	4.3	3.0	4.5
CP012	Non-alcoholic beverages	6.3	9.7	7.2	10.3	3.6	5.0	3.6	5.2
CP031	Clothing	2.2	13.5	2.3	8.3	1.1	2.2	1.1	6.1
CP032	Footwear	1.4	26.0	1.5	14.0	0.7	3.4	0.7	10.6
CP0611	Pharmaceutical products	6.5	0.0	6.9	0.0	3.5	0.0	3.5	0.0
CP1111	Restaurants, cafés, and the like	0.5	0.7	0.5	0.7	0.2	0.3	0.2	0.3
CP1213	Other appliances, articles, and products for personal care	5.3	17.9	6.6	25.6	3.3	12.1	3.3	13.5

Sources: Statistics Poland, NBP and NBP calculations.

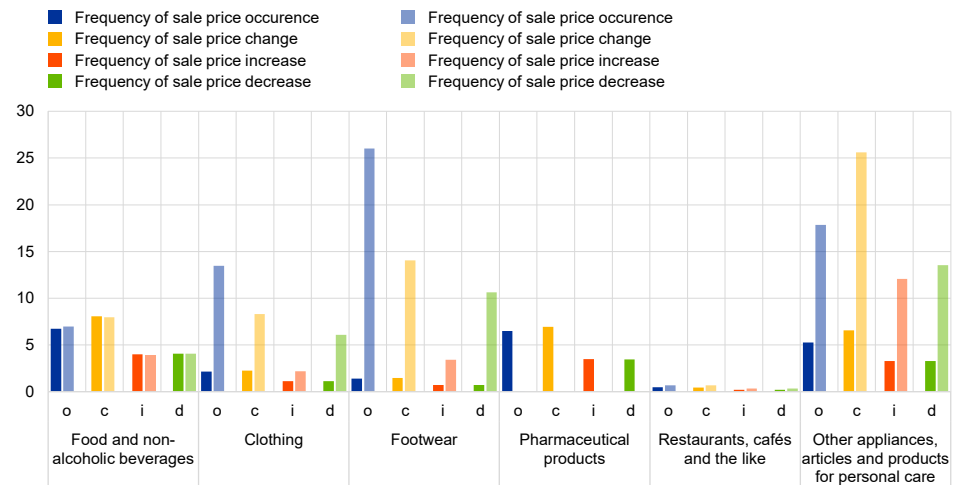
Notes: The data on offline and online prices differ in time range due to data availability. In the case of offline sales, we use data since 2000, whereas for online sales data start from February 2017 onwards due to the lack of information on sales in the earlier period. For offline prices, the Nakamura-Steinsson filter is used to detect sales (Nakamura and Steinsson 2008), whereas for online prices web-scraped information is used.

Sales are usually more frequent in online than physical stores for clothing, footwear and products for personal care. Depending on the group being analysed, sales apply to between 13.5% of clothing and 26.0% of footwear in online stores. These percentages are six to as much as 18 times higher than for physical stores. Each month, 8.3%, 14.0%, and 25.6% of the online prices of clothing, footwear and other appliances, respectively, change due to the introduction or end of a sale. This accounts for 54.2%, 50.0%, and 57.9% respectively of all price changes in these groups. At the same time, these product groups are discounted substantially more in online stores. About 75% of sale price changes in clothing and footwear are decreases, meaning that one sale is being followed by another. Numerous price cuts are caused by the rapid circulation of products in the clothing industry: as new collections enter, the prices of previous collections are gradually lowered.

Chart 16

Frequency of sale price occurrence and sale price change in physical and online stores

(percentages)



Sources: Statistics Poland and NBP calculations

Note: o denotes price occurrence, c denotes price change, i denotes price increase, d denotes price decrease.

Box 3

The ECB Daily Price Dataset

The Billion Prices Project and the E-CPI project of Narodowy Bank Polski have demonstrated the usefulness of web-scraped data for nowcasting and forecasting inflation, and as an invaluable resource for researchers. This encouraged the ECB to launch the Daily Price Dataset (DPD) project within PRISMA.

The DPD project builds a real-time database of daily online prices scraped from retailer websites and provides the necessary IT infrastructure to collect and analyse these data. The daily time series – price series of individual products as well as pre-defined, aggregated time series – are available to ESCB staff for monitoring and nowcasting inflation in the euro area and its largest member countries. The data will also be available for ad hoc research work.

The websites to be scraped are selected to obtain a representative sample of purchased goods and services available online across the euro area countries. In the current scope, the DPD collects both processed and unprocessed foods (from online supermarkets), non-energy industrial goods (NEIG) (electronics, furniture, clothing and footwear, small household appliances and personal care items), and some services (food delivery). Going forward, the coverage could be extended to additional NEIG and services available online, for example to hotel, travel or used cars.

Besides the daily prices themselves, the data contain detailed information on product characteristics, such as product names, product identifiers and specifications. This rich information set enables easy identification of single items and the tracking of their price dynamics over time. It also allows for classification of the scraped products under the European Classification of Individual Consumption According to Purpose (ECOICOP), both manually (via human intervention) and by machine learning methods. Classification under ECOICOP is necessary to mimic the methodology used by the national statistical institutions. All collected data are validated and quality-checked.

The design and implementation of the DPD infrastructure involves ECB staff from the Directorate General Economics (DGE) and the Directorate General Information Systems (DGIS), as well as a team of external software developers. After the development and the start of data production, constant maintenance of the system and data collection is required. This involves both the maintenance of data collection (e.g. adapting scrapers to changes in websites) and data quality assurance and enhancement.

Box 4

Classifying DPD data with machine learning

Unlike official CPI microdata, web-scraped data do not come with a consistent and comparable classification system for individual items, as each web shop uses its own classification system. However, in order to use the full potential of web-scraped data (see, for example, Box 2 in this paper), and to create comparability across shops, individual items need to be classified according to the same classification system that is used by euro area NSIs, i.e. ECOICOP.

Classifying all individual items collected manually is impossible, due to the sheer number of items sold online, as well as the high turnover of items available online. An additional challenge in this process is the fact that the web-scraped data are collected in the local language of the web shop. This creates the need to develop a method to automatically classify previously unclassified products in different languages with sufficiently high accuracy.

Supervised machine learning techniques offer a promising avenue to tackle the challenge of automatically classifying millions of different items. The detailed characteristics of individual items collected within DPD provide a rich information set to enable this automated classification. However, supervised machine learning techniques require a training dataset to learn the correct classification of previously unclassified items. To assess the feasibility of automated product classification via machine learning techniques, several tens of thousands of individual items from German and French online supermarkets have been manually classified. Based on these manually classified items, several promising insights on the feasibility of automated product classification via machine learning have been gained.

When classifying items in a single language, even relatively simple classification algorithms can achieve a high degree of accuracy. Using a support vector machine classifier, an accuracy level of over 95% has been achieved. While these simple classifiers require a separate training dataset of manually classified items for every language, the adaptation and training of these classifiers to a new language is relatively easy and requires only minor adaptation, ensuring the scalability of this approach.

A more sophisticated, multi-lingual approach has been developed by Lehmann et al. (2020). While training simple classifiers for every language individually shows promising results and is feasible, such an approach does not use all the information available to automatically classify items. Lehmann et al. (2020) present a multi-lingual approach that combines data in multiple languages using cross-lingual word embeddings to classify items. This approach demonstrates that combining information from multiple languages can not only increase accuracy for every single language, but also reduce the manual classification effort needed. However, the implementation of such an approach in a production system is also more complicated.

When operating DPD in production, classification is not a one-off activity. The way information is provided by online shops may change, new products with previously unseen characteristics may appear, and new shops or product groups may be added. All of this means that, after creating an initial hand-classified training dataset, constant monitoring of the performance of automated classifiers in production is needed. This implies that new products must be manually classified by humans at regular intervals. To facilitate this manual classification, a user interface has been developed. Manual classification can be supported by automated machine-learning-based classifications, if these take the form of suggestions to the human classifier. Such an approach can save human classifiers a considerable amount of time (Lehman et al., 2020).

5 Conclusions

E-commerce is growing rapidly throughout Europe. Starting with branded products that are easy to ship, it has been gaining market share in a growing number of sectors. Whereas some markets are maturing, others – such as food retail in many countries – are rapidly evolving. Some effects of e-commerce are linked to this introductory phase and are thus transitory: however, due to its staggered introduction across sectors and countries, these effects may nevertheless be apparent for several more years.

The existing evidence on offline and online price level differences is mixed, partly because of the difficulty of making comparisons: however, online prices tend to be lower, particularly when delivery costs are excluded. While this paper has not provided direct evidence of this, the pricing differences in FMCG between France and the United Kingdom point in this direction. In other words, higher online prices might reflect the added consumption of delivery services.

The presence of online competition results in more uniform pricing, both offline and online. This applies, in particular, to products subject to intense competition, such as electronics and some groceries. Multi-channel retailers broaden the sets of these products by following a largely identical pricing scheme, both online and offline.

Online and offline prices and inflation converge quickly in some markets as they mature. Once online FMCG markets have matured, there is evidence that transitory effects on aggregate inflation levels disappear. This makes online transactions a useful, but, due to their limited category coverage, still incomplete, tool for tracking overall price developments.

Online prices are more flexible in most sectors. The fact that online prices change more frequently than offline prices is a robust finding across countries and sectors. With respect to the size of the price changes, the evidence is mixed, with online price changes tending to be smaller than offline changes in Germany based on CPI data, but larger in Poland based on web-scraped data, and equal in several other countries. Overall, however, the higher frequency, combined with an – on average – unchanged size, suggests somewhat lower menu costs online. These findings are robust when controlling for the underlying share of sales in Germany, but Polish web-scraped data indicate that the frequency difference between online and offline price changes may be negligible in some product categories, once sales are taken into account.

Overall, while a higher repricing rate may lead to more flexibility in price levels, uniform pricing may mute their responsiveness to local shocks. The effects of strategic interactions between online and offline firms remain an important area of policy-relevant research. Overall, with prices becoming more flexible, we may see a steepening of the New Keynesian Philips curve. As the relevance of e-commerce is likely to increase further, the effect may intensify in the next few years.

However, some of the evidence of the high correlation between online and offline inflation at the product level suggests that online stores effectively wait for the stickier prices of offline competitors to adjust, for example by changing their prices by smaller amounts. In turn, this form of strategic complementarity may at least partially offset the effects of higher online price flexibility on the slope of the Phillips curve.

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