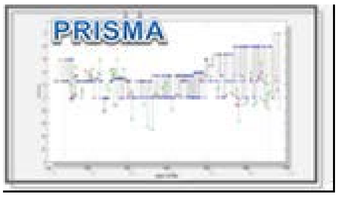
EUROPEAN CENTRAL BANK
EUROSYSTEM

Working Paper Series

Regina Kiss, Georg Strasser

Inflation heterogeneity across households



No 2898

Price-setting Microdata Analysis Network (PRISMA)

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

PRISMA is coordinated by a team chaired by Luca Dedola (ECB), and consisting of Chiara Osbat (ECB), Peter Karadi (ECB) and Georg Strasser (ECB). Fernando Alvarez (University of Chicago), Yuriy Gorodnichenko (University of California Berkeley), Raphael Schoenle (Federal Reserve Bank of Cleveland and Brandeis University) and Michael Weber (University of Chicago) act as external consultants.

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

The refereeing process of this paper has been co-ordinated by a team composed of Luca Dedola (ECB), Anton Nakov (ECB), Chiara Osbat (ECB), Elvira Prades (Banco d'Espana), Sergio Santoro (ECB), Henning Weber (Bundesbank).

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

Abstract

This paper studies the nature, evolution, and sources of inflation heterogeneity across households in France and Germany. Inflation differences are large and persistent. The two main sources of inflation heterogeneity are spatial differences in the prices paid for the same product and differences in the household-specific variety choice within a category. Income heterogeneity by itself is not a relevant determinant of inflation heterogeneity, but due to its correlation with household behaviour, a significant and time-varying inflation difference between income groups emerges. Substitution is strongly behaviour-driven and largely detached from the relative price. The dispersion of the household-level elasticity of substitution does not fully account for the heterogeneity of substitution behaviour. Substitution does not reduce the dispersion of inflation, confirming the central role of preference heterogeneity in inflation measurement.
JEL codes: D12, D30, E31, F45

Key words: inflation, household heterogeneity, shopping behaviour, substitution, inequality

Non-technical summary

Systematic inflation differences between households have distributional and welfare effects. Moreover, individual past inflation experiences might affect inflation expectations, so that a heterogeneity of inflation realizations can entail a heterogeneity of inflation expectations. This paper examines inflation heterogeneity across households in France and Germany. It documents large and persistent inflation differences between households, decomposes these differences in price and basket components, and identifies their main drivers.

The analysis is based on a large household panel reporting the purchases of fast moving consumer goods, i.e. of the products which households buy most frequently. This set of products is particularly relevant because households form their inflation expectations based on them. The GfK dataset covers German households during the years 2005–2018 and the Kantar dataset French households during 2008–2018, with purchases totalling more than 330 million and 145 million euro, respectively. Both panels contain prices, quantities, and product characteristics of the purchases of households together with some demographic information.

This paper presents four key insights. First, income (and other standard demographic characteristics) explain little of the inflation differences between households. The key driver of inflation heterogeneity is household behaviour. Income plays an indirect role: as household behaviour is weakly correlated with income, at times significant inflation differences between income groups emerge.

Second, household behaviour affects inflation heterogeneity mainly through product choice. While individual households might find lower prices for a given product, these price differences constitute only a small share of the overall inflation heterogeneity. Only price differences between larger regional units matter, e.g. a different price paid for the same product in a metropolitan region vs. a distant rural region. This translates into inflation heterogeneity at the regional level.

Third, the households' product choice within a category appears to be largely detached from the products' relative price. In other words, households often substitute into a product whose relative price has increased. Fourth, the dispersion of household-level price indices based on a fixed ex-ante basket changes little when heterogeneous preferences across goods are introduced, and becomes even larger when allowing for time variation in preferences.

These findings caution against focusing on income as the sole explanation of inflation heterogeneity among households. Instead, the main driver is household behaviour, in particular product choice. Therefore the heterogeneity of preferences – across goods and over time – needs to be taken into account. Preference heterogeneity is also behind the often counter-intuitive substitution patterns. In contrast, price search by households and the resulting differences in prices paid for identical products matter relatively little for inflation differences between households.

1 Introduction

Most aggregate price indices are based on an aggregate consumption bundle and the posted prices of reference products within narrow product categories. The derived aggregate inflation rate can deviate from the inflation experienced by an individual household, whose members might consume products and pay prices different from the reference consumer underlying the aggregate index. This inflation heterogeneity across households has regained a lot of attention in face of the recent jump in inflation rates (e.g., Claeys and Guetta-Jeanrenaud, 2022).[1]

Inflation heterogeneity across households can have severe consequences. First, systematic inflation differences across households have distributional effects. Second, if inflation varies by income (or – more generally – by any household characteristic correlated with households' marginal propensity to consume) such inflation heterogeneity affects welfare as well. Third, heterogeneous inflation experiences can entail a wide range of inflation expectations across households[2] and in turn heterogeneous household behaviour.

This paper argues that the heterogeneity of inflation perceptions[3] mirrors the heterogeneity of inflation experiences of households. We document large differences in the (Laspeyres) inflation between households. These differences persist for several years, and household substitution can offset it only partially. This leads to the important question of the determinants of this inflation heterogeneity. In particular: Are there systematic inflation differences between demographic or income groups? Does inflation amplify purchasing power differences? Do they stem from households paying different prices for the very same product, or rather from households buying different products? How relevant are the idiosyncratic household characteristics compared to the more aggregate characteristics of demographic groups or regions? And, finally, do these factors also affect the households' ability to substitute towards products getting relatively cheaper?

Guided by these questions, this paper presents four key insights: We find, first, that standard demographic characteristics explain little of the inflation differences across households. The key driver is individual household behaviour. In this vein, income heterogeneity by itself is not a relevant determinant of inflation heterogeneity. But because household be-

[1] The report by Strasser, Messner, Rumler, and Ampudia (2023) includes an early summary of some of the results presented in this paper. Research on household-level heterogeneity hidden behind the aggregate inflation rate started around the end of the 1970s (Michael, 1979; Pollak, 1980) – a time of high inflation.

[2] Ample survey evidence suggests that the consumers' inflation expectations respond to their perception of current inflation. See, e.g., Armantier, Goldman, Kosar, Topa, van der Klaauw, and Williams (2022), Cavallo, Cruces, and Perez-Truglia (2017), Dräger (2015), D'Acunto, Malmendier, Ospina, and Weber (2021), Huber, Minina, and Schmidt (2023), Stanisławska and Paloviita (2021), and Weber, D'Acunto, Gorodnichenko, and Coibion (2022).

[3] Inflation perceptions differ widely (Bańnkowska, Borlescu, Charalambakis, Da Silva, Di Laurea, Dossche, Georgarakos, Honkkila, Kennedy, and Kenny, 2021) and there is evidence that some of these differences follow socioeconomic characteristics (Arioli, Bates, Dieden, Duca, Friz, Gayer, Kenny, Meyler, and Pavlova, 2017; Del Giovane, Fabiani, and Sabbatini, 2010).

haviour is weakly correlated with income, a significant time-variation of inflation differences between income groups exists.

Second, differences in prices paid for the same product within a country play an important role for inflation heterogeneity. But these differences are mostly due to the spatial component of price changes, which accounts for more than one third of overall inflation heterogeneity. Household-specific prices explain only little. The main driver is product choice by households, which explains in France about one half and in Germany about one fourth of the variation in inflation.

Third, substitution across goods and over time by households is just as heterogeneous as inflation itself, again driven more by the households' behaviour than by demographics. A households' product choice within a category appears to be largely detached from its relative price, i.e. households often substitute into a product whose relative price has increased. The differences in the household-level elasticity of substitution do not fully account for the heterogeneity of substitution behaviour.

Fourth, accounting for substitution does not reduce the dispersion of inflation rates across households. The dispersion changes little compared to the case of a fixed ex-ante basket when heterogeneous preferences across goods are introduced, and becomes even larger when time-variation in preferences is allowed for. All this confirms the central role of preference heterogeneity – both across goods and over time – in inflation measurement.

These findings are based on a rich household panel for France and Germany, which covers a wide range of fast-moving consumer goods (FMCG). This set of goods is particularly relevant, because households form their inflation expectations based on the items that they buy most frequently, in particular groceries (D'Acunto et al., 2021). The analysis pays special attention to a specific demographic dimension, income, to verify whether low-income households face higher inflation also in Europe. Kaplan and Schulhofer-Wohl (2017) have recently shown that in the USA income differences matter significantly for household (Laspeyres) inflation.[4]

To examine the role of household behaviour we extend the methodology of Kaplan and Schulhofer-Wohl (2017) of calculating household-level inflation indices. Their approach compares indices based on household-level prices with indices based on (counterfactual) average prices. In addition to the national barcode average price we study intermediate spatial aggregation levels (barcode-average prices within groups of postal areas), and in addition to category price indices we build price indices over brand-categories and over

[4]Already the earlier literature – calculating indices for demographic groups by combining consumption expenditure survey and consumer price index data – finds that lower income groups experience higher inflation than higher income groups. The initial studies at the end of the 1970s were followed by papers focusing on income-group specific inflation in the USA (Garner, Johnson, and Kokoski, 1996; Hobijn and Lagakos, 2005), the EU-25 (Gürer and Weichenrieder, 2020) and Australia (van Kints and Breunig, 2021).

quality-categories. The latter extension explores the variety choice within a category, which turns out to be an important source of heterogeneity in both France and Germany.

The resulting inflation indices capture the effect of the three main dimensions of household behaviour causing inflation heterogeneity: differences in shopping behaviour that lead to differences in the price paid for the same product, variety choice within a product category,[5] and the choice of category (baskets).

To determine whether households can offset the inflation differences in their ex-ante basket by substitution, we analyse the difference of two cost of good indices (COGIs), the Laspeyres and Paasche indices. One might expect that households substitute away from goods getting relatively more expensive, but this is often not the case. Based on the difference of the Laspeyres and Paasche indices, almost half of the households substitute towards products getting relatively more expensive in both France and Germany (based on household-level indices with household-level prices), similarly to earlier findings for the USA (Kaplan and Schulhofer-Wohl, 2017) and Switzerland (Braun and Lein, 2020).

One might suspect that these differences in substitution across households are due to preference heterogeneity. To account both for different preferences across goods (as in Sato (1976) and Vartia (1976)) and for a change in preferences for a given good over time (as in Redding and Weinstein (2020) and Martin (2022)), we calculate cost of living indices (COLIs) at the level of the household similarly to Braun and Lein (2020). We capture the effect of substitution across goods when households have different preferences (across goods) by taking the difference of the Sato-Vartia index and the Laspeyres index, and the effect of a change in preferences for a given good over time (i.e., taste shifts) by taking the difference of the Redding-Weinstein and the Sato-Vartia index. We show that at the household level, substitution (across goods) and taste shifts (over time) are separate phenomena, as many household characteristics affect the substitution bias and the taste-shift bias in opposite directions.

Our paper builds on the large and growing literature on inflation heterogeneity among households. Early papers typically combine consumption expenditure survey data with consumer price subindices. They find a large dispersion of household-specific inflation rates for a European panel of countries (Colavecchio, Fritsche, and Graff, 2011), for Austria (Fessler and Fritzer, 2013), for the UK (Crawford and Smith, 2002) as well as for the USA (Hagemann, 1982; Hobijn and Lagakos, 2005; Michael, 1979). Aggregate data requires the assumption, however, that all households pay the same price for identical products and that they purchase varieties within a product category with identical price dynamics. More recent work, including this paper, avoids this by using large-scale FMCG scanner

[5] "Product category" refers to the product classification in the scanner data, which distinguishes, e.g., bread, milk, and yoghurt. In contrast, "ECOICOP category" refers to the coarser Classification of Individual Consumption According to Purpose (COICOP) by Eurostat.

datasets. Such data cover primarily groceries, i.e. not the universe of consumption covered by a consumer price index. But as such panel data provides both prices and quantities at the transaction level, it allows to account directly for price and product choice differences between households. Household panel data provides, moreover, the effective prices, i.e. the prices paid after discounts, whereas the prices underlying consumer price indices are posted (quote) prices. Last not least, and key for our analysis, it allows linking a transaction to a specific household and its characteristics. Studies examining household-level inflation heterogeneity with such data find for the USA substantial dispersion of household-level inflation (Kaplan and Schulhofer-Wohl, 2017; Orchard, 2020). Braun and Lein (2020) argue furthermore that preference heterogeneity is an important cause of inflation dispersion across Swiss households.

Our results confirm that lower income groups in France and Germany experience higher Laspeyres inflation, as documented in recent papers for the USA. Kaplan and Schulhofer-Wohl (2017) use COGIs to measure income-group specific inflation in the USA, while Jaravel (2019) and Argente and Lee (2020) use COLIs. Jaravel (2019) finds that over the longer term this inflation difference is due to product innovation, a result confirmed by Beck and Jaravel (2020) using global scanner data. Argente and Lee (2020) show that the dominant factor in inflation differences between US income groups changed from product prices before the Great Recession to substitution across products during the recession. By exposing the role of household characteristics and in particular of income for realized prices and substitution behaviour, we provide evidence on how inflation affects the gap between income, expenditure and consumption inequality (Aguiar and Bils, 2015; Arslan, Guler, and Taskin, 2021; Krüger and Perri, 2006). An important driver are the various dimensions of shopping behavior, which many models summarize as search effort or shopping time (e.g. Aguiar and Hurst, 2007).

The differences between households or household groups in the inflation they experience provides a natural explanation for the differences in inflation perceptions. If households respond to surveys about their perceived inflation based on the price changes they experience when shopping, measured inflation perceptions will show a similar heterogeneity as the actual price changes experienced by households, which in turn might explain a part of the heterogeneity in inflation expectations (Weber, Gorodnichenko, and Coibion, 2023). As we show in this paper, household behavior and socioeconomic characteristics play a role in household inflation experience, which implies that inflation expectations differ along these dimensions as well.

The paper is organised as follows: Section 2 describes the household panel dataset and methodology underlying the analysis. Section 3 documents the extent of inflation dispersion across households and its persistence. Section 4 aims to identify the causes of inflation heterogeneity across households. Section 5 addresses the question of whether the households can offset the inflation differences in their ex-ante baskets by substitution and Section 6 focuses on the causes of the differences across households in substitution. Section 7 revisits the connection between income and inflation heterogeneity. Section 8 concludes.

2 Data and Methodology

This section starts with a description of the key features of the French and German household panels. We then discuss the calculation of inflation indices, including the aggregation of transaction data, the data cleaning, and the main inflation concepts used throughout the paper.

2.1 Data

The analysis in the paper is based on the Kantar household panel for France and the GfK household panel for Germany. The GfK/Kantar household panel covers fast moving consumer goods (FMCG), i.e. everyday purchases at supermarkets and drugstores. More than 80% of the expenditure is on groceries (food, alcoholic and non-alcoholic beverages). The rest consists primarily of personal care products, pet food, and cleaning products.[6] These categories cover the products most frequently purchased by households and constitute an important subset of the categories underlying aggregate official price indices such as the harmonised index of consumer prices (HICP). The frequent purchasing of these products makes them interesting for at least three reasons: First, price changes in these products are known to have a strong effect on inflation perceptions (D'Acunto et al., 2021).[7] Second, the relatively frequent transactions allow following their transaction prices within granular groups of households. Third, these heterogeneous product categories might allow inferences about other heterogeneous, but harder to observe, components of the aggregate index, such as e.g. services.

2.1.1 Household Panel

The reporting unit of the panel is a household. The households in the panel scan each purchased item after their shopping trips. For each purchase, the household reports the item (usually identified by a barcode), the quantity, the expenditure, the retail chain, and the transaction date.[8] Additionally, the database provides information on the item (e.g.

[6] Appendix A.2.4 provides a detailed breakdown by ECOICOP category.

[7] According to Huber et al. (2023) the inflation perceptions of about 90% of households are mainly a result of their shopping experiences. They show further that the effect of shopping experience on inflation expectations operates entirely through inflation perceptions.

[8] There is no information on individual stores.

volume, manufacturer, brand) and on household characteristics (e.g. the age of household head, income class, region of residence or postal code). The recorded prices are effective prices, i.e. the prices the households actually paid. Effective prices can differ from posted (or shelf) prices, because they include price reductions, for example due to coupons.[9]

Table 1: The French and German household panel

Sample period	France 2008–2018	Germany 2005–2018
Number of households (thousands)	46	147
Number of transactions (millions)	148.4	334.3
Share of expenditures of top 10 retailers (%)	73.9	90.1
Number of barcodes (thousands)	574.8	612.4
Share of non-EANs (% of barcodes)	0.0	16.4
Private label (% of barcodes)	21.7	36.8

Note: Statistics based on cleaned data (step (3) in Table 7 in Appendix A.1.1). Unique households / unique barcodes counted over the entire sample period of the respective country.

The household panels for Germany (GfK) and France (Kantar) start in the year 2005 and 2008, respectively. Both end in 2018. The sample covers in any given year on average approximately 18000 households in France and 35000 in Germany. Due to entry and exit of sample participants we observe almost 46000 distinct households in France and almost 147000 in Germany for at least a part of the sample period. The products are identified by either their European Article Number (EAN) or – for a significant part of products in Germany – by a chain-specific barcode number ("non-EAN"). The analysis is based on food products (ECOICOP 01.1), non-alcoholic beverages (01.2), alcoholic beverages except wine (02.1.1 and 02.1.3), household maintenance products (05.6), pet food (09.3) and personal care products (12.1). Further key characteristics of both panels are summarized in Table 1. In total, the dataset contains almost 500 million transactions.

2.1.2 Income

To facilitate a comparison between France and Germany, we create a common grid of four income groups for France and Germany (see Appendix A.1.3). The granularity of the harmonized income grid is limited by the lack of detailed data in the early part of the French sample.

Higher income groups in our sample feature on average larger households, somewhat younger household heads, and lower expenditures per capita (see Table 9 in Appendix A.2.1). A high-income household is therefore not necessarily rich, but might just be a larger household

[9] The dataset does not flag coupon use explicitly, but reports only the final price. Argente and Lee (2020) find that high-income US households used coupons more intensively during the downturn between 2008 and 2013.

with children.[10] As an alternative measure of the economic strength of a household we use expenditures adjusted by household size.[11] The age of the household head increases with the expenditure quartile. As household size is similar across the expenditure quartiles, the expenditure per capita increases with the quartile as well. Higher income groups make more transactions and purchase more barcodes – a pattern which is even stronger for expenditure, even when adjusting for household size.

In both France and Germany low-income and low-spending households visit more shops per transaction, which might reflect that they search more intensively for lower prices. Similar patterns have been documented for US data. Pytka (2022), for example, reports that households pay higher prices for the very same product after a positive (transitory) income shock. Similarly, according to Aguiar and Hurst (2007), retired and unemployed households, i.e. households with lower income, spend more time on shopping in order to search for lower prices.

2.1.3 Data Cleaning and Aggregation

Aggregation over time The frequency of the dataset is daily. A given household, however, neither shops every day, nor does it buy exactly the same goods in every shopping trip. Calculating household-level inflation over a meaningfully large basket requires therefore aggregating the household's purchases over time.

Let us denote the price per unit of a given item i at a given shopping event s paid by household h by $\tilde{p}_{ihs}$ and the quantity purchased by $\tilde{x}_{ihs}$. All shopping events of item i by household h during quarter q are collected in the set $S(ihq)$. Using the sum of these quantities, $x_{ihq} = \sum_{s \in S(ihq)} \tilde{x}_{ihs}$, allows expressing the average price paid by household h for item i during quarter q by the volume-weighted average

$$p_{ihq} = \frac{1}{x_{ihq}} \sum_{s \in S(ihq)} \tilde{p}_{ihs} \tilde{x}_{ihs}. \tag{1}$$

Throughout this paper we refer to p_{ihq} in short as the "household-level price".

Price aggregation over households Households differ in many ways, including in their search effort. This offers manifold ways for retailers to charge different prices for the same item. As a result, the price paid by a household can be very idiosyncratic. To isolate the

[10] Another possible reason for the lower per-capita expenditures in the higher income groups might be that the data covers primarily groceries. Some richer households might spend more on (unrecorded) food service and restaurants, and, in turn, less on groceries.

[11] Expenditures are size-adjusted by dividing the total expenditures of a given household in a given quarter by the square root of household size (OECD equivalence scale). We assign households quarter-by-quarter to expenditure quartiles based on this ranking.

role of household-idiosyncratic prices, we calculate counterfactual prices: regional quantity-weighted price averages within three-digit, two-digit and one-digit postal regions, $\bar{p}_{iq}^{\boldsymbol{r3}}$, $\bar{p}_{iq}^{\boldsymbol{r2}}$ and $\bar{p}_{iq}^{\boldsymbol{r1}}$, and the national price average $\bar{p}_{iq}^{\boldsymbol{r0}} \equiv \bar{p}_{iq}^{\boldsymbol{n}}$.[12]

Transactions The data cleaning ensures that the French and the German data are comparable in terms of regional composition and product coverage. For this reason we exclude islands (Corsica) and wine (not covered by the French panel). Furthermore, we exclude barcodes which do not uniquely identify a product.[13] Appendix A.1.1 describes the steps of data cleaning and its effect in more detail.

Repurchased items We calculate the price changes over four-quarter periods, i.e. quarter $q-4$ against quarter q, in order to eliminate the first-order effect of seasonality. The household-level inflation rate is therefore based on those items which have been purchased by household h in quarter $q-4$ and repurchased in quarter q, i.e. on the intensive margin. We denote this set of items by $I(hq)$. In a given quarter, on average about 70% of households in the sample repurchase at least one barcode from four quarters ago. Almost every second household repurchases at least 25 products. These repurchases are concentrated in 35%-40% of all barcodes purchased by a given household and cover around 30% of its spending.[14]

To reduce the sampling error, we ensure that the baskets underlying the inflation calculation at the household level contain more than just a handful of items. Our baseline specification includes only households which repurchase at least 25 products.

2.2 Methodology

The analysis in this paper is based on cost of good indices (COGIs) and cost of living indices (COLIs). COGIs measure the price change of a fixed basket of goods, just like the HICP. Following Kaplan and Schulhofer-Wohl (2017), we calculate a household-level price index with household-level prices and counterfactual indices based on regional product-by-product price averages and product category price indices. To better localize the origin of

[12] In France we use NUTS-1 regions (instead of one-digit postal regions) as top-level regional aggregation, because French one-digit postal codes do not form geographically connected regions. See Appendix A.1.2 for details.

[13] In Germany 41% of barcodes in the raw data are not standard EANs, that is, these barcode numbers do not necessarily identify a product uniquely. These non-EAN products account for the majority of the 9-20% of all purchases each year whose volume per unit varies over time. Non-standard barcodes with a time-varying volume per unit would distort the measurement of price changes, thus we exclude these from the inflation calculation.

[14] See Table 10 in Appendix A.2.2. Kaplan and Schulhofer-Wohl (2017) document similar shares for the USA. There, 77% of households repurchase at least one and 72% at least five products. Likewise, US households spend less than one third of their expenditure on repurchased barcodes.

heterogeneity we introduce additionally several tiered aggregation levels: first, intermediate spatial aggregation levels (barcode-average prices within groups of postal areas), and, second, price indices over brand-categories and quality-categories.

COLIs capture the price change of a basket that yields a fixed amount of utility between two time periods, allowing for substitution in response to relative prices changes. We use three types of COLIs: the commonly used Sato-Vartia index, and two indices which capture preference heterogeneity, the Redding-Weinstein index for common varieties, and the geometric average of the Lloyd-Moulton and Backwards Lloyd-Moulton indices (Martin, 2022).

2.2.1 COGI Household-level Inflation with Household-level Prices

The index closest to the households' transactions uses $p_{ih,q}$ and $x_{ih,q}$ directly, i.e. the average price paid and the quantity purchased of item i by household h in quarter q.[15]

Definition 1 (Household-level inflation with household-level prices)**.** *The quarterly year-on-year ($q/q-4$) household-level Laspeyres price index with household-level prices is*

$$\pi_{hq}^{\boldsymbol{h}} = \frac{\sum_{i \in I(hq)} p_{ih,q} \; x_{ih,q-4}}{\sum_{i \in I(hq)} p_{ih,q-4} \; x_{ih,q-4}}. \tag{2}$$

2.2.2 Counterfactual COGI Household-level Inflation

Regional price averages The price paid by a household can be very idiosyncratic. In order to remove household-idiosyncratic pricing, we replace the household-level prices p_{ihq} in Equation (2) with the quantity-weighted average price paid for the item within postal regions as defined in Section 2.1.3.

Definition 2 (Household-level inflation with barcode-average prices)**.** *The quarterly year-on-year ($q/q-4$) household-level Laspeyres index based on regional barcode-average prices within a three-digit postal region is*

$$\pi_{hq}^{\boldsymbol{br3}} = \frac{\sum_{i \in I(hq)} \bar{p}_{iq}^{\boldsymbol{r3}} \; x_{ih,q-4}}{\sum_{i \in I(hq)} \bar{p}_{i,q-4}^{\boldsymbol{r3}} \; x_{ih,q-4}}. \tag{3}$$

Other household-level Laspeyres price indices with barcode-average prices are defined analogously using the appropriate price aggregate. For inflation within a two-digit postal region ($\pi_{hq}^{\boldsymbol{br2}}$) we replace $\bar{p}_{iq}^{\boldsymbol{r3}}$ by $\bar{p}_{iq}^{\boldsymbol{r2}}$, for inflation within a one-digit postal region ($\pi_{hq}^{\boldsymbol{br1}}$) we replace

[15] In the regressions and graphs we transform these factors into percentages. That is, regressions and graphs referring to "$\pi_{hq}^{\boldsymbol{h}}$" use in fact $100(\pi_{hq}^{\boldsymbol{h}} - 1)$.

$\bar{p}^{\boldsymbol{r3}}_{iq}$ by $\bar{p}^{\boldsymbol{r1}}_{iq}$ and for inflation based on *national* barcode-average prices ($\pi^{\boldsymbol{bn}}_{hq}$) we replace $\bar{p}^{\boldsymbol{r3}}_{iq}$ by $\bar{p}^{\boldsymbol{n}}_{iq}$, in both the numerator and denominator.

Price indices by product group In the next step we aggregate price changes within groups of products. Let the set $I(k)$ contain all items i which belong to a certain product group k. We use three product groupings, which increase in granularity. The first, (product) category, groups products along the approximately 300 product categories defined in the GfK/Kantar dataset.[16] At this level of aggregation we eliminate any heterogeneity stemming from preferences across product varieties and focus on differences in the baskets of households. Within product categories products are both vertically and horizontally differentiated. We account for this by calculating quality-category (vertical differentiation) and brand-category price indices (horizontal differentiation). The second grouping, by quality-category, interacts the (product) categories with quality, which gives approximately 600 groups. The third grouping, by brand-category, interacts (product) categories with the brand name.

For a given (product) category k or brand-category the quarterly year-on-year ($q/q-4$) Laspeyres index is

$$\pi^{\boldsymbol{\cdot}}_{kq} = \frac{\sum_{i \in I(k)} \bar{p}^{\mathbf{n}}_{iq} \sum_{h:i \in I(hq)} x_{ih,q-4}}{\sum_{i \in I(k)} \bar{p}^{\mathbf{n}}_{i,q-4} \sum_{h:i \in I(hq)} x_{ih,q-4}}. \tag{4}$$

In line with the underlying product grouping, we refer to these inflation indices as $\pi^{\boldsymbol{bc}}_{kq}$ (brand-category) and $\pi^{\boldsymbol{c}}_{kq}$ (product category).

Quality tiers are based on the relative average price per unit of volume, separately within each product category. The volume price (Kim, 2019) of item i in quarter $q-4$ is

$$p^{v}_{i,q-4} = \frac{\sum_{h:i \in I(hq)} p_{ih,q-4} x_{ih,q-4}}{v_{i,q-4} \sum_{h:i \in I(hq)} x_{ih,q-4}}$$

where $v_{i,q-4}$ is the volume per unit.[17] An item belongs to the low-quality tier within its category in a given quarter if its volume price is below the median volume price in that category of that quarter. Only products with the same quality classification in $q-4$ and q are included in the inflation calculation with quality-category price indices. The quality-category (Laspeyres) index is therefore analogous to (4)

$$\pi^{\boldsymbol{qc}}_{kq} = \frac{\sum_{i \in I(k,q-4)} p^{v}_{i,q} \sum_{h:i \in I(hq)} x_{ih,q-4}}{\sum_{i \in I(k,q-4)} p^{v}_{i,q-4} \sum_{h:i \in I(hq)} x_{ih,q-4}}, \tag{5}$$

where $I(k, q-4)$ contains all items i belonging to a specific quality-category interaction k

[16] Appendix A.2.3 shows that the scanner categories are more narrowly defined than the ECOICOP five-digit categories, and therefore more homogeneous within themselves.

[17] The volume per unit is constant over time in the French, but sometimes time-varying in the German dataset.

in $q-4$.

The *household-level inflation rate with brand-category price indices* $\pi^{\boldsymbol{bc}}_{hq}$, the *household-level inflation rate with quality-category price indices* $\pi^{\boldsymbol{qc}}_{hq}$ and the *household-level inflation rate with category price indices* $\pi^{\boldsymbol{c}}_{hq}$ are then given by

Definition 3 (Household-level inflation with category price indices)**.** *The quarterly year-on-year ($q/q-4$) household-level Laspeyres index as average of category-level inflation is*

$$\pi^{\cdot}_{hq} = \sum_k \pi^{\cdot}_{kq} \hat{x}_{kh,q-4}, \tag{6}$$

where $\pi^{\cdot}_{kq}$ is the respective price index of product group k given by Equation (4) or (5) and the respective consumption shares are

$$\hat{x}_{kh,q-4} = \frac{\sum_{i\in I(k)\cap I(hq)} p_{ih,q-4} x_{ih,q-4}}{\sum_{i\in I(hq)} p_{ih,q-4} x_{ih,q-4}}.$$

Comparison with HICP The price index based on our sample of household-level transactions tracks the "food and non-alcoholic beverages" HICP subindex well (Figure 8 in Appendix A.2.5). This HICP subindex serves as a reference for our purposes, as more than 80% of the expenditure in the household panel is on food or beverages.[18]

2.2.3 COLI Household-level Inflation with Household-level Prices

COGIs measure pure price changes by requiring that the basket remains the same between both periods. In contrast, the COLIs measure the change in expenditures required to maintain the same level of utility between the two periods, therefore they take into account consumers' demand functions. We use three types of COLI indices in our analysis, which are all derived from homothetic constant elasticity of substitution (CES) preferences: The Sato-Vartia index in Sato (1976) and Vartia (1976) ("SV index"), the aggregate CES exact price index for common varieties[19] of Redding and Weinstein (2020) ("RW index"), and the average of the Lloyd-Moulton and backwards Lloyd-Moulton indices in Martin (2022) ("LLM index").

The Redding and Weinstein (2020) index allows for preference shifts over time. Braun and

[18] See Appendix A.2.4 for a comparison of the expenditure shares in the household panel with the shares in the basket underlying the HICP.

[19] The Redding and Weinstein (2020) index accounts additionally for product entry and exit. Distinguishing products that exited the market from products that are available but not purchased by a panellist would require in addition retail scanner data. As such data is not available for us, we limit the index calculation to continued products.

Lein (2020) adapt this index to the household-level as

$$\pi_{hq}^{\boldsymbol{RW}} = \frac{\tilde{p}_{h,q}}{\tilde{p}_{h,q-4}} \left(\frac{\tilde{s}_{h,q}}{\tilde{s}_{h,q-4}} \right)^{\frac{1}{\sigma_h - 1}}, \tag{7}$$

where a tilde denotes a geometric average across items, i.e. $\tilde{x}_{h,q} = \sqrt[N]{\Pi_i x_{ih,q}}$.[20] The underlying expenditure shares have the common form for COLIs based on homothetic CES utility

$$s_{ih,q} = \frac{p_{ih,q} q_{ih,q}}{\sum_{l \in I(hq)} p_{lh,q} q_{lh,q}} = \frac{(p_{ih,q}/\varphi_{ih,q})^{1-\sigma^h}}{\sum_{l \in I(hq)} (p_{lh,q}/\varphi_{lh,q})^{1-\sigma^h}}, \tag{8}$$

where $\varphi_{ih,q} > 0$ is the preference parameter of household h for item i in quarter q. The parameter of key interest is the household-specific elasticity of substitution denoted by σ^h. The estimation of these elasticities is described in Appendix A.3.

The Sato-Vartia index abstracts from such preference shifts. As pointed out by Redding and Weinstein (2020) and Braun and Lein (2020), the Redding-Weinstein inflation rate can be decomposed in a Sato-Vartia inflation rate that captures preferences which are heterogeneous across goods but constant over time ($\varphi_{ihq} = \varphi_{ihq-4}$), and a "taste-shift bias" term that captures the shift in preferences over time

$$ln\left(\pi_{hq}^{\boldsymbol{RW}}\right) = \underbrace{\sum_{i \in I(hq)} \omega_{ih,q} ln \left(\frac{p_{ih,q}}{p_{ih,q-4}} \right)}_{\text{Sato-Vartia}} - \underbrace{\sum_{i \in I(hq)} \omega_{ih,q} ln \left(\frac{\varphi_{ih,q}}{\varphi_{ih,q-4}} \right)}_{\text{taste-shift bias}}, \tag{9}$$

where for $s_{ih,q} \neq s_{ih,q-4}$ the weights are

$$\omega_{ih,q} = \frac{\frac{s_{ih,q} - s_{ih,q-4}}{ln(s_{ih,q}) - ln(s_{ih,q-4})}}{\sum_{l \in I(hq)} \frac{s_{lh,q} - s_{lh,q-4}}{ln(s_{lh,q}) - ln(s_{lh,q-4})}}. \tag{10}$$

For products whose expenditure shares do not change over time ($s_{ih,q} = s_{ih,q-4}$) the weights $\omega_{ih,q}$ equal the expenditure shares.[21]

The Redding-Weinstein index is an unconditional COLI, as it does not restrict any of the welfare-determining factors, namely prices, expenditures and tastes. Without an additional assumption the cost of living could change even when all prices and expenditures are unchanged. To rule out this possibility, the Redding-Weinstein index assumes that the geometric average of the taste parameters φ_{ihq} across varieties is constant over time.

[20] Osbat, Conflitti, Eiglsperger, Goldhammer, Kuik, Menz, Rumler, Moreno, Segers, Wieland, Bellocca, Siliverstovs, and Toure (2023) note that COLIs can be designed to account for the heterogeneity of consumers according to their income in two ways: non-homothetic price indices or homothetic indices that allow for heterogeneous preference parameters at the group-level. We follow the second approach, but allow for heterogeneous preference parameters even at the household level.

[21] Taking the limit $s_{ih,q} \to s_{ih,q-4}$ gives $\omega_{ih,q} \to s_{ih,q} = s_{ih,q-4} \equiv \omega_{ih}$. In the limiting case of Cobb-Douglas preferences all products are weighted by their expenditure share.

In contrast to unconditional COLIs, conditional COLIs fix all welfare-determining factors except prices, and put thus less demand on the data than, e.g., the Redding-Weinstein index. Besides the Sato-Vartia index, also the two Lloyd-Moulton indices have this feature, but account additionally for a change in preferences over time. The *Lloyd-Moulton index* fixes tastes φ and expenditure shares s in the ex-ante period $q-4$:

$$\pi_{h,q}^{\boldsymbol{LM}} = \frac{P_{h,q}(p_q, \varphi_{q-4})}{P_{h,q-4}(p_{q-4}, \varphi_{q-4})} = \left[\sum_{i \in I(hq)} s_{ih,q-4} \left(\frac{p_{ih,q}}{p_{ih,q-4}} \right)^{1-\sigma_h} \right]^{\frac{1}{1-\sigma_h}}, \tag{11}$$

while the *Backwards Lloyd-Moulton index* fixes them in period q:

$$\pi_{h,q}^{\boldsymbol{BLM}} = \frac{P_{h,q}(p_q, \varphi_q)}{P_{h,q-4}(p_{q-4}, \varphi_q)} = \left[\sum_{i \in I(hq)} s_{ih,q} \left(\frac{p_{ih,q-4}}{p_{ih,q}} \right)^{1-\sigma_h} \right]^{\frac{-1}{1-\sigma_h}}. \tag{12}$$

By comparing conditional and unconditional COLIs when tastes change over time, Martin (2022) shows that the geometric average of (11) and (12),

$$\pi_{h,q}^{\boldsymbol{LLM}} = \sqrt{\pi_{h,q}^{LM} \pi_{h,q}^{BLM}}, \tag{13}$$

is close to a COLI that conditions on intermediate tastes, such as the Sato-Vartia index, and that such a COLI averages higher than an unconditional COLI such as the Redding-Weinstein index (7). He furthermore highlights that an unconditional COLI that uses normalized parameters (as e.g. Redding-Weinstein) is not invariant to the normalization chosen, which can affect the wedge between the conditional and unconditional COLIs. The difference between the Redding-Weinstein and the Sato-Vartia index in Equation (9) therefore cannot unambiguously be assigned to the taste-shock bias.

3 Size and Persistence of Inflation Heterogeneity

Inflation differs widely between households, both in France and in Germany. The green lines in Figure 1 plot the interquartile range of household-level inflation rates with household-level prices in France and Germany, averaging at 3.2 and 3.9 percentage points, respectively. In both countries the interquartile range is wide, stable over time, and thus largely uncorrelated with aggregate inflation. The magnitude of this heterogeneity can be gauged against the aggregate inflation based on the same scanner data,[22] which averages at -0.2% in France and at 1.3% in Germany. The heterogeneity among households at any point in time is large even relative to the fluctuations in aggregate inflation during the entire sample period, where the standard deviations amount to 1.4 and 2.4 percentage points in France and in

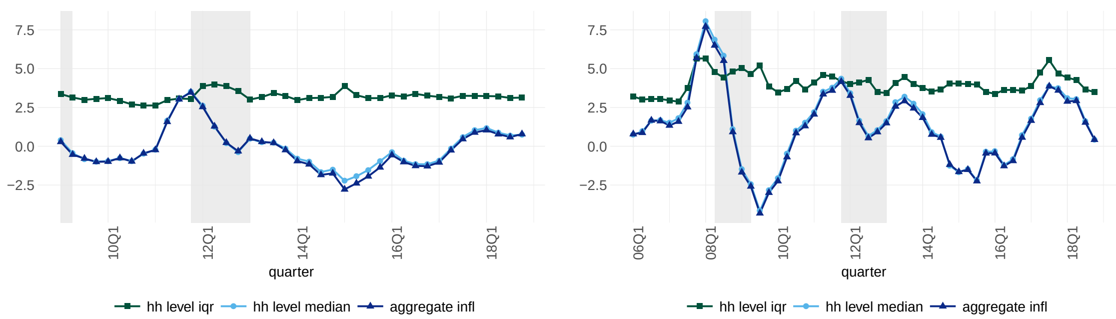
[22]The median of household-level inflation (Definition 1) moves closely with the aggregate inflation rate calculated from scanner data (Definition 4 in Section A.2.5) mainly because both are based on the same repurchase requirement at the household-level.

Germany, respectively.

This large dispersion is nevertheless smaller than the one that Kaplan and Schulhofer-Wohl (2017) document for the USA. They find an interquartile range of between 6.2 and 9.0 percentage points for a period during which the official consumer price index averages 2.6% (with a standard deviation of 1.9 percentage points).[23]

Figure 1: Dispersion of household-level inflation rates over time

(a) France **(b)** Germany



Note: The light blue line plots the median of quarterly year-on-year household-level Laspeyres inflation $\pi^{\boldsymbol{h}}_{hq}$. As comparison, the dark blue line shows the corresponding aggregate inflation based on scanner weights and scanner prices $\pi^{\boldsymbol{s}}_q$ (Definition 4, based on GfK/Kantar product categories). Both inflation rates are based on the transactions of households repurchasing at least 25 products in both quarters. The green line plots the interquartile range of $\pi^{\boldsymbol{h}}_{hq}$.

One might suspect that the large dispersion of household-level inflation with household-level prices is transitory, therefore we compare also multi-year inflation rates. Even based on three-year inflation rates, the interquartile range remains substantial with 2.0 and 2.1 percentage points in France and Germany, respectively (Appendix Figure 9). The inflation differences across households are therefore quite persistent.

To see the persistence of household-level inflation *within* the three-year subperiods, i.e. from one year to the next, we calculate the autocorrelation function ρ^{δ}_h at the household-level for horizons δ of four, eight, and twelve quarters for households that are present in our sample for at least 12 quarters in a row.[24] The slightly negative median of the autocorrelation (Figure 2) at any horizon confirms the presence of some inflation variation due to the timing of purchases. The autocorrelation is not statistically significant, however,

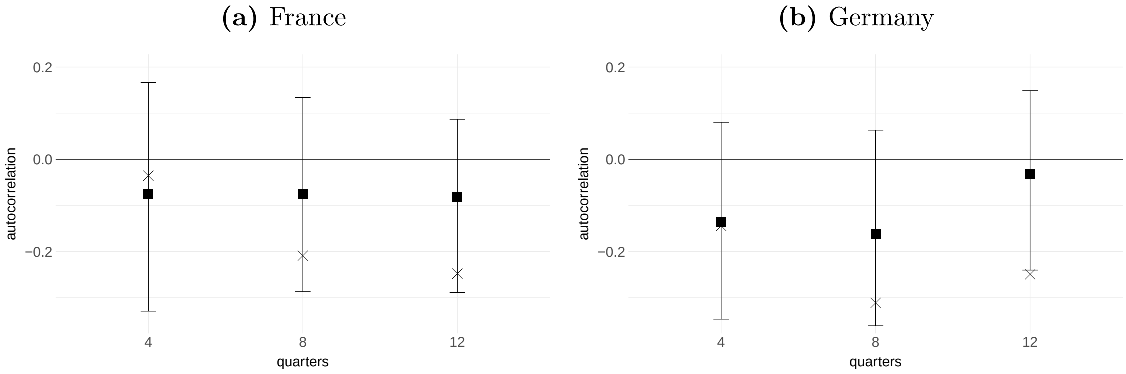
[23] Kaplan and Schulhofer-Wohl (2017) require the repurchase of at least 5 items between q and $q-4$ in their baseline indices, while we require at least 25. Relaxing this repurchase requirement does not change our results.

[24] The autocorrelation ρ^{δ}_h for horizon δ is

$$\rho^{\delta}_h = \frac{[1/(N_{h,\delta}+\delta)]\sum_q(\pi^{\boldsymbol{h}}_{hq}-\bar{\pi}^{\boldsymbol{h}}_h)(\pi^{\boldsymbol{h}}_{h,q-\delta}-\bar{\pi}^{\boldsymbol{h}}_h)}{(1/N_{h,0})\sum_q(\pi^{\boldsymbol{h}}_{hq}-\bar{\pi}^{\boldsymbol{h}}_h)^2},$$

where $\bar{\pi}^{\boldsymbol{h}}_h$ is the average inflation of household h, $N_{h,0}$ the number of quarters available for household h, and $N_{h,\delta}$ the number of quarter pairs entering the respective numerator.

Figure 2: Autocorrelation of inflation for households



Note: The figure shows quantiles of the 4-, 8-, and 12-quarter autocorrelation ρ_h^δ. Only households with at least 25 products purchased both in q and $q-4$. The horizontal dashes mark the 10th and 90th percentile of the autocorrelation across households, while the box marks the median. The crosses mark the autocorrelation of the HICP "food and non-alcoholic beverages" subindex.

and with only -0.1 far too small to drastically reduce the large inflation heterogeneity over longer horizons. Beyond a one-year horizon the inflation heterogeneity (marked by boxes in Figure 2) is more persistent than aggregate inflation itself (marked by crosses in Figure 2). These results for one-year periods resemble those of Kaplan and Schulhofer-Wohl (2017) for the USA where the one-year serial autocorrelation is approximately -0.1, too (bottom panel in their Figure 6).[25]

4 Causes of Inflation Heterogeneity

The wide range of inflation experiences of households poses the question of its causes. This section first explores the role of regional factors, time and demographics. Thereafter it examines household behaviour to determine whether the heterogeneity in inflation rates stems from the differences in prices paid for the same product, the variety choice within a product category, or the baskets of the households.

4.1 Space, Time, and Demographics

In both countries spatial fixed effects[26] explain barely any variation in inflation rates across households. Local time variation matters considerably more. It explains up to 17% of

[25] Another way of measuring the persistence of household-level inflation deviations from the same-period average is the cross-sectional correlation of inflation across households (Figure 10 in Appendix A.4.2). This correlation is close to zero in both France and Germany, but slightly negative at the one-year horizon. This shows that the price paid by individual households reverts quickly, but only moderately, back to the overall price path.

[26] Fixed effects down to the three-digit postal area level. See column 3 of Table 14 in Appendix A.5.

total variation at the three-digit postal area level and up to 34% at the five-digit postal area level, which might reflect regional business cycles or regional promotional pricing. Household fixed effects, in turn, explain 10-16% of the variation of household-level inflation rates (Appendix Table 14).

Do these household fixed effects reflect systematic differences in standard demographic characteristics such as age or income? As baseline specification, we regress household-level Laspeyres inflation $\pi_{hq}^{\boldsymbol{h}}$ on key demographic variables of households. This includes the age of the household head in decades, the income of the head of the household as average per month in thousand euros, its change relative to the same quarter a year earlier, the number of household members, and a proxy for the presence of a baby in the household.[27] The longer sample in Germany allows separating the age effect from the cohort effect captured by the birth year. Collecting these demographic variables in the matrix $X_{h,q}$, the regression equation is

$$\pi_{hq}^{\boldsymbol{h}} = \alpha_{r(h),q} + \beta X_{h,q} + \lambda Z_{r3(h),q} + \epsilon_{h,q}, \tag{14}$$

where the regional quarter fixed effects $\alpha_{r(h),q}$ and the regional control variables in matrix $Z_{r3(h),q}$ capture the business and inflation cycle in region $r(h)$ and demographic developments in region $r3(h)$, respectively.[28] The error term $\epsilon_{h,q}$ is clustered by region. Because of the high dimensionality of the fixed effects we rely in these regressions on the estimation routines of Correia (2017). To separate time variation from cross-sectional heterogeneity (and as an analogue to the fixed effects regression in the first paragraph), we also estimate a variant of Equation (14) with time averages, i.e. $\pi_h^{\boldsymbol{h}} = \alpha_{r3(h)} + \beta X_h + \epsilon_h$, where $\pi_h^{\boldsymbol{h}}$ is the average deviation of (the logarithm of) household inflation $\pi_{hq}^{\boldsymbol{h}}$ from the sample average inflation in the respective quarter.[29]

The explanatory power of standard household demographics for inflation is small, even in the cross-section. Columns (1) and (4) of Table 2 report a within R^2 of less than 3% in both countries.[30] In other words, the bulk of inflation differences between households must stem from household characteristics which are not or only imperfectly related to household demographics.

There are nevertheless systematic differences between demographic groups, as many de-

[27] The baby dummy indicates the purchase of baby items in the respective quarter. The regression includes the squared values of age, income and household size to capture potential nonlinearities. The regression includes furthermore dummies for tail groups with very few observations: In Germany a dummy for the lowest income group (less than 500 euro per month), for household heads born before 1930 or after 2000, and in both countries a dummy for household heads younger than 20 years.

[28] We denote the two-digit, respectively three-digit, postal area in which household h is located by $r2(h)$, respectively $r3(h)$. The regional characteristics $Z_{r3(h),q}$ include the panelist median income, panelist median household size, population density, and income per capita equivalent, each by three-digit postal area.

[29] For this time-average regression we use only households which did not switch the three-digit postal area within a region, and for which we are able to calculate y-o-y inflation rates for at least four quarters.

[30] The low R^2 is a common feature of similar regressions in earlier studies as well (e.g. for the USA by Kaplan and Schulhofer-Wohl (2017), for Switzerland by Braun and Lein (2020)). They argue that the variance of the household-level inflation is much larger than the variance of the explanatory variables.

Table 2: Effect of demographic factors on Laspeyres inflation

	(1)	(2)	(3)	(4)	(5)	(6)
		France			Germany	
dep. variable	$\pi^{\boldsymbol{h}}_h$	$\pi^{\boldsymbol{h}}_{hq}$	$\pi^{\boldsymbol{h}}_{hq}$	$\pi^{\boldsymbol{h}}_h$	$\pi^{\boldsymbol{h}}_{hq}$	$\pi^{\boldsymbol{h}}_{hq}$
income	-0.096***	-0.150***	-0.155***	-0.018	-0.038*	-0.023
	(0.036)	(0.032)	(0.032)	(0.031)	(0.019)	(0.020)
income^2	0.002	0.008*	0.010**	-0.001	0.002	0.001
	(0.005)	(0.004)	(0.005)	(0.005)	(0.003)	(0.003)
Δ income		0.004	0.011		0.021**	0.020*
		(0.022)	(0.021)		(0.010)	(0.010)
expenditure quartile	-0.221***	-0.128***		-0.217***	-0.158***	
	(0.013)	(0.008)		(0.011)	(0.006)	
expenditure per capita			-0.908***			-1.344***
			(0.051)			(0.038)
Δ expenditure per capita			1.025***			1.050***
			(0.075)			(0.054)
birth year				-0.011***	-0.016***	-0.016***
				(0.003)	(0.004)	(0.004)
age	0.351***	0.349***	0.378***	-0.327***	-0.400***	-0.366***
	(0.078)	(0.058)	(0.058)	(0.059)	(0.050)	(0.049)
age^2	-0.026***	-0.026***	-0.029***	0.032***	0.034***	0.030***
	(0.007)	(0.006)	(0.006)	(0.005)	(0.003)	(0.003)
household size	-0.059	0.121*	0.088	0.180***	0.148***	0.136***
	(0.074)	(0.064)	(0.063)	(0.030)	(0.020)	(0.019)
household size^2	0.017	-0.017	-0.011	-0.011**	-0.007**	-0.005*
	(0.013)	(0.011)	(0.011)	(0.005)	(0.003)	(0.003)
baby	0.061	0.007	0.006	-0.152***	-0.120***	-0.103***
	(0.042)	(0.019)	(0.019)	(0.035)	(0.014)	(0.014)
panel median income in 3zip		-0.213***	-0.166*		-0.236***	-0.059
		(0.069)	(0.092)		(0.072)	(0.069)
panel median hh-size in 3zip		0.083*	0.095**		0.027	0.033
		(0.047)	(0.047)		(0.041)	(0.036)
population density		0.185***	0.095		-0.159***	-0.268**
		(0.023)	(0.111)		(0.053)	(0.123)
income per cap. eq.		0.005	-0.002		-0.005	-0.003
		(0.005)	(0.009)		(0.004)	(0.008)
Fixed effects	zip3	qtr	qtr×zip2	zip3	qtr	qtr×zip2
# observations	15122	244736	244733	29784	606097	606092
R^2	0.090	0.157	0.176	0.053	0.334	0.343
R^2 within	0.029	0.005	0.006	0.027	0.004	0.005

*Dependent variable: Household-level average Laspeyres inflation rate $\pi^{\boldsymbol{h}}_h$ in columns (1) and (4), and $\pi^{\boldsymbol{h}}_{hq}$ otherwise, all in percent p.a.. The sample period for France is 2009-2018 and for Germany 2005-2018. Age measured in decades, income and expenditure in 1000 euros, changes relative to same quarter in previous year. Baby dummy indicates the purchase of baby items in the respective quarter. Aggregates with the three-digit postal area are in logs. Population density in inhabitants per are in 2018. Constant and dummies for tail income, age, and birth year groups with few observations not reported. Robust standard errors clustered at the zip2 level in parentheses. *** p<0.01, ** p<0.05, * p<0.1* mographic variables in columns (1) and (4) of Table 2 are highly significant. In France, Laspeyres inflation increases throughout most of the life cycle (at a decreasing rate), as reported in the second block of Table 2. This might be a mix of a generational and an age effect. In Germany earlier (older) generations also face higher Laspeyres inflation, which might reflect their lower mobility.[31] For a given birth cohort of German households, however, inflation decreases until around age 50, more than offsetting the generational effect. Only towards retirement inflation increases with age as in France. In Germany, moreover, larger households face significantly higher inflation – unless the additional household member is a baby.

Low-income households face significantly higher Laspeyres inflation in France. Ceteris paribus, the cross-sectional inflation difference between households with a head earning 2000 euros and a head earning 4000 euros per month amounts to almost 0.2 percentage points per year. In Germany this income-level effect is superseded by an income-change effect (column 5). If the income of a German household increases over time, then its inflation tends to increase as well. The alternative measure of economic strength, expenditure, tells the same story for both countries. Households in a higher expenditure quartile experience significantly lower inflation. Columns (3) and (6) show that – analogous to income – also households with a persistently higher expenditure per capita experience lower inflation. If they have just became more affluent during the past year, however, their inflation barely changes.

Controlling for regional business cycles does not change these patterns. Columns (2) and (5) suggest that an important part of regional heterogeneity (absorbed by the fixed effects in columns (1) and (4)) are income differences between regions. In the rightmost columns (3) and (6) we replace the quarter fixed effects by their interactions with the two-digit postal area, $\alpha_{r2(h),q}$, to ensure that the household variables capture not a neighbourhood, but a pure household effect. Indeed, the relation between inflation and income seen at the household level exists at the regional level too – on top of the household effect. The household-specific and regional coefficient estimates remain largely unchanged.[32]

[31]During the sample period, price comparison websites were not common in food retail. Therefore this hints more towards a lower loyalty to local stores than towards a higher technology-affinity of later (younger) generations.

[32]Interestingly, the household-size effect present in Germany at the household level shows up in France at the regional level. In France, three-digit postal areas populated by larger households (which might be rather rural or suburban) faced a significantly higher inflation during the sample period. Furthermore, inflation seems to have differed during the sample period depending on the population density of a region, but in different ways. In France more densely populated regions faced higher, whereas in Germany more densely populated regions faced lower inflation. Overall income per capita in a region (as opposed to median panelist income) does not explain the inflation differences in any way.

4.2 Household Behavior

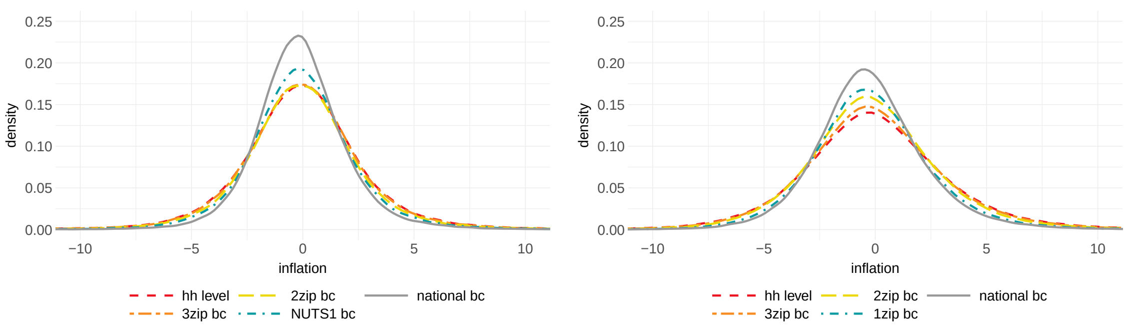
To identify the behavioral origin of inflation heterogeneity we augment the methodology of Kaplan and Schulhofer-Wohl (2017) as sketched in Section 2.2 by intermediate regional price averages and by indices within product category. We then examine if behavioural variables can explain inflation heterogeneity better than the demographic variables in the baseline regression (14).

4.2.1 Prices, Variety Choice, Baskets and their Relative Importance

Consider several households purchasing the same product (uniquely identified by its barcode) in a given quarter. The product is identical, but the households will typically differ in the purchase location, the exact day of purchase (within the quarter), and potentially individual discounts. As a result, households might pay very different prices for the same product in a given quarter. Do these price differences translate into an inflation difference between households? To answer this question, we calculate counterfactual inflation rates based on prices averaged across households residing in a given region, as given by Definition 2. As the size of the regional aggregate increases, first individual and then also local price differences are removed. The resulting inflation rate abstracts from the household's effort to obtain a good price for a given product. Importantly, the product choice remains household-specific.

Figure 3: Distribution of household-level inflation rates with household-level and regional prices

(a) France (b) Germany



Note: Year-on-year Laspeyres indices $\pi_{hq}^{\boldsymbol{h}}$ and $\pi_{hq}^{\boldsymbol{br\cdot}}$ as defined in Sections 2.2.1 and 2.2.2 for all fourth-quarter-pairs in the sample pooled together. The densities are estimated by using an Epanechnikov kernel. France: 66398 panelist-quarter observations (2009–2018), Germany: 160718 panelist-quarter observations (2006–2018).

Figure 3 reveals that the dispersion of household-level inflation rates with regional barcode-average prices (three-digit and two-digit postal areas plotted as orange and yellow lines, respectively) are very close to the dispersion with household-level prices (red lines) in both countries. Despite averaging the prices over many households, the interquartile range (IQR) shrinks only little from 3.2 (France) and 3.9 (Germany) with household-level prices to 3.0 and 3.6, respectively (Table 3). One household might get a better deal than another at some instance, but other households in turn get a better deal at other instances. Therefore the idiosyncratic price dispersion across households is of only secondary relevance for the overall inflation heterogeneity.[33]

Table 3: Relative importance of prices, variety and baskets

price aggregate	household-level $\pi^{\boldsymbol{h}}_{hq}$	3-digit zip $\pi^{\boldsymbol{br3}}_{hq}$	2-digit zip $\pi^{\boldsymbol{br2}}_{hq}$	national barcode $\pi^{\boldsymbol{bn}}_{hq}$	brand-category $\pi^{\boldsymbol{bc}}_{hq}$	quality-category $\pi^{\boldsymbol{qc}}_{hq}$	product category $\pi^{\boldsymbol{c}}_{hq}$
(a) interquartile range							
France	3.18	3.14	3.03	2.43	1.76	0.85	0.74
Germany	3.94	3.86	3.64	3.01	2.57	2.20	2.03
USA	7.33	n.a.	n.a.	3.99	n.a.	n.a.	1.96
(b) variance ratio vs. $\pi^{\boldsymbol{h}}_{hq}$							
France	1	0.97	0.90	0.58	0.27	0.06	0.04
Germany	1	0.93	0.82	0.54	0.39	0.27	0.23
USA	1	n.a.	n.a.	0.38	n.a.	n.a.	0.14
(c) R^2							
France	1	0.98	0.94	0.68	0.41	0.21	0.19
Germany	1	0.95	0.88	0.69	0.59	0.52	0.48

Note: The top block reports the average interquartile range of the given price index across quarters. The second block reports the ratios of the variance of the respective counterfactual price index relative to the variance of the benchmark index $\pi^{\boldsymbol{h}}_{hq}$ with household-level prices in the first column. The results for the USA are taken from Table 1 in Kaplan and Schulhofer-Wohl (2017) based on households repurchasing at least five products between q and $q-4$, while the other rows require the repurchase of at least 25 products. The R^2s are from a regression of $\pi^{\boldsymbol{h}}_{hq}$ on the respective index (both are averages across quarters per household).

The picture changes when prices are averaged over larger geographical areas. When averaging within large top-level regions in each country[34] a modest compression of the distribution is already discernible (blue line in Figure 3). In line with this, averaging nation-wide reduces inflation dispersion a lot (grey lines in Figure 3), with the IQR shrinking to 2.4 and 3.0 respectively.[35] The relative variance shrinks even more strongly, but remains above one

[33] Siliverstovs (2023) shows that the price paid by households in Germany for seven categories (dominated by unpackaged items and items sold by weight) increases with income. Categories include, e.g., "bread", "beer", or "fresh sausages". The price paid for "fresh sausages", for example, varies from 7.5 EUR/kg at the lower end up to 9.0 EUR/kg at the upper end of the income distribution. As the underlying products are not necessarily identical – they can have different barcodes – these price differences most likely reflect differences in quality, sausage type and shopping channel (discounter vs. supermarket) between household groups.

[34] NUTS-1 regions in France, one-digit postal areas in Germany. See Appendix A.1.2 for details on the choice of top-level geographically connected regions.

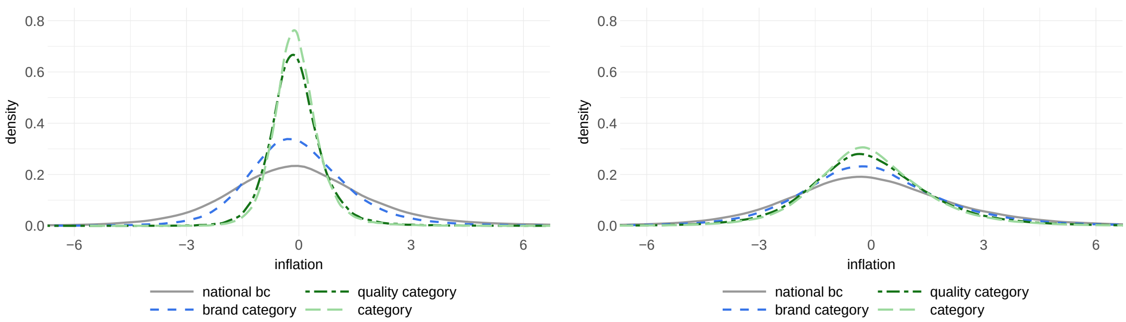
[35] These patterns hold throughout the entire sample period (Figure 12 in Appendix A.6). Figure 13 in the same appendix shows very similar results for one particular quarterly cross-section, the low-inflation quarter

half of the variance with household-level prices (panel (b) of Table 3).

This suggests that inflation varies across regions within a country. Section 4.1 shows that an important part of regional heterogeneity are income differences between regions and that regions with a higher income of the median household face *lower* inflation. This implies that in our sample local price setting is not driven by the search effort of the households,[36] because otherwise firms with customer retention concerns (Paciello, Pozzi, and Trachter, 2019) could increase their prices more in regions with more high-income households.

Figure 4: Distribution of household-level inflation rates with national barcode average prices, and brand-category, quality-category and category price indices (Q4)

(a) France **(b)** Germany



Note: Q4-on-Q4 Laspeyres indices $\bar{p}_{iq}^{\boldsymbol{n}}$, $\pi_{hq}^{\boldsymbol{qc}}$ and $\pi_{hq}^{\boldsymbol{c}}$ as defined in Section 2.2.2. Based on the transactions of households (re)purchasing at least 25 products in both quarters. The densities pool all 4^{th} quarter pairs using an Epanechnikov kernel. France: 65413 panelist-quarter observations, Germany: 157514 panelist-quarter observations.

The decomposition of the household-level variance[37] into its components in panel (b) of Table 3 confirms that household-idiosyncratic prices contribute relatively little to overall inflation heterogeneity. The household-specific component, which captures differences in, e.g., coupon use, search effort for a good price, or personalized offers (all for a given product), contributes only about 3% (France) to 7% (Germany) to the total variance (second part of Table 3). The primary price differences occur between top-level regions, e.g. between Paris and the Bretagne, not between regional subunits. The spatial component contributes almost 40% to the total variance.

Product choice within a given brand and the choice of brand within a given quality level explain together 52% (France) and 27% (Germany). The central role of product choice is in line with the finding of Braun and Lein (2020) for Switzerland, where variety choice within a category is the most important source of inflation heterogeneity. This stresses the

pair 2016Q4/2015Q4.

[36] Aguiar and Hurst (2007) show that price search increases as the opportunity cost of time decreases. Households with lower productivity and presumably lower income might have a lower opportunity cost of time and thus might search more for prices.

[37] The covariances do not materially affect the decomposition (Appendix Table 15).

importance of accounting for preference heterogeneity as in COLIs.[38]

In France, the choice of quality, as well as the set of product categories are not a driver of inflation heterogeneity. Together, they account for merely 6% of the total variance. We find that household-level inflation rates with brand-category price indices are somewhat less dispersed than those with national barcode average prices, while indices with quality-category price indices and category price indices are markedly less dispersed in France. This indicates that for France differences in product choice across quality tiers might be not as important as within quality tiers (left panel of Figure 4). Thus, in France the primary drivers of heterogeneity are price differences between top-level regions, and the households' product choice for a given quality level.

In Germany, however, the differences in the composition of the consumption basket (in terms of product categories) are an important driver, accounting for 23% of the total variance. The choice of the quality level contributes an additional 4%. Thus, in Germany besides differences between top-level regions and the households' product choice also the basket composition plays an important role (right panel of Figure 4).[39]

In the USA differences in the prices paid for the same product are by far the most important source of inflation heterogeneity across households. The last row of panels (a) and (b) of Table 3 repeat the values reported in Kaplan and Schulhofer-Wohl (2017). These IQRs are considerably larger than in France and in Germany, but unfortunately we do not know whether, at which regional aggregation level, spatial heterogeneity in the USA arises. A plausible conjecture is that the higher spatial variation in the USA is mainly due to the larger distances between the households in the US sample.

Overall, differences in prices paid for the same product within a country do play an important role. But these differences are mostly due to the spatial component of price changes, which accounts for more than one third of overall inflation heterogeneity. Household-specific prices explain only little. The main driver is product choice, which explains in France about one half ($0.58 - 0.06$ in panel (b) of Table 3) and in Germany about one fourth ($0.54 - 0.27$) of the variance. In Germany, most of the remainder is due to basket composition, which a household might be able to modify to some extent, but at the cost of fundamentally adapting its consumption bundle.

[38]This section describes the results when pooling all fourth-quarters in the sample. In Appendix A.6 we show that these patterns hold also for individual cross-sections, e.g. the during the low-inflation period 2016Q4/2015Q4 (Figure 15). A time-series plot of the interquartile ranges of the cross-sectional distributions at each point in time (Figure 16) shows that the relative magnitudes persist throughout the sample period.

[39]The high R^2 of a regression of the benchmark household-level index on the counterfactual household-level indices shown in panel (c) of Table 3 indicates that also at the household level and despite its small variance, even inflation based on a product-category price index is highly correlated with the household-level inflation.

4.2.2 Household-level Inflation and the Behaviour of Households

Household fixed effects explain only 10-16% of the variation of household-level inflation rates (Appendix A.5), therefore 84-90% of the overall variance is due to time-variation *within* the same household. If the demographic situation of the household or the general economic environment change, the household might change its behaviour. First, it might adjust its shopping intensity by spending more days shopping or visiting more shops per day. Behind shopping intensity there might be either price search or the purchase of a larger variety of goods – the former possibly more for lower-income households, the latter more for higher-income households. We include transactions per shopping occasion in our regressions to capture the size of the basket of the household. Second, the households' preferences might shift and consequently its choice of varieties within a category. Third, the overall composition of the households' purchases might change, i.e. the shares of broad product categories in its consumption basket.

To establish a direct link between household behaviour and household-level Laspeyres inflation, we augment the baseline regression (14) with behavioural variables $Y_{h,q}$.

$$\pi_{hq}^{\boldsymbol{h}} = \alpha_{r2(h),q} + \beta X_{h,q} + \gamma Y_{h,q} + \lambda Z_{r3(h),q} + \epsilon_{h,q} \tag{15}$$

The matrix $Y_{h,q}$ includes the (log of the) number of shopping days, stores per shopping day, and transactions per shopping occasion (each of them as lagged value or as annual change),[40] the expenditure shares of the main shopping channels, the chain concentration ratio (Gini), chain loyalty, the expenditure share of the main two-digit ECOICOP product categories, the brand concentration ratio (Gini index), brand loyalty, and the expenditure share of private label products.

Table 4: Effect of household characteristics on Laspeyres inflation

	(1)	(2)	(3) IV	(4)	(5)	(6)	(7) IV	(8)
		France				Germany		
	$\pi_h^{\boldsymbol{h}}$	$\pi_{hq}^{\boldsymbol{h}}$	$\pi_{hq}^{\boldsymbol{h}}$	$\pi_{hq}^{\boldsymbol{bn}}$	$\pi_h^{\boldsymbol{h}}$	$\pi_{hq}^{\boldsymbol{h}}$	$\pi_{hq}^{\boldsymbol{h}}$	$\pi_{hq}^{\boldsymbol{bn}}$
income	0.012 (0.034)	-0.031 (0.028)	-0.012 (0.034)	-0.029 (0.018)	0.016 (0.030)	0.020 (0.018)	0.015 (0.024)	-0.005 (0.014)
income^2	-0.004 (0.005)	0.001 (0.004)	-0.000 0.005	0.001 (0.003)	-0.004 (0.005)	-0.003 (0.003)	-0.001 (0.003)	0.000 (0.002)
Δ income		0.000 (0.020)	-0.009 (0.025)	-0.007 (0.015)		0.012 (0.010)	0.002 (0.015)	-0.004 (0.009)
expenditure quartile	0.066*** (0.022)	0.039*** (0.009)		0.037*** (0.007)	0.011 (0.024)	-0.032*** (0.008)		-0.026*** (0.006)
expenditure per capita			-0.543* (0.288)				-1.049*** (0.224)	
Δ expenditure per capita			0.164 (1.262)				0.853 (1.232)	
age	-0.042 (0.071)	0.089* (0.048)	0.262*** (0.089)	0.162*** (0.041)	-0.185*** (0.049)	-0.205*** (0.033)	-0.142*** (0.046)	-0.136*** (0.031)

(Continued on following page)

[40]One shopping occasion is a unique combination of panelist × keyaccount × day.

	(1)	(2)	(3) IV	(4)	(5)	(6)	(7) IV	(8)
	France				Germany			
	π^{h}_{h}	π^{h}_{hq}	π^{h}_{hq}	π^{bn}_{hq}	π^{h}_{h}	π^{h}_{hq}	π^{h}_{hq}	π^{bn}_{hq}
age^2	0.008	-0.004	-0.014*	-0.012***	0.026***	0.029***	0.022***	0.022***
	(0.007)	(0.005)	(0.007)	(0.008)	(0.004)	(0.003)	(0.004)	(0.003)
household size	0.131*	0.169***	-0.049	0.154***	0.296***	0.208***	0.127***	0.159***
	(0.071)	(0.055)	(0.103)	(0.046)	(0.035)	(0.020)	(0.031)	(0.016)
household size^2	-0.007	-0.018**	0.013	-0.022***	-0.027***	-0.017***	-0.010**	-0.014***
	(0.012)	(0.009)	(0.016)	(0.008)	(0.005)	(0.003)	(0.004)	(0.002)
shopping days $q-4$	-0.340***	-0.180***		-0.164***	-0.325***	-0.214***		-0.155***
	(0.075)	(0.031)		(0.023)	(0.047)	(0.017)		(0.012)
Δ shopping days			-0.478				-0.357	
			(1.568)				(0.320)	
stores / day $q-4$	-0.100	0.053		0.087*	-0.302***	-0.247***		-0.199***
	(0.143)	(0.059)		(0.048)	(0.070)	(0.034)		(0.024)
Δ stores / day			0.010				-0.474	
			(0.781)				(0.319)	
transactions / shopping $q-4$	-0.512***	-0.363***		-0.291***	-0.382***	-0.277***		-0.253***
	(0.079)	(0.028)		(0.022)	(0.049)	(0.022)		(0.016)
Δ trans. / shopping			1.258***				0.517	
			(0.487)				(0.324)	
chain concentration	0.197**	0.094**	-0.093	0.091***	0.088	0.042	0.938	0.100***
	(0.092)	(0.045)	(0.389)	(0.033)	(0.077)	(0.033)	(0.362)	(0.025)
chain loyalty	0.323***	0.147***	-1.692	0.097***	-0.476***	-0.148***	1.511**	0.004
	(0.109)	(0.027)	(1.325)	(0.023)	(0.149)	(0.028)	(0.645)	(0.022)
exp. share of discounters	0.903***	0.832***	2.045***	1.255***	0.638***	0.592***	1.056***	0.360***
	(0.169)	(0.108)	(0.199)	(0.073)	(0.185)	(0.101)	(0.173)	(0.076)
exp. share of specialists	1.284***	1.169***	2.139***	1.411***	1.554***	1.528***	2.192***	1.364***
	(0.321)	(0.157)	(0.302)	(0.113)	(0.219)	(0.123)	(0.194)	(0.096)
exp. share of supermarkets	-0.237	-0.219**	0.456*	0.093	0.762***	0.928***	1.008***	0.543***
	(0.157)	(0.098)	(0.261)	(0.060)	(0.189)	(0.104)	(0.177)	(0.076)
exp. share of hypermarkets	-0.234	-0.295***	0.576*	0.170***	0.695***	0.715***	0.981***	0.613***
	(0.158)	(0.091)	(0.312)	(0.057)	(0.182)	(0.096)	(0.184)	(0.072)
brand concentration	1.275**	1.157***	0.113	1.047***	-0.135	0.069	-1.435***	0.217***
	(0.531)	(0.220)	(1.033)	(0.159)	(0.171)	(0.082)	(0.445)	(0.066)
brand loyalty	-1.127***	-0.924***	-0.790	-0.068***	0.114	-0.427***	-1.119**	-0.005
	(0.223)	(0.102)	(0.644)	(0.083)	(0.129)	(0.060)	(0.533)	(0.045)
exp. share of private label	1.691***	1.423***	1.750***	1.669***	1.021***	0.970***	0.730***	1.354***
	(0.275)	(0.113)	(0.401)	(0.090)	(0.101)	(0.063)	(0.100)	(0.053)
exp. share of food	0.366	0.342**	0.422	0.102	1.705***	1.788***	1.989***	1.756***
	(0.225)	(0.141)	(0.282)	(0.113)	(0.178)	(0.099)	(0.191)	(0.078)
exp. share of non-alc. bev.	1.480***	1.179***	0.861**	0.697***	0.541**	1.194***	0.254	0.969***
	(0.359)	(0.194)	(0.412)	(0.159)	(0.232)	(0.128)	(0.251)	(0.101)
exp. share of alc. bev.	2.660***	2.558***	2.824***	2.371***	0.567***	0.740***	0.761***	0.723***
	(0.291)	(0.201)	(0.318)	(0.158)	(0.201)	(0.103)	(0.195)	(0.088)
exp. share of hobby/pet	0.681*	0.773***	0.260	0.514**	-0.986***	0.585***	-0.691***	-0.847***
	(0.384)	(0.201)	(0.430)	(0.234)	(0.247)	(0.131)	(0.252)	(0.111)
panel median income in 3zip	-0.159*	-0.179**	-0.189**	-0.088	-0.193**	-0.105*	-0.107*	-0.043
	(0.082)	(0.075)	(0.079)	(0.569)	(0.092)	(0.062)	(0.064)	(0.045)
panel median hh-size in 3zip	0.013	0.072**	0.093*	0.066**	0.049	0.056*	0.117***	0.066**
	(0.068)	(0.036)	(0.048)	(0.030)	(0.062)	(0.033)	(0.045)	(0.028)
population density	0.143	0.180***	0.231***	0.027	-0.189	-0.336***	-0.324***	-0.354***
	(0.088)	(0.066)	(0.074)	(0.044)	(0.143)	(0.121)	(0.114)	(0.079)
Fixed effects	zip2	qtr×zip2	qtr×zip2	qtr×zip2	zip2	qtr×zip2	qtr×zip2	qtr×zip2
# observations	15164	244722	171490	244722	29787	606005	496114	606005
R^2	0.181	0.200	n.a.	0.307	0.062	0.346	n.a.	0.483
R^2 within	0.171	0.034	n.a.	0.061	0.057	0.009	n.a.	0.018

Dependent variables: Household-level Laspeyres inflation rate $\pi_{hq}^{\boldsymbol{h}}$ in percent p.a., its average $\pi_h^{\boldsymbol{h}}$, or household-level inflation with national barcode-average prices $\pi_{hq}^{\boldsymbol{bn}}$. The sample period for France is 2009-2018 and for Germany 2005-2018. Age measured in decades, income in 1000 euros, changes relative to same quarter in previous year. Number of shopping occasions, number of shopping days and number of transactions per shopping occasion in logs. Population density in 1000 inhabitants per square kilometre in 2018. In columns (1) and (4) the independent variables are time averages by household. Constant, fixed effects, and dummies for tail income and age with few observations are not reported. Standard errors clustered at the two-digit postal code level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 4 shows the coefficient estimates of Equation (15). The behavioural variables are highly significant. The increase in the within-R^2 tells us that these behavioural variables have additional explanatory power.

In comparison to the earlier regression with only demographic variables reported in Table 2 the significance of income declines and the expenditure quartile estimates now differ between France and Germany. This suggests that income affects inflation heterogeneity rather indirectly through household behaviour. Expenditure per capita, however, is significantly negative in the instrumental variable regression in both countries. More spending might entail more attention and thus more price comparisons. At the regional level (seventh box of Table 4), however, the income effect remains significant. That is, although inflation at the household level is better explained by the household's behaviour than by its income, it remains a robust finding that more affluent regions face lower Laspeyres inflation.

Age and household size, quite in contrast, continue to matter *in addition to* household behaviour. Larger households, presumably families, face higher Laspeyres inflation. The same applies to age for households with a household head older than 35 years. This indicates that there are some subtle aspects of inflation in France and Germany related to age and household size, respectively, that are not captured by the behavioural variables $Y_{h,q}$. The final Section 7.1 (Table 6) will show, however, that the overall contribution of demographic variables is small relative to the behavioural ones.

The behaviour of households might itself respond to inflation, i.e. the behavioural variables might be endogenous to (earlier) price changes. The endogeneity bias appears to be limited, however. In columns (3) and (7) we instrument all current behavioural variables with their values lagged by one year and with demographic variables. With the exception of shopping occasions and brand concentration, which turn insignificant, the broad sign and significance patterns of columns (2) and (6) remain.

The third and fourth block of Table 4 aim to capture the shopping behaviour of households (shopping intensity, choice of store types and chains), which determines the prices that they pay for the same good. Aguiar and Hurst (2007), for example, explain a part of the heterogeneity in prices paid for identical goods with differences in shopping frequency. Households with a track record of intensive shopping dampen their inflation based on the days spent shopping and the number of stores per day, presumably due to search for prices. However it seems that having more transactions per shopping occasion, which is typical for higher income households that buy more varieties, is also associated with lower inflation. Comparing the counterfactual barcode-average prices (columns (4) and (8)) with the actual prices (columns (2) and (6)) shows that households that have a higher shopping intensity dampen their inflation also when the price differences of the same good are not considered, only differences stemming from variety choice or baskets.

The effect of chain loyalty does not provide a uniform picture.[41] But the estimates for both countries show that households focusing their purchases on discounters or specialist stores faced larger inflation during the sample period. The same applies to households spending a high share on private label products.[42]

The fifth block of Table 4 addresses the household's variety choice within a category. Households with a limited choice set, proxied by a high brand concentration, end up with a significantly higher inflation, especially if they paid the national average price (columns (4)+(8)).[43] Repeated purchases of the same brand (brand loyalty), however, seems to entail that the household monitors prices of that brand waiting for a (low) sale price, which is reflected in the large negative coefficients for the household-level inflation rate $\pi^{\boldsymbol{h}}_{hq}$.

The role of the top-level basket choice is covered by the variables in the sixth block of the table. Relative to the omitted product categories household maintenance and drugstore items, the expenditure share of beverages and food is an inflation driver in both countries: a high spending share on necessities is another proxy for the financial tightness of a household and despite their price search effort, poorer households face higher inflation.

Overall, inflation is best explained by a combination of shopping behaviour, variety choice and baskets. After controlling for household behaviour, income has no explanatory power for inflation.

5 Substitution

In this section we examine whether households can offset inflation differences in their ex-ante $(q-4)$ basket by substitution. For this purpose, we calculate the difference of the Laspeyres index (which implies no substitution by fixing the basket in $q-4$) and the Paasche

[41] Indeed, Yan, Tian, Dixon, Heravi, and Morgan (2014) argue that shopping around can lead to higher prices paid.

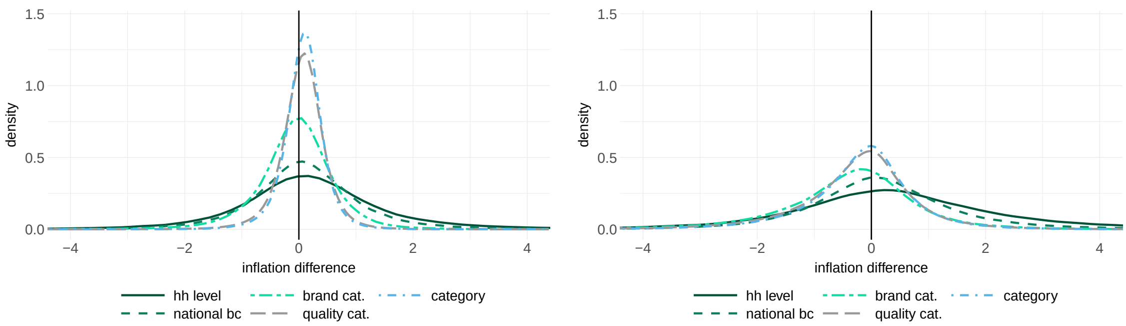
[42] This might reflect that some discounters have upgraded their assortment and positioning in recent years. Likewise, the quality of many private labels has improved. These markets and products might still be the cheaper ones, but their prices increased relatively more than others.

[43] Consumers compare prices only with a limited choice set, typically defined by a set of brands (Bronnenberg and Vanhonacker, 1996). That is, price changes of brands not part of the choice set do not lead to a consumer response.

index (which implies full substitution by fixing the basket in q). When the household-level inflation rates are calculated with household-level prices we find similarly as earlier studies (Kaplan and Schulhofer-Wohl (2017) for the USA, Braun and Lein (2020) for Switzerland) that households often substitute towards more expensive products. Reassuringly, the difference of the Laspeyres and Paasche indices for the median household is slightly positive in both France and in Germany (dark blue line in Figure 5), but only little. Based on the pattern in the household-level indices with household-level prices Kaplan and Schulhofer-Wohl (2017) argue that this counterintuitive pattern might be a result of either non-homothetic preferences or taste (preference) shocks, while Braun and Lein (2020) explain it by preference heterogeneity (constant as well as time-varying shocks) across households.

Figure 5: Difference of Laspeyres and Paasche indices (Q4)

(a) France **(b)** Germany



Note: Year-on-year Laspeyres minus Paasche indices $\pi^{\boldsymbol{h}}_{hq}$, $\bar{p}^{\boldsymbol{n}}_{iq}$, $\pi^{\boldsymbol{bc}}_{hq}$, $\pi^{\boldsymbol{qc}}_{hq}$ and $\pi^{\boldsymbol{c}}_{hq}$ as defined in Sections 2.2.1 and 2.2.2 for all Q4-s in our sample pooled together. Based on the transactions of households repurchasing at least 25 products in both quarters. Estimation of the densities uses the Epanechnikov kernel. France: 49294 panelist-quarter observations. The bandwidth used is 0.1. Medians: 0.16, 0.09, -0.03, 0.08, 0.09. Probability mass above zero: 0.486, 0.483, 0.469, 0.556, 0.595. Germany: 131102 panelist-quarter observations. The bandwidth used is 0.1. Medians: 0.35, 0.12, -0.29, -0.15, -0.11. Probability mass above zero: 0.605, 0.488, 0.346, 0.414, 0.421.

We first examine whether other factors influence the patterns in the data. For instance sales or coupons: if a given product was bought at a discounted price in $q-4$ and then at a non-discounted price in q, then the difference of the Laspeyres and Paasche indices for the given household would be also negative. To filter out such effects, we calculate the difference of Laspeyres and Paasche indices also with barcode-average prices (mid-blue line in Figure 5). But even with barcode-average prices the measured substitution does not get stronger, which renders price discounts (sales, coupons) an unlikely cause of the weak substitution we observe.

Excluding substitution within brands by calculating the Laspeyres-Paasche differential with brand-category average price indices makes the substitution towards more expensive products even stronger (light blue line in Figure 5).[44] When aggregating up further by excluding

[44] At price aggregation beyond the product level, substitution between barcode-identified products is mixed with substitution of one product for another. At this aggregation level a negative difference between

also substitution within and across quality-tiers this counterintuitive direction of substitution disappears in Germany and becomes weaker in France (light green and dark green lines in Figure 5).[45]

Based on these results, sales and discounts are not behind the negative difference of the Laspeyres and Paasche indices. But as many households substitute towards more expensive products within product categories (i.e. within/across brands and quality-tiers), we conclude in line with Braun and Lein (2020) that preference heterogeneity across households might be behind these patterns.

6 Causes of Differences in Substitution Behavior

In this section we examine the causes of the differences across households regarding substitution. To account for the effect of substitution on household utility, we explicitly introduce heterogenous household preferences. We compare the COLIs defined in Section 2.2.3, which allow for preference heterogeneity across households, with the Laspeyres-Paasche differential. The estimation of household-level elasticities of substitution is based on the methodologies of Feenstra (1994) and Broda and Weinstein (2006).[46]

Estimating elasticities of substitution under CES preferences assumes that they are identical for all product pairs. Such elasticities can only be interpreted in the context of the underlying set of products. The six three-digit COICOPs used throughout the paper[47] form a quite heterogenous set of products with quite heterogeneous coverage by household baskets. We therefore restrict the estimation of elasticities and the calculation of COLIs to food (01.1) and beverages (01.2, 02.1.1, 02.1.3) only,[48] which cover products that are reasonably substitutable among each other and consumed regularly by most households.

The elasticity of substitution is very dispersed across households in both France and Germany with a median around 4.5 (Figure 19 in Appendix A.7). The wide range of elasticity estimates across households suggests that also the substitution behaviour differs strongly.

Accounting for the different preferences across goods and allowing for product substitution across them, however, does not change the inflation rate for the median household. The

Laspeyres and Paasche is therefore possible. It can stem from a replacement of one product for another, i.e. substitution towards a (still) cheaper product despite a relatively stronger price increase.

[45]The patterns hold for one particular cross-section as well. Figure 17 in Appendix A.7 shows the sign and ordering of the median Laspeyres-Paasche differential is stable over time. Figure 18 shows as example the distribution for the 2016Q4/2015Q4 quarter pair during the low-inflation period.

[46]These are summarized in Appendix A.3 and described in more detail by Redding and Weinstein (2020) and Braun and Lein (2020).

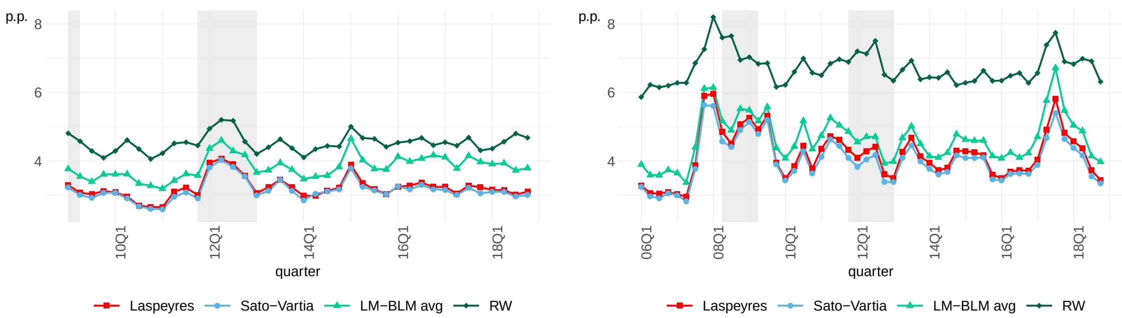
[47]I.e. food (01.1), non-alcoholic beverages (01.2), alcohol (02.1.1 and 02.1.3), household maintenance (05.6), pet food (09.3), personal care (12.1).

[48]The estimated elasticities do not change substantially, if the set of goods is restricted to food (01.1) only (Figure 20 in Appendix A.7).

median of the quarterly year-on-year Sato-Vartia index moves in lockstep with the Laspeyres index, despite the latter abstracting from substitution by fixing the basket (Figure 21 in Appendix A.7). It thus comes at no surprise that also the time-variation in preferences for a given good (Redding-Weinstein and geometric average of Lloyd-Moulton and the Backwards Lloyd-Moulton indices) barely affects the level of inflation of the median household.

Figure 6: Interquartile range of COGI vs. COLI

(a) France **(b)** Germany



Note: Interquartile range of quarterly year-on-year household-level indices. 'Laspeyres' denotes Laspeyres indices $\pi^{\boldsymbol{h}}_{hq}$ as defined in Section 2.2.1. 'Sato-Vartia' denotes the Sato-Vartia index, 'LM-BLM avg' denotes the geometric average of the Lloyd-Moulton and the Backwards Lloyd-Moulton indices π^{LLM}_{hq} and 'RW' denotes the Redding-Weinstein CCV index π^{RW}_{hq} as defined in Section 2.2.3. Goods are restricted to food and beverages. Households that repurchase at least 25 products in both quarters. For further restrictions on the households see Appendix A.3.

The heterogeneity of preferences across goods alone does not change the dispersion of household-level inflation estimates either. Figure 6 shows that the Laspeyres index with its fixed ex-ante basket behaves just like the Sato-Vartia index despite the latter allowing for heterogeneous substitution behaviour. The crucial dimension of heterogeneity is rather the time-variation in preferences. Both indices allowing for this display a persistently higher dispersion. The dispersion is slightly higher when average tastes between two periods are considered: the IQR widens by 15-20% in the case of the geometric average of the two Lloyd-Moulton indices. The dispersion is significantly higher when tastes can vary over time: the IQR based on the Redding-Weinstein index is 44% (France) and 67% (Germany) larger than that of the Sato-Vartia index, which shows that the "taste-shift bias" is central for understanding inflation heterogeneity.

The netting out of preference heterogeneity in median inflation hides that individual households substitute very differently, and that therefore the difference between pre- and post-substitution inflation varies widely between households. To understand which observable behaviour explains these substitution differences we replace the dependent variable in regression specification (15) by either the difference between the Laspeyres and the Paasche indices, or by the substitution bias as captured by the difference of the Laspeyres and Sato-Vartia indices, $\pi^{\boldsymbol{h}}_{hq} - \pi^{\boldsymbol{SV}}_{hq}$, or by the taste-shift bias as captured by the difference of the

Sato-Vartia and Redding-Weinstein indices, $\pi_{hq}^{\boldsymbol{SV}} - \pi_{hq}^{\boldsymbol{RW}}$. The set of independent variables includes those of regression (15) – as in columns (2) and (4) of Table 4 – for parsimony without the squared values of income, household size and age, and augmented by our estimate of the household's elasticity of substitution.

The Laspeyres index is calculated for an ex-ante (base-period) basket. As it rules out any substitution, it can be considered an upper bound to inflation. On the opposite extreme, the Paasche index is calculated for the later-period basket. As this reflects the full realized substitution, it is a lower bound to inflation. The Laspeyres-Paasche difference provides therefore an upper bound on substitution (as measured by COLIs) without further assumptions on the households' utility function. As a measure of substitution it implicitly assumes that the substitution of one product by another does not affect the utility of the household. We use this in the first and fourth column of Table 5 to examine what household characteristics and other factors determine substitution,

Some intuitive commonalities between both countries emerge: Higher income households substitute less, independently of a recent income change.[49] Households spending a lot tend to substitute more, which hints towards some economies of scale in (collecting the information for successful) substitution. Households clustering their transactions in a few locations end up substituting more successfully, potentially because they have a better overview of the alternatives. Unsurprisingly, high brand concentration and high brand loyalty limit the room for substitution. The inverted signs on chain loyalty versus brand loyalty highlight that it is not the habit of buying at the same outlet which limits substitution, but rather the proclivity for certain brands. The latter renders the consumer less price sensitive. It sticks to its preferred brand even if its price increases more than competing products. In contrast, *where* a household shops tells little about its substitution effort. The insignificance of the discounter share, for example, might reflect that within classic discounters the possibilities of substituting one brand for another are fairly limited.

The Laspeyres-Paasche difference focuses on the change in quantities. By treating prices and quantities as independent, it abstracts from any elasticity of substitution. The substitution bias measures how much a COLI index accounting for substitution deviates from a fixed-basket index. Despite the inclusion of this standard household-level parameter of substitution used in most economic models, other household characteristics remain significant. In other words, differences in the household-level elasticity of substitution cannot fully account for the heterogeneity in substitution behaviour.

All variables contribute less strongly to the SV difference (columns (2) and (5)) than to the Paasche difference (columns (1) and (4)), reflecting that substitution implies a tradeoff

[49]This observation is opposite to the finding of Argente and Lee (2020) for the USA, where higher income households substitute more during a recession. As our sample is not limited to recessions, this effect might be offset by the behavior of high-income households in non-recession periods.

Table 5: Household characteristics and substitution

	France			Germany		
	$\pi_{hq}^{h} - \pi_{hq}^{hP}$	$\pi_{hq}^{h} - \pi_{hq}^{SV}$	$\pi_{hq}^{SV} - \pi_{hq}^{RW}$	$\pi_{hq}^{h} - \pi_{hq}^{hP}$	$\pi_{hq}^{h} - \pi_{hq}^{SV}$	$\pi_{hq}^{SV} - \pi_{hq}^{RW}$
income	-0.018***	-0.010***	-0.015	-0.011***	-0.001	-0.032***
	(0.004)	(0.003)	(0.012)	(0.003)	(0.002)	(0.011)
Δ income	0.000	0.005	0.032	-0.004	-0.001	-0.001
	(0.009)	(0.006)	(0.028)	(0.006)	(0.003)	(0.021)
expenditure quartile	0.013***	0.010***	0.428***	0.030***	0.017***	0.955***
	(0.004)	(0.003)	(0.019)	(0.006)	(0.004)	(0.020)
age	0.004	0.004	-0.031***	-0.015***	0.000	-0.003
	(0.006)	(0.003)	(0.012)	(0.003)	(0.002)	(0.011)
household size	0.008	0.003	0.282***	0.089***	0.044***	0.300***
	(0.007)	(0.005)	(0.019)	(0.005)	(0.003)	(0.013)
shopping days $q-4$	0.086***	0.041***	-1.814***	-0.094***	-0.056***	-2.632***
	(0.019)	(0.013)	(0.058)	(0.011)	(0.006)	(0.036)
stores / day $q-4$	0.154***	0.049**	-1.532***	-0.071***	-0.038***	-2.320***
	(0.033)	(0.023)	(0.116)	(0.021)	(0.012)	(0.059)
transactions / shopping $q-4$	-0.073***	-0.036***	-1.755***	-0.259***	-0.133***	-2.280***
	(0.018)	(0.011)	(0.055)	(0.014)	(0.008)	(0.046)
exp. share of discounters	0.040	0.023	-0.164	0.107	0.085**	-1.909***
	(0.050)	(0.029)	(0.140)	(0.073)	(0.041)	(0.220)
exp. share of specialists	0.235**	0.190***	-1.122***	-0.185**	-0.062	-2.356***
	(0.065)	(0.050)	(0.213)	(0.080)	(0.044)	(0.225)
exp. share of supermarkets	0.056	0.027	0.184	0.011	0.033	-1.991***
	(0.042)	(0.024)	(0.131)	(0.074)	(0.041)	(0.231)
exp. share of hypermarkets	0.088	0.042	0.070	0.162**	0.101**	-1.908***
	(0.044)	(0.026)	(0.124)	(0.070)	(0.040)	(0.219)
chain concentration	0.007	0.004	0.452***	-0.327***	-0.136***	0.645***
	(0.023)	(0.014)	(0.064)	(0.022)	(0.013)	(0.080)
chain loyalty	0.077***	0.045***	-0.264***	0.098***	0.053***	-0.080
	(0.016)	(0.010)	(0.055)	(0.018)	(0.010)	(0.058)
brand concentration	-0.837***	-0.461***	8.200***	-0.547***	-0.260***	8.806***
	(0.111)	(0.069)	(0.419)	(0.065)	(0.037)	(0.215)
brand loyalty	-0.147***	-0.068***	1.235***	-0.986***	-0.445***	3.493***
	(0.051)	(0.032)	(0.167)	(0.044)	(0.025)	(0.127)
exp. share of private label	0.150***	0.117***	-1.759***	-0.444***	-0.207***	-1.120***
	(0.054)	(0.032)	(0.182)	(0.040)	(0.023)	(0.109)
elasticity of substitution		0.007***	0.018***		0.026***	0.054***
		(0.001)	(0.004)		(0.001)	(0.005)
exp. share of food	0.251***	0.132***	1.020***	0.252***	0.066*	4.277***
	(0.059)	(0.040)	(0.196)	(0.068)	(0.044)	(0.219)
exp. share of non-alc. bev.	0.172*	0.072	2.692***	0.526***	0.126***	7.329***
	(0.096)	(0.066)	(0.414)	(0.078)	(0.044)	(0.268)
exp. share of alc. bev.	0.076	0.066	3.225***	0.162**	0.002	3.387***
	(0.093)	(0.061)	(0.470)	(0.072)	(0.040)	(0.291)
exp. share of hobby/pet	0.238**	0.120	-1.022**	0.744***	0.227***	0.209
	(0.118)	(0.080)	(0.419)	(0.086)	(0.053)	(0.297)
# observations	244722	160138	160138	433675	370924	370924
R^2	0.019	0.027	0.047	0.020	0.024	0.080
R^2 within	0.003	0.004	0.021	0.007	0.009	0.038

Note: Dependent variables: Household-level difference of Laspeyres minus Paasche inflation rate (columns 1 and 4), difference of Laspeyres minus Sato-Vartia inflation rate (columns 2 and 5), and difference of Sato-Vartia minus Redding-Weinstein inflation rate (columns 3 and 6), all in percentage points p.a.. The sample period for France is 2009-2018 and for Germany 2005-2018. Age measured in decades, income in 1000 euros, changes relative to same quarter in previous year. Number of shopping occasions, number of shopping days and number of transactions per shopping occasion in logs. Population density in 1000 inhabitants per square kilometre in 2018. Constant, quarter × zip2 fixed effect, dummies for tail income and age with few observations, and regional controls (panel median income, panel median household size and population density within a three-digit postal area) are not reported. Standard errors clustered at the two-digit postal code level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

for the household, which the Paasche index ignores. As a result, the SV difference and with this also the inflation-dampening effect of household characteristics via substitution are smaller.

The third and sixth columns of Table 5 turn to the determinants of the taste shifts. We regress the taste change bias given by Equation (9) on our set of household characteristics and other factors. Note that the elasticity of substitution is a parameter of the Redding-Weinstein index, i.e. its significance is to be expected. A higher number of days spent shopping, stores visited per day, transactions per shopping occasion, and higher expenditure shares at specialist stores and on private label products all come with taste shifts that are inflation-augmenting, i.e. with a negative taste-shift bias. Households might spend more days shopping or visit multiple stores due to either consuming a larger variety of goods or searching for lower prices. Behind the finding that a higher number of days spent shopping and stores visited per day lead to inflation-augmenting taste-shift bias are probably higher-income households that consume a large variety of goods. Depending on the country, also higher income (Germany) or higher age (France) entail inflation augmenting taste-shifts. In contrast, higher relative expenditure, larger households, a higher concentration of purchases on a few chains or brands, a higher elasticity of substitution, and higher expenditure shares on food and beverages come with taste shifts that are inflation-offsetting, i.e. with a positive taste-shift bias. These taste shifts might reflect a more conscious and planned product selection. Importantly, many household characteristics affect the substitution bias and the taste-shift bias in opposite directions. At the household level, substitution (across goods) and taste shifts (over time) are separate phenomena. Both are thus important components of household heterogeneity.

7 Inflation and Income

The results so far highlight the central role that household behaviour plays in an household's inflation rate. Household demographics, in contrast, play hardly any role. If household behaviour was random, then the resulting inflation dispersion might lead to tail inflation dynamics and inflation expectation dynamics, which – combined with nonlinearities – in macroeconomic models can entail macroeconomic implications. The effect of this dispersion on the aggregate mean dynamics would be contained, however, because it would affect all types of economic agents in the same way.

This assessment would change if household behaviour was related to other economically relevant household characteristics. If, for example, household behaviour was systematically related to its marginal propensity to consume (MPC), then based on the evidence presented in this paper also inflation would vary systematically with the MPC. As the consumption response to inflation differs between MPC groups, inflation heterogeneity in this case would affect aggregate mean consumption as well – in addition to the dispersion effect.

Indeed there is evidence that income groups differ in their shopping behaviour, e.g. in terms of substitution (Argente and Lee, 2020) and cost-conscious shopping (Griffith, Leibtag, Leicester, and Nevo, 2009). In line with this concern, Ampudia, Ehrmann, and Strasser (2023) and Cravino, Lan, and Levchenko (2020) show that the effect of monetary policy on inflation differs by income group.

In this section we therefore separate idiosyncratic from systematic inflation components and explore within the latter the relation between systematic household behaviour and ex-ante observable household characteristics, such as income.

7.1 Relative Importance of Household Behavior and Household Demographics

The relative relevance of multiple potential determinants of household-level inflation rates $\pi_{hq}^{\boldsymbol{h}}$ can be assessed based on their contribution to the coefficient of determination (R^2). We first remove the contribution of regional business cycles with the auxiliary regression $\pi_{hq}^{\boldsymbol{h}} = \alpha_{r2(h),q} + \upsilon_{h,q}$. The resulting residuals $\upsilon_{h,q}$ then enter (14) and (15) as dependent variable. The decomposition of the R^2 along household behaviour and demographic variables follows the additive approach of Shorrocks (1982) and Shapley (1953).

The upper panel of Table 6 reports the decomposition along ten groups of variables, which cover a large set of household-specific behavioural variables, demographic characteristics and regional (three-digit postal area) variables. Even this large set of covariates explains only at most 5% of the variation in Laspeyres inflation in France, and at most 2% in Germany. In other words, at least 95% of the variation are not only idiosyncratic to the household; – they are furthermore not captured by variables describing individual household behaviour. This unexplained variation is therefore best described by a random household-level noise term. This random variation introduces inflation dispersion across households, which under linearity has no effect on average consumption.

Household behaviour explains more than 70% of the systematic variation. The main driver is shopping behaviour, captured by the first three rows of Table 6, it explains almost 50% in France and 35% in Germany. Among them, the shopping channel, i.e. whether the household shops at supermarkets or discounters, is most prominent. Shopping intensity is also important, however as mentioned earlier more days spent shopping or more stores visited per day can come from either search for low prices (lower income households) or a large number of varieties purchased (higher income households). The fourth row captures the second driver in France (explaining more than 30%): variety choice within a product group, in particular brand preferences. In Germany variety choice seems less relevant.

Table 6: R^2 decomposition by groups of explanatory characteristics (%)

(a) Demographics, regional, and behavioural

explanatory characteristics	France Laspeyres	France Paasche	France L-P	Germany Laspeyres	Germany Paasche	Germany L-P
shopping channels	32.4	31.5	11.6	19.7	21.5	6.5
shopping intensity	15.2	11.8	30.9	14.1	10.0	38.3
chain loyalty	1.2	1.1	1.2	0.7	3.2	10.1
variety choice	30.4	35.1	29.8	10.0	15.8	13.7
basket	6.8	7.1	6.0	27.7	23.6	8.3
expenditure	8.7	9.6	1.9	15.7	11.3	2.1
income	1.7	1.1	3.2	0.6	0.5	1.1
age	1.4	0.9	8.3	9.1	11.8	4.9
household situation	1.6	1.5	4.6	3.2	1.9	14.2
region characteristics	0.4	0.2	2.4	0.3	0.3	0.8
# observations	108762	108762	108762	345049	345049	345049
R^2	0.048	0.049	0.006	0.016	0.020	0.008

(b) Demographics and regional only

explanatory characteristics	France Laspeyres	France Paasche	France L-P	Germany Laspeyres	Germany Paasche	Germany L-P
expenditure	60.0	73.2	8.4	57.9	49.0	6.5
income	18.1	11.1	22.5	1.1	1.3	3.4
age	13.8	9.6	40.0	29.5	38.2	23.7
household situation	5.9	4.8	19.3	10.8	10.9	63.7
region characteristics	2.2	1.2	9.8	0.7	0.7	2.6
# observations	108770	108770	108770	345080	345080	345080
R^2	0.008	0.008	0.001	0.006	0.006	0.001

Note: Shorrocks-Shapley decomposition of the R^2 of regression equations (14) and (15). The dependent variables are the Laspeyres and Paasche versions of $\pi^{\boldsymbol{h}}_{hq}$, and the Laspeyres-minus-Paasche inflation differential (columns "L-P"), each after removing time variation at the two-digit postal code level. The groups of explanatory variables are a) shopping channels (expenditure share of discounters, specialists, supermarkets, hypermarkets, and year-on-year change in each; store type concentration Gini index, store type loyalty); b) shopping intensity (number of shopping occasions, number of shopping days, transaction per shopping occasion, year-on-year change in each); c) chain loyalty (chain concentration Gini index, chain loyalty) d) variety choice (brand concentration Gini index, brand loyalty, expenditure share and transaction share of private label products, average expenditure share on cheap products within categories); e) basket (expenditure share of main two-digit ECOICOPs, i.e. non-alcohol, alcohol, household maintenance, hobbies/pets, personal care; share of income spent of purchases reported; year-on-year change in each); f) expenditure (quintile within sample, expenditure by capita equivalent, and its year-on-year change); g) income (income, income^2, year-on-year change in quarterly income, income tail dummy); h) age (age, age^2, birth year, age and cohort tail dummies); i) household situation: household size, size^2, size change, dummies capturing change in the head of the household, baby, child; j) region characteristics of three-digit postal areas (median panelist age, median panel log household size, median panel log income, year-on-year change in each, population density, income per capita)

There, instead, the household's high-level consumption basket, i.e. the relative weights of the various product categories dominate the effect of varieties within categories.

Compared to household behaviour, the demographic variables in the lower five rows of the upper panel explain relatively little. Only variables related to total expenditure explain 9% and 16% in France and Germany, respectively. The much smaller contribution of income suggests that expenditure reveals the household's preferences and constraints better than self-reported income. Interestingly, regional characteristics as measured by average income and population within three-digit postal areas (relative to the average within the respective two-digit postal area) are not a relevant driver of inflation heterogeneity in either country. In other words, inflation heterogeneity does not stem from intra-regional heterogeneity.

Both behavioural and demographic variables might capture, respectively proxy, differences in the MPC between households. If inflation and MPC were positively correlated, then this could amplify the effect of inflation on consumption, because a hand-to-mouth household would be forced to reduce (real) consumption one-to-one with inflation.

The lower panel of Table 6 shows that only a small part of this variation is captured by ex-ante observable standard demographic variables. Demographic and regional variables explain less than one percent of total variation, most of it by variables related to expenditure. Reported income plays again only a minor role. Comparing the upper and lower panels shows that by including behavioural variables the contribution of standard demographic variables shrinks drastically. This indicates that the demographic situation of the household affects the household-level inflation partly via household behaviour.

7.2 The Role of Income

Among the demographic characteristics income is particularly interesting, because economic theory provides some behavioural predictions. During the common sample period 2008–2018, the lowest income group faced a higher Laspeyres inflation rate than the highest income group. Its annual average Laspeyres inflation rate was 0.06 percentage points higher in Germany and 0.23 percentage points higher in France.[50]

Kaplan and Schulhofer-Wohl (2017) report the same ordering of income groups for the USA for an earlier time period with higher inflation. The larger inflation spread between income groups in the US sample suggests that (Laspeyres) inflation differences between income groups increase with average inflation, a point vividly illustrated for six euro area countries in Ampudia et al. (2023).

[50] Based on inflation indices weighting households equally within each income group ("democratic approach"). See columns 1–3 of Table 17 in Appendix A.8.2. The autocorrelation of inflation at the household level is slightly negative and similar in all four income groups (Appendix A.8.3).

Grouping households by expenditure quartiles gives the same ordering in terms of Laspeyres inflation.[51] In terms of Paasche inflation, however, the ordering reverts: Poorer households (i.e. here households with lower reported spending) face higher inflation before, but lower inflation after substitution. In short, poorer households seem to substitute more.

Does income have an indirect effect through household behaviour on inflation heterogeneity? For this question we return to regression (15). We use all significant variables in columns (2) or (6) of Table 4, replace the income variables with an interaction term between the four income groups[52] and the quarter dummies, and accordingly use only two-digit postal area fixed effects. Based on this regression we calculate contrasts of predictive margins between the highest and the lowest income group in each country.

Figure 7 shows time-varying inflation differences between income groups of up to one percentage point per year. Importantly, the ordering of income groups is not persistent. In fact, the income group with the higher inflation changes several times. In Germany, shown in the lower panel, the low-income group faced considerably higher inflation during 2011–2013. In 2014, however, inflation was higher for the high-income group. In France this pattern is delayed by about one year, but otherwise similar. The finding of higher inflation for low income households around 2012 is an interesting commonality with the results reported by Argente and Lee (2020) for the USA, and suggests a global shock to the prices of products consumed by low-income households. Argente and Lee (2020) argue that during the recession high-income US households adjusted their shopping behavior and increased substitution more than low-income households. This time variation might explain the periodic resurgence of a debate about inflation differences between income groups.[53]

This rejoins the common wisdom on the relevance of income for inflation differences (Jaravel, 2021) with our finding that income per se is not a primary driver of inflation differences. The prevalence of many household characteristics and behaviours which affect inflation correlates with the income group – not perfectly, but sufficiently strongly to entail at times significant inflation differences between income groups. As many of these behaviours are cyclical, only the small inflation difference of on average 0.1-0.2 percentage points per year remains after integrating over longer horizons.

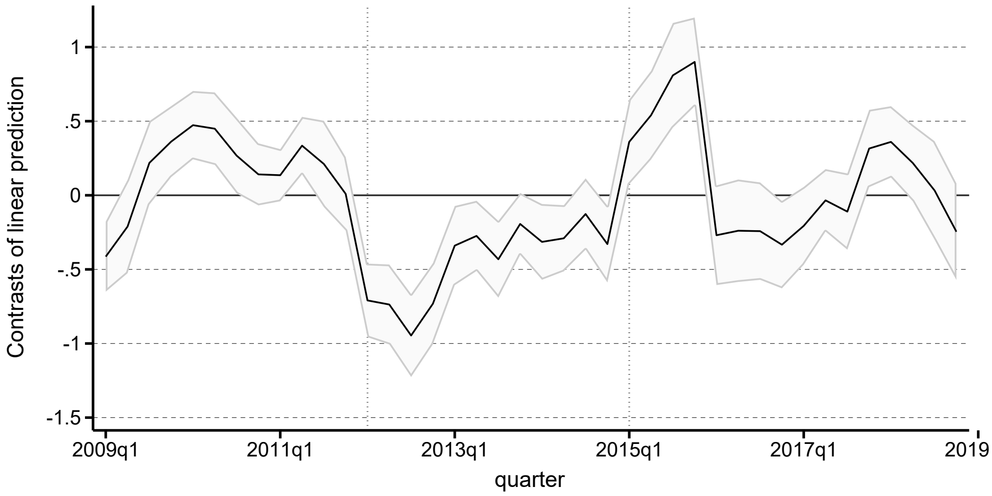
[51] See Appendix Table 18.

[52] Results for a finer income group categorization are reported in Strasser et al. (2023).

[53] Recent work by Nord (2022) stresses the general equilibrium effect of (demand-weighted) shopping effort on prices. He estimates that in the USA price differences between and across varieties can offset around one-tenth of expenditure inequality between income groups.

Figure 7: Contrasts of predictive margins of income class

(a) France



(b) Germany

Note: Contrast of predictive margins of inflation between high-income and low-income households as defined in Table 8. Laspeyres inflation, percentage points p.a., 95% confidence bands in grey.

8 Conclusion

Inflation varies widely between households. In this paper we examine the micro facts and mechanics behind this well-known observation. We document a large dispersion of inflation rates across households, with the interquartile range exceeding three percentage points in both France and Germany throughout the sample period. Despite modest mean reversion at a one-year horizon, the inflation differences across households are very persistent. This paper highlights three sources of this massive inflation heterogeneity.

1. *Differences in prices paid for the same product within a country.* These differences are mostly due to the spatial component of price changes, which accounts for more than one third of overall inflation heterogeneity.
2. *Behavior of the individual household, in particular product choice.* Standard demographic characteristics explain little. Income heterogeneity by itself is not a primary determinant of inflation heterogeneity, but because household behaviour is weakly correlated with income, inflation differences between income groups emerge.
3. *Substitution (success).* The substitution success of households is just as heterogeneous as inflation itself, again driven more by household behaviour than demographics. Household product choice within a category appears to be largely detached from the relative price. Neither accounting for substitution nor allowing for heterogeneous or time-varying preferences reduces the dispersion of inflation across households.

Households are very heterogeneous even within seemingly narrowly defined groups, such as e.g. the low-income group. They differ in their shopping behaviour and their consumption basket and therefore end up with very different inflation rates – despite all being low-income households. This implies that assumptions such as, e.g., common real interest rates or common inflation expectations might not be good descriptions of reality. Focusing on a single dimension of inflation heterogeneity, such as income, would fall far short of accounting for the heterogeneity in the population of consumers.

References

Aguiar, M. and M. Bils (2015, September). Has consumption inequality mirrored income inequality? *American Economic Review 105*(9), 2725–2756.

Aguiar, M. and E. Hurst (2007, December). Life-cycle prices and production. *American Economic Review 97*(5), 1533–1559.

Ampudia, M., M. Ehrmann, and G. Strasser (2023, October). The effect of monetary policy on inflation heterogeneity along the income distribution. Working Paper 2858, European Central Bank.

Argente, D. and M. Lee (2020). Cost of living inequality during the Great Recession. *Journal of the European Economic Association 19*(2), 913–952.

Arioli, R., C. Bates, H. C. Dieden, I. Duca, R. Friz, C. Gayer, G. Kenny, A. Meyler, and I. Pavlova (2017, April). EU consumers' quantitative inflation perceptions and expectations: an evaluation. Occasional Paper 186, European Central Bank.

Armantier, O., L. Goldman, G. Kosar, G. Topa, W. van der Klaauw, and J. C. Williams (2022, February). What are consumers' inflation expectations telling us today? Liberty Street Economics. Federal Reserve Bank of New York.

Arslan, Y., B. Guler, and T. Taskin (2021, February). Price search, consumption inequality and expenditure inequality over the life-cycle. *International Economic Review 62*(1), 295–320.

Bańnkowska, K., A. M. Borlescu, E. Charalambakis, A. D. Da Silva, D. Di Laurea, M. Dossche, D. Georgarakos, J. Honkkila, N. Kennedy, and Kenny (2021, December). ECB consumer expectations survey: an overview and first evaluation. Occasional Paper 287, European Central Bank.

Beck, G. W. and X. Jaravel (2020). Prices and global inequality: New evidence from worldwide scanner data. Mimeo.

Braun, R. and S. M. Lein (2020). Heterogeneity in inflation and preferences across households. Mimeo.

Broda, C. and D. E. Weinstein (2006). Globalization and the gains from variety. *Quarterly Journal of Economics 121*(2), 541–585.

Bronnenberg, B. J. and W. R. Vanhonacker (1996). Limited choice sets, local price response and implied measures of price competition. *Journal of Marketing Research 33*(2), 163–173.

Cavallo, A., G. Cruces, and R. Perez-Truglia (2017, July). Inflation expectations, learning, and supermarket prices: Evidence from survey experiments. *American Economic Journal: Macroeconomics 9*(3), 1–35.

Claeys, G. and L. Guetta-Jeanrenaud (2022, February). Who is suffering most from rising inflation? Bruegel Blog. https://www.bruegel.org/2022/02/who-is-suffering-most-from-rising-inflation/.

Colavecchio, R., U. Fritsche, and M. Graff (2011, February). Inflation inequality in Europe. Macroeconomics and Finance Series 201102, University of Hamburg, Department of Socioeconomics.

Correia, S. (2017). Linear models with high-dimensional fixed effects: An efficient and feasible estimator. Working paper, Duke University.

Cravino, J., T. Lan, and A. A. Levchenko (2020). Price stickiness along the income distribution and the effects of monetary policy. *Journal of Monetary Economics 110*(C), 19–32.

Crawford, I. and Z. Smith (2002). Distributional aspects of inflation. Commentary 90, Institute for Fiscal Studies.

Del Giovane, P., S. Fabiani, and R. Sabbatini (2010). What's behind "inflation perceptions"? A survey-based analysis of Italian consumers. In P. Del Giovane and R. Sabbatini (Eds.), *The Euro, Inflation and Consumer's Perceptions: Lessons from Italy*, Chapter 6, pp. 157–197. Berlin, Heidelberg: Springer.

Dräger, L. (2015, October). Inflation perceptions and expectations in Sweden – Are media reports the missing link? *Oxford Bulletin of Economics and Statistics 77*(5), 681–700.

D'Acunto, F., U. Malmendier, J. Ospina, and M. Weber (2021). Exposure to grocery prices and inflation expectations. *Journal of Political Economy 129*(5), 1615–1639.

Feenstra, R. C. (1994). New product varieties and the measurement of international prices. *American Economic Review 84*(1), 157–177.

Fessler, P. and F. Fritzer (2013). The distribution of inflation among Austrian households. *Monetary Policy & the Economy 13*(Q3), 12–28.

Garner, T. I., D. S. Johnson, and M. F. Kokoski (1996). An experimental consumer price index for the poor. *Monthly Labor Review 119*(9), 32–42.

Griffith, R., E. Leibtag, A. Leicester, and A. Nevo (2009). Consumer shopping behavior: How much do consumers save? *Journal of Economic Perspectives 23*(2), 99–120.

Gürer, E. and A. Weichenrieder (2020). Pro-rich inflation in Europe: Implications for the measurement of inequality. *German Economic Review 21*(1), 107–138.

Hagemann, R. P. (1982). The variability of inflation rates across household types. *Journal of Money, Credit and Banking 14*(4), 494–510.

Hobijn, B. and D. Lagakos (2005). Inflation inequality in the United States. *Review of Income and Wealth 51*(4), 581–606.

Huber, S. J., D. Minina, and T. Schmidt (2023). The pass-through from inflation perceptions to inflation expectations. Discussion Paper 17/2023, Deutsche Bundesbank.

Jaravel, X. (2019). The unequal gains from product innovations: Evidence from the U.S. retail sector. *Quarterly Journal of Economics 134*(2), 715–783.

Jaravel, X. (2021). Inflation inequality: Measurement, causes, and policy implications. *Annual Review of Economics 13*, 599—629.

Kaplan, G. and S. Schulhofer-Wohl (2017). Inflation at the household level. *Journal of Monetary Economics 91*(C), 19–38.

Kim, S. (2019). Quality, price stickiness, and monetary policy. *Journal of Macroeconomics 61*(C), 1–1.

Krüger, D. and F. Perri (2006, 01). Does income inequality lead to consumption inequality? evidence and theory. *Review of Economic Studies 73*(1), 163–193.

Martin, R. S. (2022). Revisiting taste change in cost-of-living measurement. *Journal of Economic and Social Measurement 46*(2), 109–147.

Michael, R. T. (1979). Variation across households in the rate of inflation. *Journal of Money, Credit and Banking 11*(1), 32–46.

Michelacci, C., L. Paciello, and A. Pozzi (2019). The extensive margin of aggregate consumption demand. Discussion Paper 13687, CEPR.

Nord, L. (2022, December). Shopping, demand composition, and equilibrium prices. Mimeo. University of Pennsylvania.

Orchard, J. (2020, February). Household inflation and aggregate inflation. Mimeo. University of California, San Diego.

Osbat, C., C. Conflitti, M. Eiglsperger, B. Goldhammer, F. Kuik, J.-O. Menz, F. Rumler, M. S. Moreno, L. Segers, E. Wieland, G.-P. Bellocca, B. Siliverstovs, and A. Toure (2023, July). Measuring inflation with heterogeneous preferences, taste shifts and product innovation: methodological challenges and evidence from microdata. Occasional Paper 323, European Central Bank.

Paciello, L., A. Pozzi, and N. Trachter (2019). Price dynamics with customer markets. *International Economic Review 60*(1), 413–446.

Pollak, R. A. (1980). Group cost-of-living indexes. *American Economic Review 70*(2), 273–278.

Pytka, K. (2022). Shopping frictions and household heterogeneity: Theory and empirics. Mimeo. University of Mannheim.

Redding, S. J. and D. E. Weinstein (2020). Measuring aggregate price indices with taste shocks: Theory and evidence for CES preferences. *Quarterly Journal of Economics 135*(1), 503–560.

Sato, K. (1976). The ideal log-change index number. *Review of Economics and Statistics 58*(2), 223–228.

Shapley, L. S. (1953). A value for n-person games. In H. W. Kuhn and A. W. Tucker (Eds.), *Contributions to the Theory of Games*, Volume 2, pp. 307–317. Princeton University Press.

Shorrocks, A. (1982). Inequality decomposition by factor components. *Econometrica 50*(1), 193–211.

Siliverstovs, B. (2023, March). You are what you eat and you eat what you earn. Evidence from the German household scanner data panel. Mimeo. Bank of Latvia; KOF Swiss Economic Institute, ETH Zurich.

Stanisławska, E. and M. Paloviita (2021). Medium- vs. short-term consumer inflation expectations: Evidence from a new euro area survey. Research Discussion Paper 10/2021, Bank of Finland.

Strasser, G., T. Messner, F. Rumler, and M. Ampudia (2023, July). Inflation heterogeneity at the household level. Occasional Paper 325, European Central Bank.

van Kints, M. and R. Breunig (2021). Inflation variability across Australian households: Implications for inequality and indexation policy. *Economic Record 97*(316), 1–23.

Vartia, Y. O. (1976). Ideal log-change index numbers. *Scandinavian Journal of Statistics 3*(3), 121–126.

Weber, M., F. D'Acunto, Y. Gorodnichenko, and O. Coibion (2022, Summer). The subjective inflation expectations of households and firms: Measurement, determinants, and implications. *Journal of Economic Perspectives 36*(3), 157–184.

Weber, M., Y. Gorodnichenko, and O. Coibion (2023, March). The expected, perceived, and realized inflation of US households before and during the COVID19 pandemic. *IMF Economic Review 71*(1), 326–368.

Yan, J., K. Tian, H. D. Dixon, S. Heravi, and P. Morgan (2014). Shop around and you pay more. Working Paper 4940, CESifo.

A Appendix

A.1 Data Preparation and Cleaning

A.1.1 Data Cleaning

The data cleaning starts with the transaction-level data. We apply each cleaning step to both France and Germany, but some have an effect only in one of the two countries. Items with EANs are generally more consistently defined than those with a non-EAN barcode. In the French data there are only EAN barcodes, while in the German raw data 40% of purchased items feature non-EAN barcodes.

A small set of items have no barcodes in the German data (row 2 in Table 7). Then we identify the ambiguous assignment of items to barcodes. This can occur if neither a barcode description, nor brand or manufacturer information is available, and the barcode is a non-EAN. Based on this criterion, we drop purchases of 19 non-EAN barcodes for Germany whose barcode description contains only "Keine Mengenabfrage" and which have neither brand nor manufacturer information. Such seemingly generic product types cover a wide variety of products, which are not comparable. The exclusion of these 19 non-EAN barcodes in Germany reduces the total number of transactions by 87.52 million (row 3 in Table 7). Furthermore, in the French data a subset of EANs has no volume information (row 4 in Table 7).

The following steps, still at the transaction-level, focus on barcodes that are not well defined with respect to chains that are selling them. Non-EANs are chain-specific and might be used by different chains for different products. In some cases the non-EANs contain a chain identifier. The German data contains some non-EANs that are either inconsistent with the chain or that are spread across chains. We drop transactions involving such barcodes (row 5 and 6 in Table 7). An example for inconsistent non-EANs are barcodes starting with "ALV", that are sold at Aldi in the case of 99.998% of the transactions, but in a few instances reported as purchased at another chain. An example for non-EANs that are spread across chains are barcodes starting with "CBV", transactions in which are not limited to Aldi (11.4% of transactions), but spread across almost all chains.

After these cleaning steps at the transaction-level we aggregate the data to the household-item-quarter level. In order to compare a homogeneous market we exclude purchases by households residing on Corsica.[54] We also restrict the sample to the product categories with relevant coverage by GfK/Kantar, i.e. to ECOICOP 01.1 (food) and 01.2 (non-alcoholic beverages), 02.1.1. and 02.1.3. (alcoholic beverages except wine), 05.6 (household maintenance), 09.3 (pet food) and 12.1 (personal care). Because the French survey does not

[54]The overseas departments of France are not part of the sample.

include wine, we exclude it for consistency reasons from the German sample as well (row 9 in Table 7).

In some instances households differ in the *volume per unit* they report for the products. For example, one household reports as unit of cheese "10 grams" whereas another household reports "100 grams". However households typically report consistently over time, therefore we drop only observations with multiple volume per unit levels for the same barcode within a quarter for a given household (row 10 in Table 7).

A detailed analysis of the data reveals that in a few instances multipacks are inconsistently reported. The same household may report the *unit* purchased of a given EAN once in pieces (e.g. beer bottles) and once in packs (e.g. beer crates). To ensure comparability across periods, we use a single threshold for the entire sample period. For each barcode, we only keep observations with a price that is less than five times the barcode median and more than one-fifth of the barcode median. When we apply this rule, the total number of household-barcode-quarter observations drops by 0.21 million in Germany and by 0.03 million in France (row 11 in Table 7).

In the next steps we consider the time dimension of the panel. A given households repurchases only 10% of items (20% of expenditure) in both quarter q and quarter $q-4$. We filter out all barcodes for which the volume per unit (volume sales / unit sales) differs between quarter q and $q-4$. In the German dataset between 9 and 20% of the purchases in a given year are of a barcode with time-varying volume sales. Unsurprisingly, the majority of these barcodes are non-EANs, but there are also a few EANs with this characteristic. In Germany, 34.79 million household-item-quarter observations represent repurchases between q and $q-4$, from which we remove 0.09 million due to purchases where the volume per unit is not constant between q and $q-4$ (rows 13 and 14 in Table 7). In France the volume per unit is constant over time by definition, therefore the household-barcode-quarter observations remain at 13.33 million for repeat purchases.

The last section of Table 7 explores the effect of imposing a minimum basket size (at the household level) for the calculation of a meaningful household-level inflation rate. The number of household-quarter observations in the cleaned dataset (row 10) shrinks by less than 0.01 million and by 0.05 million (row 17) and by about 0.11 million and 0.44 million (row 18) for France and Germany respectively, if we require that households repurchase at least 5 and at least 25 products. The requirement of at least 25 repurchased products reduces the sampled expenditure by less than 20%.

Table 7: Effect of data cleaning

		observations (millions)		expenditure (million euro)	
		France	Germany	France	Germany
(1)	raw data: *transactions*	150.26	430.77	411.03	887.94
	drop: products without barcodes	0	0.001	0	0.001
	drop: barcode without quantity	0	87.52	0	216.98
	drop: barcode without volume sales	0.63	0	1.80	0
	drop: non-EAN barcode inconsist. with chain	0	0.01	0	0.03
	drop: non-EAN barcode not spec. to a chain	0	4.71	0	16.28
	equals: *transactions*	149.64	338.52	409.22	654.65
(2)	equals: *household-item-quarter*	**108.41**	**245.56**	**409.23**	**654.65**
	drop: Corsica	0.15	0	0.64	0
	drop: wine	–	1.78	–	12.34
	drop: non-main ECOICOPs	0.78	0.65	4.01	3.05
	drop: barcodes with multiple vpu levels	0	0.25	0	1.83
	drop: price outliers	0.03	0.21	0.14	0.62
(3)	equals: *household-item-quarter*	**107.44**	**242.69**	**404.44**	**636.82**
(4)	thereof: ≥ 1 repeat purchase	13.33	34.79	68.24	137.66
	drop: volume per unit change (q vs. $q-4$)	0	0.09	0	0.32
(5)	equals: *household-item-quarter*	**13.33**	**34.70**	**68.24**	**137.34**
(6)	equals: *household-quarter*	0.36	1.05	68.24	137.34
(7)	thereof: ≥ 5 repeat purchases	0.36	1.00	68.18	136.87
(8)	thereof: ≥ 25 repeat purchases	0.25	0.61	59.06	113.75

Note: "Repeat purchases" refers to the number of products purchased both in quarter $q-4$ and again in quarter q. Sum over the entire sample period available for the respective country (France 2008–2018, Germany 2005–2018). When dropping 'non-main ECOICOPs' in step (2), the following ECOICOPs are kept: 1.1 (food) and 1.2 (non-alcoholic beverages), 2.1.1. and 2.1.3. (alcoholic beverages except wine), 5.6 (household maintenance), 9.3 (pet food) and 12.1 (personal care).

A.1.2 Top-level Regional Aggregation in France

In Germany the one-digit postal areas are connected regions. In France, however, this is not the case. As an analogue to the German one-digit postal areas we use in France NUTS-1 regions as top-level regional aggregation, and map the two-digit postal codes to them. Corresponding to the 10 German one-digit postal areas we thus end up with 12 French regions, because Corsica and overseas departments are not part of our sample.[55]

A.1.3 Cross-country Harmonization of the Income Variable

Both the French and the German dataset report income as the monthly net income of the household, grouped in bins. The definition of these bins differs between the French and German dataset. We harmonize the bin definitions in order to facilitate a cross-country comparison.

For France only a 5-category income variable ("social class") is available for the entire sample period. A more detailed 18-category income class variable is reported additionally starting in the first quarter of 2014. This constrains the granularity of income in a cross-country comparison. Comparing the cutoff points of the bins in France and Germany allows us to define four similar income groups in the two countries (Table 8). Accordingly, we use in France the 5-category income class, aggregating up the bottom two classes in order to arrive at four income groups. For Germany the raw dataset provides 16 income classes in the early and 17 in the later part of the sample,[56] which we also merge into four income groups. The resulting four income groups feature similar cutoff points in both countries and split the households within each country in roughly equally-sized groups.

Table 8: Comparison of (harmonized) income groups

	France 2008-2018		Germany 2005-2018	
c	Definition EUR/month	$\#H(c)$	Definition EUR/month	$\#H(c)$
1	< 1499	2212	< 1499	6588
2	1500 - 2299	3191	1500 - 2249	7464
3	2300 - 2999	2888	2250 - 2999	5939
4	≥ 3000	4372	≥ 3000	6743

Note: $\#H(c)$ is the average number of households in income group c in a given quarter.

[55] 1) Ile-De-France, 2) Centre Val De Loire, 3) Bourgogne-Franche-Comte, 4) Normandie, 5) Nord-Pas De Calais-Picardie, 6) Alsace-Champagne-Ardenne-Lorraine, 7) Pays De La Loire, 8) Bretagne, 9) Aquitaine-Limousin-Poitou-Charentes, 10) Languedoc-Roussillon-Midi-Pyrenees, 11) Auvergne-Rhone-Alpes, 12) Provence-Alpes-Cote d'Azur

[56] Starting in 2010Q1 the top income class is split in two.

When constructing a single income variable, e.g. for regression analysis, we use the most detailed information available. The income variable is based on the midpoint of each income bin. In France this is therefore based on the 5-category "social class" until the year 2013 and on the 18-category "income class" from 2014 onward, and in Germany on the 16-category "income class" until 2010Q1 and the 17-category "income class" thereafter.

A.2 Data description

A.2.1 Characteristics of Income and Expenditure Groups

Table 9 summarizes the characteristics of households by income group and by expenditure quartile.

Table 9: Characteristics of income groups and expenditure quartiles

(a) France

	Income groups				Expenditure quartiles			
	1 (low)	2	3	4 (high)	1 (low)	2	3	4 (high)
Exp. (euro)	502.6	620.6	733.9	802.7	461.0	681.7	874.4	1162.3
Size	1.8	2.3	2.8	3.0	2.5	2.6	2.7	2.7
Exp./capita	311.0	304.1	286.1	283.2	205.8	293.0	368.7	494.6
Exp./sqrt(size)	382.4	419.0	446.6	468.0	297.7	432.6	550.2	734.6
Age	43.5	43.9	42.8	42.9	42.8	44.1	44.9	46.1
Transactions	203	239	272	284	186	256	312	386
Barcodes	150	177	201	210	144	192	227	271
Sh. occ./trans.	0.112	0.096	0.083	0.078	0.098	0.087	0.082	0.078

(b) Germany

	Income groups				Expenditure quartiles			
	1 (low)	2	3	4 (high)	1 (low)	2	3	4 (high)
Exp. (euro)	240.1	325.1	370.5	377.0	172.1	434.9	592.5	823.5
Size	1.8	2.4	2.8	3.0	2.5	2.4	2.4	2.4
Exp./capita	153.3	157.6	151.2	141.8	80.2	203.62	275.0	385.4
Exp./sqrt(size)	186.3	219.8	231.3	226.8	113.6	288.5	392.0	547.7
Age	45.4	47.1	46.6	46.5	38.9	43.2	45.5	45.9
Transactions	138	176	192	185	95	233	306	398
Barcodes	102	131	144	141	78.2	174	220	274
Sh. occ./trans.	0.174	0.149	0.136	0.135	0.158	0.128	0.125	0.121

Note: Income groups defined as in Table 8 in Appendix A.1.3. Expenditure quartiles based on household-size adjusted quarterly expenditures. Variables (except age and household size) defined as average per quarter per household. Dataset based on cleaning step (3) in Table 7. "Income" refers to the net income of the household. "Age" refer to the head of the household. In Germany "age" is an average across age categories."Shopping occasions" refers to a trip to a shop (if several shops are visited on the same day, they count as separate shopping occasions). "Sh. occ./trans." refers to shopping occasions per transactions.

Households with a higher income of the head of the household tend to be larger. Because of this the income per capita of high-income households is smaller than that of low-income households – despite a higher income. A better measure of the affluence of a household appears to be the expenditure quartile, shown in the right part of the table. Quarterly reported expenditure per capita in the highest expenditure quartile is with almost 500 euro more than twice the expenditure of the lowest quartile.

A.2.2 Repeat Purchases

The household-level inflation rates are based on those items which have been repurchased by the household at least once, i.e. been purchased in both quarter $q-4$ and quarter q. Households which did not repurchase any product are not considered. Table 10 reports the sample coverage for three minimum thresholds on the number of repurchased items. In effect, only the intensive margin of expenditures is considered in our price indices.[57]

Table 10: Repeat purchases (q and $q-4$, in %)

		Households with ... repurchased barcodes		
share of (%)	country	≥1	≥5	≥25
... households	France	70.0	69.2	47.7
	Germany	73.8	70.6	42.9
... barcodes repurchased	France	37.5	37.4	35.2
	Germany	42.6	42.5	39.8
... expenditure on rep. barcodes	France	25.3	25.5	28.9
	Germany	27.0	27.7	32.2

Note: Dataset based on cleaning step (3) in Table 7. The table contains the percentage of households repurchasing at least a given number of products (first pair of rows), the share of repurchased products (barcodes) among all products purchased by a given household (second pair of rows), and the share of household expenditure spent on repurchased products (third pair of rows). Each reported number is an average across all quarters in the sample. The denominator in the first pair of rows are the number of reporting households in quarter q, in the second pair of rows the total number of barcodes in quarter q, and in the third pair of rows the total expenditure of the given household repurchasing 1, 5 or 25 products (as specified in the header) in quarter q.

A.2.3 ECOICOP Five-digit and Household-panel Product Categories

Table 11 shows that the ECOICOP-5 categories are much coarser than the GfK/Kantar categories within the main ECOICOP-3/4 categories. In our analysis of household-level inflation rates we prefer the GfK categories as they allow setting up more homogeneous

[57] Adding the extensive margin (product removals and additions to the household's basket between $q-4$ and q) would be interesting for future work with our data. Michelacci, Paciello, and Pozzi (2019) find that half of the cyclical change in non-durable consumption expenditure in the US is due to the extensive margin.

categories that contain mainly horizontally and vertically differentiated products and not entirely different product types.

Table 11: Number of GfK/Kantar and ECOICOP-5 categories within ECOICOP-3/4 categories

ECOICOP-3/4	category name	Germany # of GfK	Germany # of ECOICOP-5	France # of Kantar	France # of ECOICOP-5
01.1	Food	159	41	162	44
01.2	Non-alcoholic beverages	20	6	9	3
02.1.1	Spirits	7	2	8	3
02.1.3	Beer	2	2	1	1
05.6	Household maintenance	48	2	49	2
09.3	Other recreational items	14	3	1	1
12.1	Personal care	63	3	79	2
Total		313	59	309	56

Note: Number of GfK/Kantar and ECOICOP-5 categories for each of the ECOICOP-3/4 categories in our dataset. Wine (ECOICOP 02.1.2) is not part of the French dataset. In order to have comparability between Germany and France, we include among the "alcoholic beverages" (ECOICOP 02.1) only "spirits" and "beer".

A.2.4 Expenditure Shares in the HICP and in the Household Panel

This appendix compares product coverage of the household panel with the one of the HICP. For this comparison with HICP (sub)indices we manually assign every GfK product category to an ECOICOP-5 category.

Tables 12 and 13 compare the expenditure shares in the household panel with the ones in HICP in the year 2016. The table lists all two-digit ECOICOP categories as well as those 4-digit categories, which are part of the GfK/Kantar sample. The latter account for approximately 20-23% in both countries depending on the dataset definition.

Column 2 is based on the complete dataset after cleaning. Column 3 is based on a dataset of only those households that repurchase at least five products between q and $q-4$. Column 4 is based on a dataset of only those households that repurchase at least twenty-five products between q and $q-4$. Unsurprisingly, imposing the repeat purchase requirement barely affects the food and alcohol expenditure shares, but significantly lowers the share of non-durable household goods and products for personal care, which are purchased less frequently.

In Germany the expenditure share within ECOICOP 01 (food and non-alcoholic beverages) in the GfK sample and in the HICP are similar. The only serious deviation is in the categories "bread" and "food products n.e.c.", suggesting that many bread products are

Table 12: Expenditure shares per ECOICOP category (France, 2016, in %)

ECOICOP	Category	HICP	Kantar all	Kantar ≥ 5	Kantar ≥ 25
01	**Food and non-alcoholic beverages**	15.95	76.58	79.22	79.68
01.1.1	Bread and cereals	2.62	11.00	9.69	9.89
01.1.2	Meat	3.90	7.17	7.62	7.89
01.1.3	Fish and seafood	0.90	3.67	2.82	2.83
01.1.4	Milk, cheese and eggs	2.19	14.20	19.31	19.29
01.1.5	Oils and fats	0.33	2.70	4.16	4.17
01.1.6	Fruit	1.11	2.14	1.75	1.77
01.1.7	Vegetables	1.69	5.37	5.09	5.22
01.1.8	Sugar and confectionery	1.23	9.71	7.98	7.95
01.1.9	Food products n.e.c.	0.61	10.91	7.94	8.00
01.2.1	Coffee, tea and cocoa	0.42	3.04	3.85	3.71
01.2.2	Mineral waters, soft drinks	0.96	6.68	9.02	8.94
02	**Alcohol, tobacco**	4.29	4.76	5.88	5.50
02.1.1	Spirits	0.76	3.15	4.25	3.98
02.1.3	Beer	0.35	1.62	1.63	1.52
03	**Clothing and footwear**	4.77	–	–	–
04	**Housing, water, electricity, gas**	15.63	–	–	–
05	**Furnishings, household maintenance**	5.94	7.23	5.18	5.29
05.6.1	Non-durable household goods	0.92	7.23	5.18	5.29
06	**Health**	4.59	–	–	–
07	**Transport**	16.20	–	–	–
08	**Communications**	3.22	–	–	–
09	**Recreation and culture**	8.96	2.57	3.84	3.65
09.3.4	Pets and related products	0.44	2.57	3.84	3.65
10	**Education**	0.34	–	–	–
11	**Restaurants and hotels**	8.14	–	–	–
12	**Miscellaneous goods and services**	11.98	8.85	5.87	5.88
12.1.2	Electrical appliances for personal care	0.08	0.11	0.03	0.03
12.1.3	Products for personal care	2.16	8.74	5.85	5.86
	Number of household-item-quarters	–	10.82	1.45	1.24

Note: The HICP shares in the first column are from Eurostat. Kantar-all refers to the dataset based on cleaning step (3) in Table 7, Kantar-5 and Kantar-25 refers to the dataset based on cleaning step (5) in Table 7 of only those households that repurchase at least 5 and 25 products respectively.

Table 13: Expenditure shares per ECOICOP category (Germany, 2016, in %)

ECOICOP	Category	HICP	GfK all	GfK ≥ 5	GfK ≥ 25
01	**Food and non-alcoholic beverages**	11.79	78.90	80.47	80.92
01.1.1	Bread and cereals	2.03	6.57	5.72	5.78
01.1.2	Meat	2.38	12.65	11.69	12.04
01.1.3	Fish and seafood	0.43	1.72	1.40	1.42
01.1.4	Milk, cheese and eggs	1.55	13.43	16.78	16.55
01.1.5	Oils and fats	0.28	2.81	4.45	4.45
01.1.6	Fruit	1.08	3.63	3.10	3.22
01.1.7	Vegetables	1.34	5.51	4.88	5.04
01.1.8	Sugar and confectionery	0.89	9.48	6.93	7.04
01.1.9	Food products n.e.c.	0.50	10.88	7.52	7.70
01.2.1	Coffee, tea and cocoa	0.43	4.65	6.32	6.19
01.2.2	Mineral waters, soft drinks	0.89	7.58	11.69	11.49
02	**Alcohol, tobacco**	4.41	5.20	8.43	7.77
02.1.1	Spirits	0.24	1.92	2.32	2.14
02.1.3	Beer	0.99	3.28	6.11	5.63
03	**Clothing and footwear**	5.21	–	–	–
04	**Housing, water, electricity, gas**	21.59	–	–	–
05	**Furnishings, household maintenance**	5.79	4.33	2.20	2.30
05.6.1	Non-durable household goods	0.58	4.33	2.20	2.30
06	**Health**	5.54	-	–	–
07	**Transport**	14.92	–	–	–
08	**Communications**	3.20	–	–	–
09	**Recreation and culture**	12.69	2.93	3.28	3.30
09.3.4	Pets and related products	0.46	2.93	3.28	3.30
10	**Education**	1.06	–	-	–
11	**Restaurants and hotels**	5.61	–	–	–
12	**Miscellaneous goods and services**	8.17	8.64	5.62	5.71
12.1.2	Electrical appliances for personal care	0.05	0.20	0.02	0.02
12.1.3	Products for personal care	1.31	8.45	5.60	5.69
	Number of household-item-quarters	–	18.48	2.81	2.26

Note: The HICP shares in the first column are from Eurostat. GfK-all refers to the dataset based on cleaning step (3) in Table 7, GfK-5 and GfK-25 refers to the dataset based on cleaning step (5) in Table 7 of only those households that repurchase at least 5 and 25 products respectively.

classified in the GfK data in the residual food category. In France the differences within ECOICOP 01 are more widespread. Apart from a likely classification of many "meat" products as "food products n.e.c.", the average French Kantar consumer spends more on "sugar and confectionery" and "mineral waters, soft drinks" than the HICP consumer.

A.2.5 Comparison with HICP

The aggregate price index based on household-level transactions tracks the "food and non-alcoholic beverages" subindex of the HICP well.

The Eurostat HICP database provides quarterly price levels at the five-digit ECOICOP level (categories are, e.g., "fresh whole milk", "fresh low fat milk"), which implies an HICP inflation in category k during quarter q of $\pi_{kq}^{HICP} = p_{kq}^{HICP}/p_{k,q-4}^{HICP}$. Aggregate inflation rates based on scanner data can be defined based on either π_{kq}^{HICP} or on $\pi_{kq}^{\boldsymbol{s}}$ as given by Equation (4), where the product groups k refer to the five-digit ECOICOP levels.[58]

Definition 4 (Aggregate inflation based on household expenditure)**.** *Using the GfK/Kantar expenditure shares by product category k*

$$\hat{x}_{k,q-4} = \frac{\sum_h \sum_{i \in I(k) \cap I(hq)} p_{ih,q-4} x_{ih,q-4}}{\sum_h \sum_{i \in I(hq)} p_{ih,q-4} x_{ih,q-4}},$$

the quarterly year-on-year $(q/q-4)$ aggregate Laspeyres inflation is

$$\pi_q^{HICP} = \sum_k \pi_{kq}^{HICP} \hat{x}_{k,q-4} \tag{16}$$

when based on HICP price indices, and

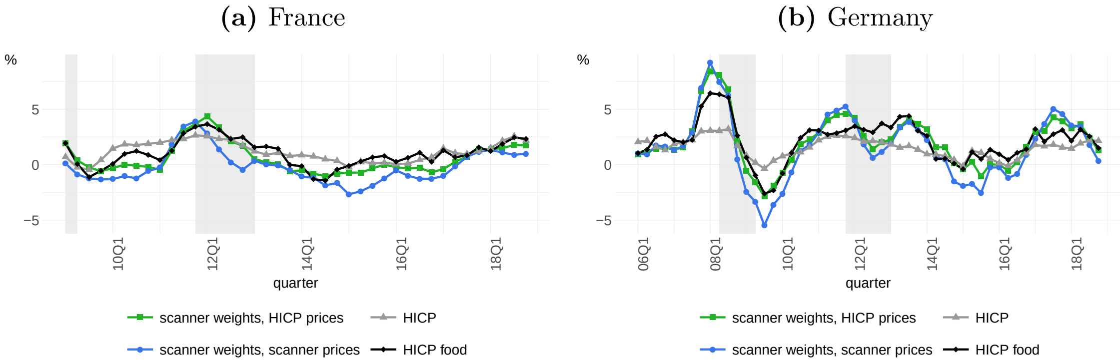
$$\pi_q^{\boldsymbol{s}} = \sum_k \pi_{kq}^{s} \hat{x}_{k,q-4} \tag{17}$$

when based on price indices derived from scanner data.

The resulting inflation series for food and non-alcoholic beverage items (i.e. items in ECOICOP 01) follow similar dynamics as the HICP food. Figure 8 shows that scanner quantities combined with HICP prices as in π_q^{HICP} (green line) follow the HICP food (black line) closely. Replacing HICP prices with scanner average prices (blue line) results in a considerably larger amplitude. This highlights that the inflation experienced by households in their day-to-day transactions might show starker fluctuation than aggregate inflation, which is based on the posted prices of reference products collected for the HICP, as opposed to the prices actually paid by households.

[58] These aggregate price indices can be recast as expenditure-weighted averages of the household-level inflation with category price indices (Kaplan and Schulhofer-Wohl, 2017).

Figure 8: Aggregate inflation rates ($q/q-4$, in % p.a.)



Note: "scanner weights, HICP prices" and "scanner weights, scanner prices" are the quarterly year-on-year Laspeyres indices given by Definition 4 based on the ECOICOP 01 transactions of households repurchasing at least 25 of those products in both quarters. "HICP food" is the HICP food and non-alcoholic beverages (ECOICOP 01) subindex.

A.3 Estimating the Elasticity of Substitution

The estimation of the elasticity of substitution per household σ^h is based on the methodology of Feenstra (1994) and Broda and Weinstein (2006), as described in Braun and Lein (2020) (appendix B) and Redding and Weinstein (2020) (online appendix A.11). Our results are therefore directly comparable to those of Braun and Lein (2020). We estimate the same regression equation with weighted least squares for each household and recover from the estimated coefficients the household-specific elasticity of substitution σ_h:

$$\begin{aligned}[]
[\Delta ln(\bar{p}_{ih,q})]^2 &= \frac{\omega}{(1+\omega)(\sigma^h-1)}[\Delta ln(\bar{s}_{ih,q})]^2 \\
&+ \frac{1-\omega(\sigma^h-2)}{(1+\omega)(\sigma^h-1)}[\Delta ln(\bar{p}_{ih,q})\Delta ln(\bar{s}_{ih,q})] + \epsilon_{ih,q}\sigma_{ih,q},
\end{aligned} \tag{18}$$

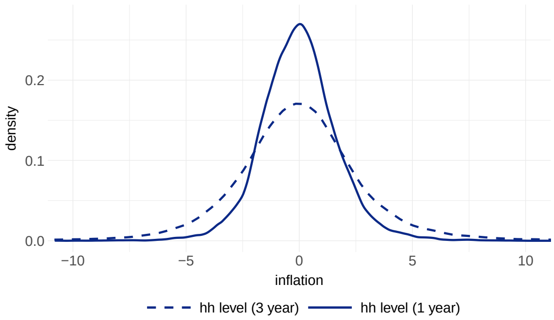
where Δ denotes a four-quarter time difference, e.g., $\Delta ln(\bar{x}_{ih,q}) = ln(\bar{x}_{ih,q}) - ln(\bar{x}_{ih,q-4})$, and $\bar{x}_{ih,q}$ denotes the difference of x from its geometric average across items i, i.e. $ln(\bar{x}_{ih,q}) = ln(x_{ih,q}) - ln(\tilde{x}_{hq})$, where $\tilde{x}_{hq} = \sqrt[N]{\Pi_i x_{ihq}}$. These variables are calculated at the household-item-quarter level, and averaged across quarters before entering the regression. The observation weights in the regression $\sqrt{w_q^3/v_q}$ are household-item specific and combine the number of transactions per household per item in a given quarter q, denoted v_q, with the number of quarters the given household-item combination is available, denoted w_q.

The estimation of household-level elasticities relies on the time dimension of the panel. To ensure a basic level of comparability across households, we restrict the sample to households which provide a minimum amount of information over time. The elasticities are therefore only estimated for households that (i) (re)purchase at least 25 products of $q-4$ in q, and which (ii) are present in the sample for at least eight (not necessarily consecutive) quarters – restricted to (iii) purchases of food and alcohol (ECOICOPs 01.1, 01.2, 02.1.1, 02.1.3). After the estimation, elasticity estimates which are not significant at the 5% level are dropped. Similar to Braun and Lein (2020), the elasticities are winsorized at 20.[59]

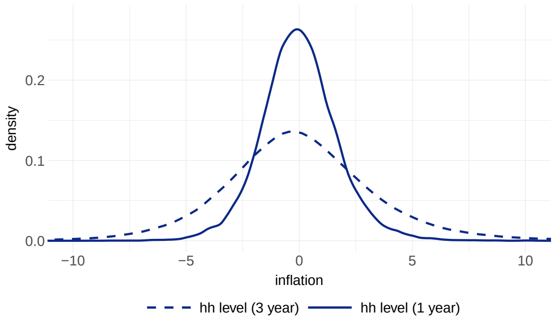
A.4 Persistence Inflation at the Household Level

A.4.1 Heterogeneity of Multi-year Inflation Rates

Figure 9: Persistence of household-level inflation rates with household-level prices



(a) France



(b) Germany

Note: Calculations use the Q4 year-on-year Laspeyres household-level indices $\pi^{\boldsymbol{h}}_{hq}$ in Definition 1. "hh level (3 year)" denotes annual household-level inflation rates for the 3-year subperiods 2018–2015, 2015–2012, 2012–2009, 2009–2006 (the latter only for Germany) using data only for those households that are present in all Q4-s in the given subperiod. The annual household-level inflation rates are demeaned (mean across all households for the given subperiod is subtracted). "hh level (1 year)" denotes all Q4 year-on-year household-level inflation rates of the sample pooled together and they are demeaned (the mean of $\pi^{\boldsymbol{h}}_{hq}$ across all households for the given Q4 is subtracted). The densities are based on the Epanechnikov kernel. France: 60497 panelist-quarter observations, 11002 panelist-subperiod observations. Germany: 151770 panelist-quarter observations, 33110 panelist subperiod observations.

Averaging inflation over longer time periods averages out the period-by-period variation in the set of purchased products. This appendix shows that even long-term averages of inflation are widely dispersed between households. Figure 9 compares the distribution of household-level inflation calculated over one-year horizons with the analogous distribution calculated over three-year horizons. Whereas the interquartile range (IQR) shrinks over longer horizons, it remains substantial. In both France and Germany the IQR remains above two percentage points for inflation over a three-year horizon (instead of three and four percentage points over one-year periods, respectively). In both countries, the 90% interval of households centered around the mean spans more than five percentage points.

[59]There is no elasticity estimate below 1.01 – neither for France nor for Germany.

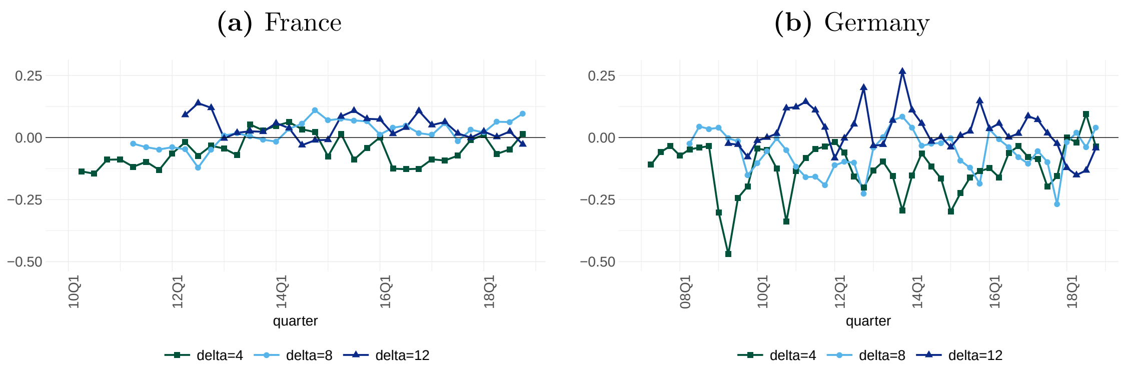
A.4.2 Cross-sectional Inflation Correlation across Households

We define the cross-sectional correlation across households over a horizon of δ quarters in period q as

$$\varrho_q^\delta = \frac{(1/N_{q,\delta})\sum_h(\pi_{hq}^{\boldsymbol{h}} - \bar{\pi}_q^{\boldsymbol{h}})(\pi_{h,q-\delta}^{\boldsymbol{h}} - \bar{\pi}_{q-\delta}^{\boldsymbol{h}})}{\sqrt{(1/N_q)\sum_h(\pi_{hq}^{\boldsymbol{h}} - \bar{\pi}_q^{\boldsymbol{h}})^2}\sqrt{(1/N_{q-\delta})\sum_h(\pi_{h,q-\delta}^{\boldsymbol{h}} - \bar{\pi}_{q-\delta}^{\boldsymbol{h}})^2}},$$

where $\pi_{hq}^{\boldsymbol{h}}$ is the household-level inflation rate with household-level prices and $\bar{\pi}_q^{\boldsymbol{h}}$ is the equal-weighted average of $\pi_{hq}^{\boldsymbol{h}}$ across households in quarter q. $N_{q,\delta}$ is the number of quarter pairs entering the numerator, and N_q the number of households entering the variance calculation in quarter q.

Figure 10: Cross-sectional inflation correlation across households



Note: Cross-sectional correlation ϱ_q^δ (based on $\pi_{hq}^{\boldsymbol{h}}$ in Definition 1).

Figure 10 plots this cross-sectional correlation across households $\varrho_q^\delta = Corr(\pi_{hq}^{\boldsymbol{h}}, \pi_{h,q-\delta}^{\boldsymbol{h}})$ over a horizon of $\delta \in \{4, 8, 12\}$ quarters in quarter q. Over longer horizons, the correlation fluctuates around zero, but at a one-year horizon it is slightly negative. This might capture "shopping noise", i.e. a random bounce between good and bad deals from quarter to quarter, which mechanically leads to a negative cross-sectional correlation.

A.5 Space and Time as Determinants of Household Inflation Heterogeneity

Space and time are of only a secondary relevance for inflation heterogeneity across households.

Table 14 shows the coefficient of determination (R^2) of regressions of household-level inflation minus aggregate inflation, $\pi_{hq}^{\boldsymbol{h}} - \pi_q^{HICP}$, on sets of dummy variables differing in granularity. Column (3) presents the results from a regression on spacial dummies (region,

Table 14: Coefficient of determination (R-squared) along space and time dimensions

	(1) # of groups	(2) #hh / group	(3) level	(4) + qtr dummies	(5) × qtr dummies	(6) × vs. +
(a) *France*						
region	8	2171	0.001	0.043	0.047	0.003
2-digit zip	94	185	0.003	0.045	0.069	0.024
3-digit zip	791	22	0.010	0.052	0.171	0.119
5-digit zip	2935	6	0.030	0.072	0.338	0.266
household	17369	1	0.157	0.197	1.000	–
(b) *Germany*						
region	16	2122	0.000	0.046	0.051	0.005
2-digit zip	95	357	0.001	0.046	0.059	0.013
3-digit zip	667	51	0.002	0.048	0.116	0.068
5-digit zip	4885	7	0.016	0.061	0.325	0.264
household	33946	1	0.107	0.147	1.000	–

Note: The number of cross-sectional groups in the respective country is reported in column (1) along with the average number of households per group in column (2). Dependent variable in columns (3)-(5) is the deviation of household-level Laspeyres inflation $\pi^{\boldsymbol{h}}_{hq}$ from aggregate inflation π^{HICP}_q. Excluding singletons, i.e. households present for only one quarter and sole households within a five-digit postal areas. 180564 observations for France, 497419 for Germany.

two-digit, three-digit, and five-digit postal areas). In both countries region fixed effects down to the three-digit postal code level explain barely anything of the variance of the deviation of household-level inflation from aggregate inflation. Household fixed effects explain only 10-15% of the variation in household-level inflation rates. This implies, conversely, that 85-90% of the overall variance is due to time variation *within* the same household, such as time-varying characteristics or time-varying shopping behaviour of the household.

Unconditional time variation captured by quarterly dummies captures about 4% of the total variation in both countries (column (4) of Table 14). As it is orthogonal to the cross-sectional dimension, this applies at any granularity of the cross-sectional dummies.

Column (5) interacts the cross-sectional with the quarterly dummies.[60] Such regional time variation matters only at a three-digit postal area and finer levels, which might reflect for example local business cycles or local promotional sales. Time variation at coarser spacial aggregates does not explain much beyond the aggregate time variation (column 4).

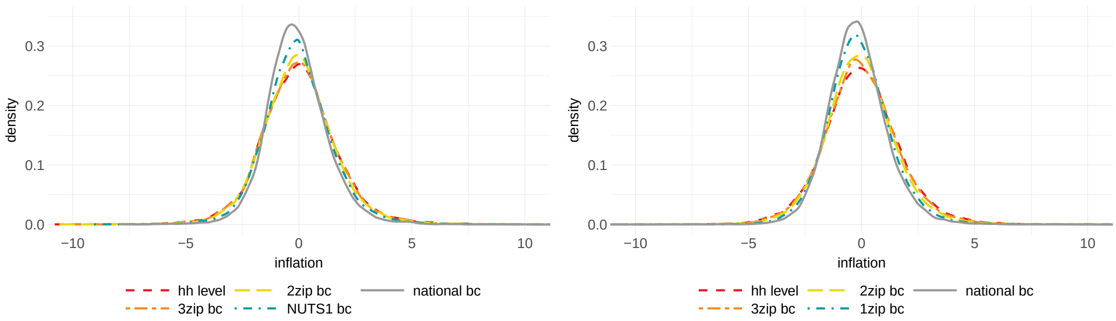
[60] The interaction of household and quarterly dummies gives by construction an R^2 of one.

A.6 Prices, variety and baskets

Table 15 shows that the spatial component of price changes accounts for more than one third of inflation heterogeneity. Household-specific prices explain only little. The main driver that households can influence is product choice, which explains in France about one half and in Germany about one fourth of the variance. In Germany, most of the remainder is due to basket composition, which a household might be able to modify to some extent, but at the cost of fundamentally adapting its consumption bundle.

Figure 11 reproduces Figure 3, but averaging over three-year intervals to remove time variation. Even inflation calculated over three-year horizons is very dispersed. The averaging of prices over more households and regions reduces this dispersion only modestly. The IQR (France/Germany) is 2.02/2.05 at the household level, still 1.93/1.89 at the two digit postal area level, 1.80/1.72 at the top regional level, and 1.62/1.59 at the national level. Overall, household- or region-specific inflation differences (accruing over three years) can explain only one fourth of the IQR of inflation between households.

Figure 11: Distribution of household-level 3yr inflation rates with household-level and regional prices



(a) France (b) Germany

Note: Calculations use the Q4 year-on-year Laspeyres household-level indices $\pi_{hq}^{\boldsymbol{h}}$ and $\pi_{hq}^{\boldsymbol{br\cdot}}$ as defined in Sections 2.2.1 and 2.2.2 based on the transactions of households repurchasing at least 25 products in both quarters. Based on these household-level inflation rates annual household-level inflation rates for the 3-year subperiods 2018–2015, 2015–2012, 2012–2009, 2009–2006 (the latter only for Germany) are calculated. Only for those households that are present in all Q4-s in the given subperiod. All annual household-level inflation rates are demeaned by using the annual rates based on $\pi_{hq}^{\boldsymbol{h}}$ for the given subperiod. The densities are estimated by using an Epanechnikov kernel. France: 11002 panelist-subperiod observations. Germany: 33110 panelist-subperiod observations.

Figure 12 plots the interquartile range of household-level inflation rates over time.

Figure 13 reproduces Figure 3 for a specific quarter pair.

Figure 14 reproduces Figure 4, but averaging over three-year intervals to remove time variation.

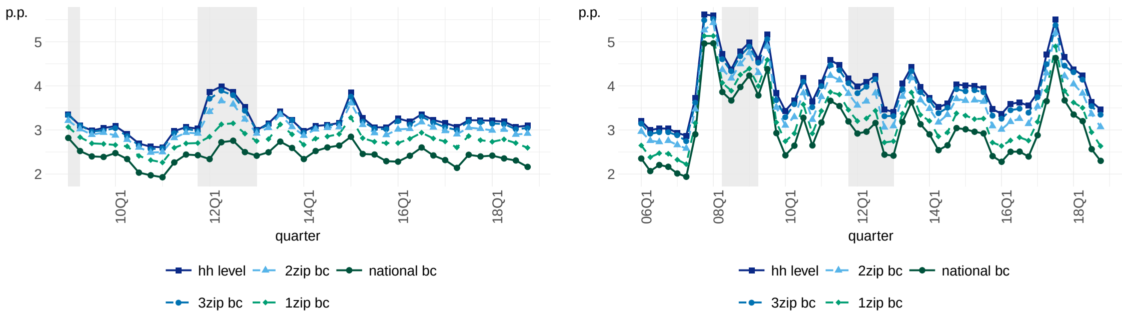
Table 15: Variance decomposition of household-level inflation

	France var.	France %	Germany var.	Germany %
$var[log(\pi_{hq}^{\boldsymbol{h}})]$	9.77	100	11.66	100
Household component				
$var[log(\pi_{hq}^{hc})]$	0.20	2	0.77	7
$var[log(\pi_{hq}^{\boldsymbol{br3}})]$	9.45		10.93	
$2cov[log(\pi_{hq}^{\boldsymbol{br3}}), log(\pi_{hq}^{hc})]$	0.11		-0.04	
Spatial component				
$var[log(\pi_{hq}^{rc})]$	3.45	35	4.57	39
$var[log(\pi_{hq}^{\boldsymbol{bn}})]$	5.52		6.50	
$2cov[log(\pi_{hq}^{\boldsymbol{bn}}), log(\pi_{hq}^{rc})]$	0.49		-0.14	
Product component				
$var[log(\pi_{hq}^{nc})]$	2.73	28	1.66	14
$var[log(\pi_{hq}^{\boldsymbol{bc}})]$	2.59		4.75	
$2cov[log(\pi_{hq}^{\boldsymbol{bc}}), log(\pi_{hq}^{nc})]$	0.20		0.10	
Brand component				
$var[log(\pi_{hq}^{bc})]$	2.04	21	1.48	13
$var[log(\pi_{hq}^{\boldsymbol{qc}})]$	0.56		0.56	
$2cov[log(\pi_{hq}^{\boldsymbol{qc}}), log(\pi_{hq}^{bc})]$	-0.01		-0.18	
Quality component				
$var[log(\pi_{hq}^{qc})]$	0.14	1	0.56	5
$var[log(\pi_{hq}^{\boldsymbol{c}})]$	0.41		2.94	
$2cov[log(\pi_{hq}^{\boldsymbol{c}}), log(\pi_{hq}^{qc})]$	0.01		-0.05	
GfK/Kantar category component				
$var[log(\pi_{hq}^{pc})]$	0.21	2	1.30	11
$var[log(\pi_{hq}^{\boldsymbol{c_{coicop}}})]$	0.19	2	1.39	12
$2cov[log(\pi_{hq}^{\boldsymbol{c_{coicop}}}), log(\pi_{hq}^{pc})]$	0.01		0.25	
sum of covariances		8		-1

Note: The upper block of the table decomposes the variance of the household-level index with household-level prices in a given quarter into the variance of the index with three-digit zip average prices, the variance of a household-specific component (hc) and a covariance term according to $var[log(\pi_{hq}^{\boldsymbol{h}})] = var[log(\pi_{hq}^{hc})] + var[log(\pi_{hq}^{\boldsymbol{br3}})] + 2cov[log(\pi_{hq}^{\boldsymbol{br3}}), log(\pi_{hq}^{hc})]$. The second block of the table decomposes the variance of the household-level index with three-digit zip average prices into the variance of the index with national barcode average prices, the variance of a region (three-digit zip) specific component (rc) and a covariance term according to $var[log(\pi_{hq}^{\boldsymbol{br3}})] = var[log(\pi_{hq}^{rc})] + var[log(\pi_{hq}^{\boldsymbol{bn}})] + 2cov[log(\pi_{hq}^{\boldsymbol{bn}}), log(\pi_{hq}^{rc})]$. The lower blocks decompose the remaining variance for each counterfactual index analogously. The reported variances are the averages of quarterly cross-sectional variances in percent-squared.

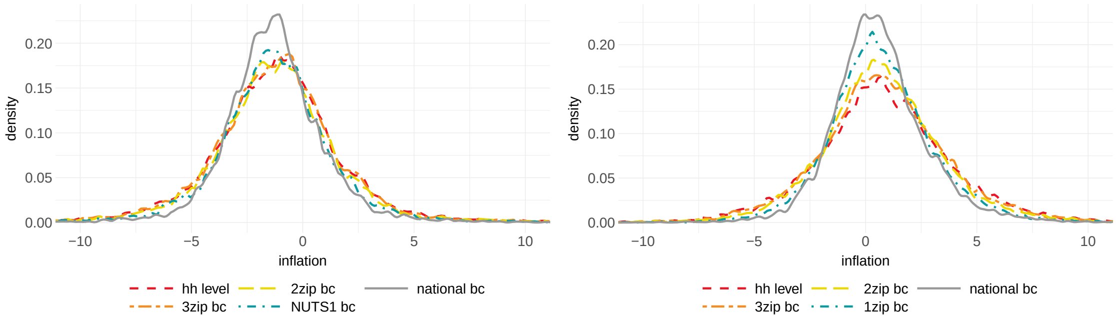
Figure 12: Interquartile range of household-level inflation rates with household-level and regional prices

(a) France **(b)** Germany



Note: Interquartile ranges of quarterly year-on-year Laspeyres indices $\pi_{hq}^{\boldsymbol{h}}$ and $\pi_{hq}^{\boldsymbol{br\cdot}}$ as defined in Sections 2.2.1 and 2.2.2 based on the transactions of households repurchasing at least 25 products in both quarters.

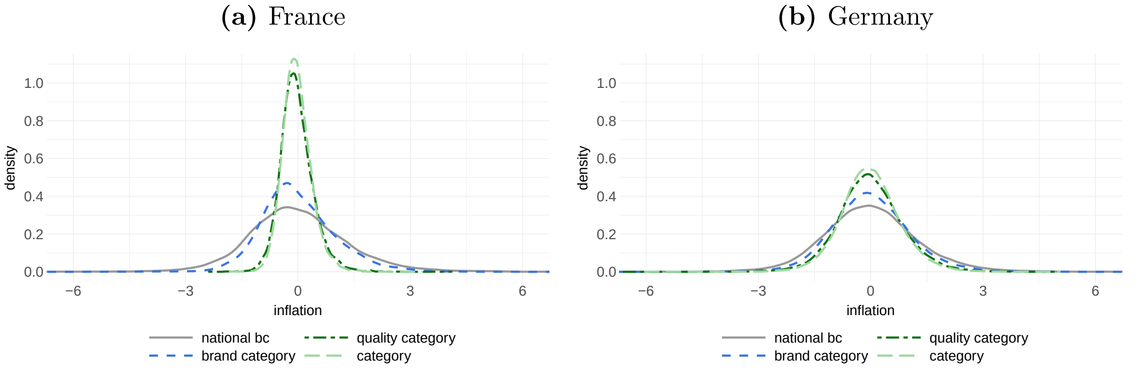
Figure 13: Distribution of household-level inflation rates with household-level and regional prices (2016Q4/2015Q4)



(a) France **(b)** Germany

Note: Q4 year-on-year Laspeyres indices $\pi_{hq}^{\boldsymbol{h}}$ and $\pi_{hq}^{\boldsymbol{br\cdot}}$ as defined in Sections 2.2.1 and 2.2.2 based on the transactions of households repurchasing at least 25 products in both quarters. The densities are estimated by using an Epanechnikov kernel. France: 7439 panelist-quarter observations. The bandwidth used is 0.1. Germany: 12858 panelist-quarter observations. The bandwidth used is 0.1.

Figure 14: Distribution of household-level 3yr inflation rates with national barcode, brand category, quality-category and category price indices



Note: Calculations use the Q4 year-on-year Laspeyres indices $\pi_{hq}^{\boldsymbol{bn}}$, $\pi_{hq}^{\boldsymbol{bc}}$, $\pi_{hq}^{\boldsymbol{qc}}$ and $\pi_{hq}^{\boldsymbol{c}}$ as defined in Section 2.2.2 based on the transactions of households repurchasing at least 25 products in both quarters. Based on these household-level inflation rates annual household-level inflation rates for the 3-year subperiods 2018–2015, 2015–2012, 2012–2009, 2009–2006 (the latter only for Germany) are calculated. Only for those households that are present in all Q4-s in the given subperiod. All annual household-level inflation rates are demeaned by using the annual rates based on $\pi_{hq}^{\boldsymbol{bn}}$ for the given subperiod. The densities are estimated by using an Epanechnikov kernel. France: 10792 panelist-subperiod observations. Germany: 32220 panelist-subperiod observations.

Figure 15 reproduces Figure 4 for a specific quarter pair.

Figure 16 plots the interquartile range of household-level inflation rates (with averaged prices) over time.

A.7 Substitution

Figure 17 shows that the Laspeyres-Paasche differential is small and larger constant in France, but larger and more volatile in Germany.

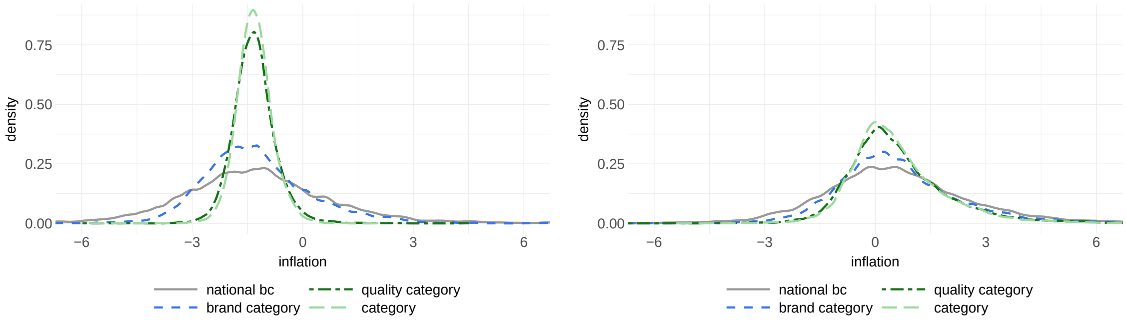
Figure 18 reproduces Figure 5 for a specific quarter pair.

Figures 19 and 20 show the distribution of the estimated elasticities across households. The median elasticity for food products (Figure 20) is similar to the one estimated with (alcoholic and non-alcoholic) beverages included (Figure 19): About 5.3 in France and about 4.1 in Germany.

Figure 21 plots the medians of four quarterly year-on-year household-level indices over time.

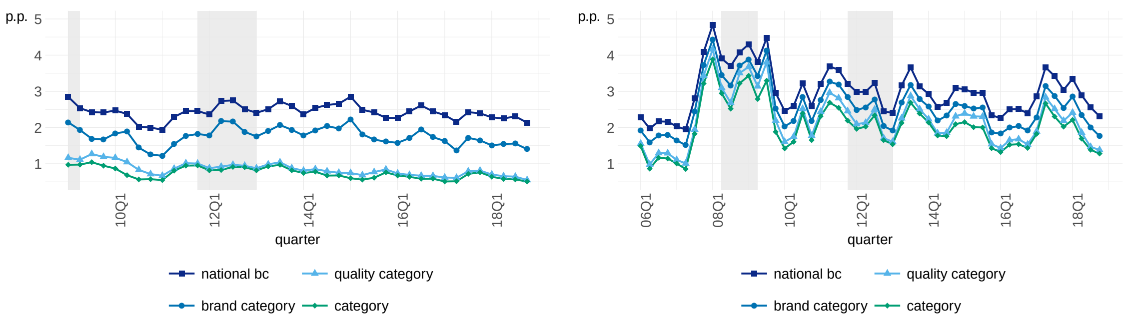
Figure 15: Distribution of household-level inflation rates with national barcode, brand category, quality-category and category price indices (2016Q4/2015Q4)

(a) France (b) Germany



Note: Q4 year-on-year Laspeyres indices $\bar{p}^{\boldsymbol{n}}_{iq}$, $\pi^{\boldsymbol{qc}}_{hq}$ and $\pi^{\boldsymbol{c}}_{hq}$ as defined in Section 2.2.2 based on the transactions of households repurchasing at least 25 products in both quarters. The densities are estimated by using an Epanechnikov kernel. France: 7370 panelist-quarter observations. Number of categories: 268, number of quality-categories: 530, number of brand-categories: 7882 (brands: 2170), number of products: 57395. The bandwidth used is 0.1. Germany: 12674 panelist-quarter observations. Number of categories: 302, number of quality-categories: 600, number of brand-categories: 11923 (brands: 5689), number of products: 60787. The bandwidth used is 0.1.

Figure 16: Interquartile range of household-level inflation rates with national barcode, brand-category, quality-category and category price indices

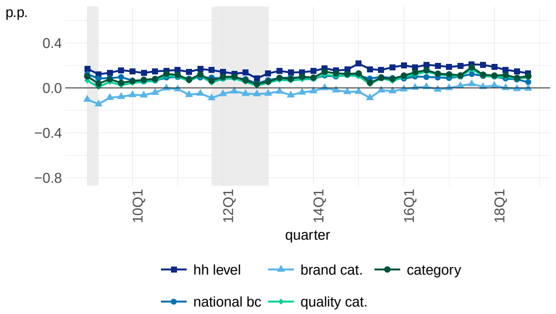


(a) France (b) Germany

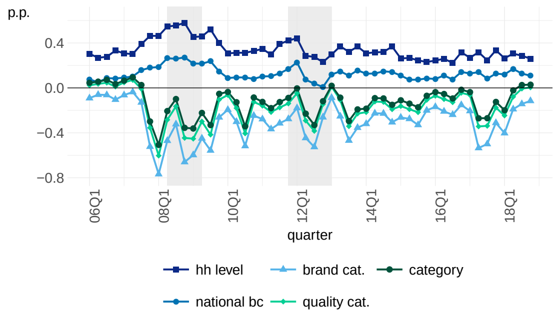
Note: Interquartile ranges of quarterly year-on-year Laspeyres indices $\bar{p}^{\boldsymbol{n}}_{iq}$, $\pi^{\boldsymbol{qc}}_{hq}$ and $\pi^{\boldsymbol{c}}_{hq}$ as defined in Section 2.2.2 based on the transactions of households repurchasing at least 25 products in both quarters.

Figure 17: Difference of Laspeyres and Paasche indices for the median household

(a) France



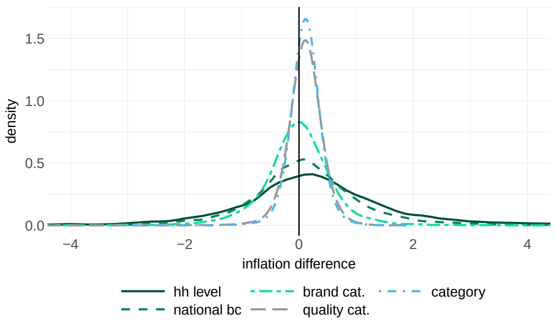
(b) Germany



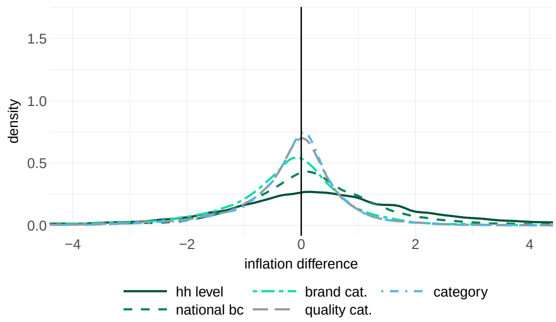
Note: Medians of the difference of the quarterly year-on-year Laspeyres and Paasche household-level indices. Quarterly year-on-year Laspeyres indices $\pi^{\boldsymbol{h}}_{hq}$, $\bar{p}^{\boldsymbol{n}}_{iq}$, $\pi^{\boldsymbol{bc}}_{hq}$, $\pi^{\boldsymbol{qc}}_{hq}$ and $\pi^{\boldsymbol{c}}_{hq}$ as defined in Sections 2.2.1 and 2.2.2 and Paasche indices defined analogously with weights for q. Based on the transactions of households repurchasing at least 25 products in both quarters.

Figure 18: Difference of Laspeyres and Paasche indices (2016Q4/2015Q4)

(a) France



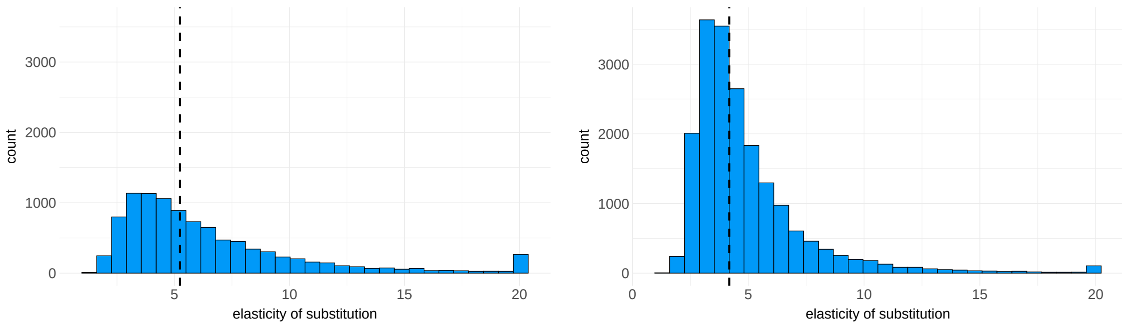
(b) Germany



Note: Q4 year-on-year Laspeyres minus Paasche indices $\pi^{\boldsymbol{h}}_{hq}$, $\bar{p}^{\boldsymbol{n}}_{iq}$, $\pi^{\boldsymbol{bc}}_{hq}$, $\pi^{\boldsymbol{qc}}_{hq}$ and $\pi^{\boldsymbol{c}}_{hq}$ as defined in Sections 2.2.1 and 2.2.2 based on the transactions of households repurchasing at least 25 products in both quarters. Estimation of the densities uses the Epanechnikov kernel. France: 5570 panelist-quarter observations. The bandwidth used is 0.1. Medians: 0.22, 0.09, -0.01, 0.11, 0.11. Probability mass above zero: 0.579, 0.542, 0.449, 0.642, 0.669. Germany: 10754 panelist-quarter observations. The bandwidth used is 0.1. Medians: 0.34, 0.14, -0.17, -0.06, -0.03. Probability mass above zero: 0.580, 0.542, 0.393, 0.440, 0.454.

Figure 19: Histogram of the estimated elasticities of substitution

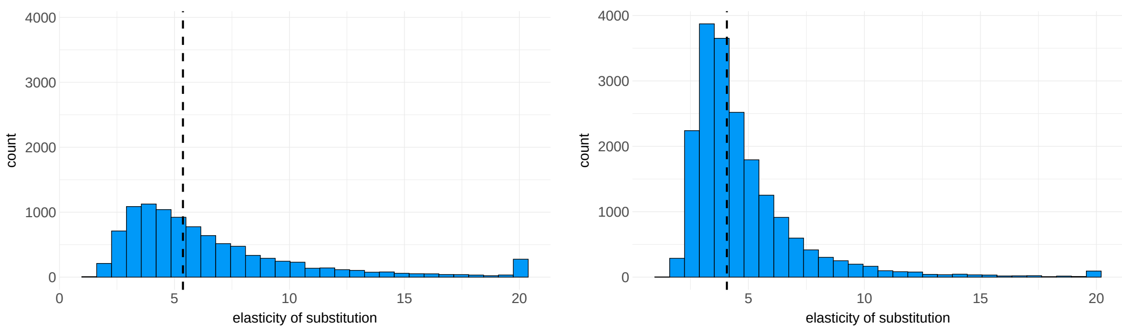
(a) France **(b)** Germany



Note: The elasticity of substitution is estimated for each household as described in Appendix A.3. The vertical dashed lines denote the medians, 5.24 for France, 4.18 for Germany. The total number of households is 9872 for France, 18960 for Germany. The sample period used for the estimation is 2008q1–2018q4 in both countries.

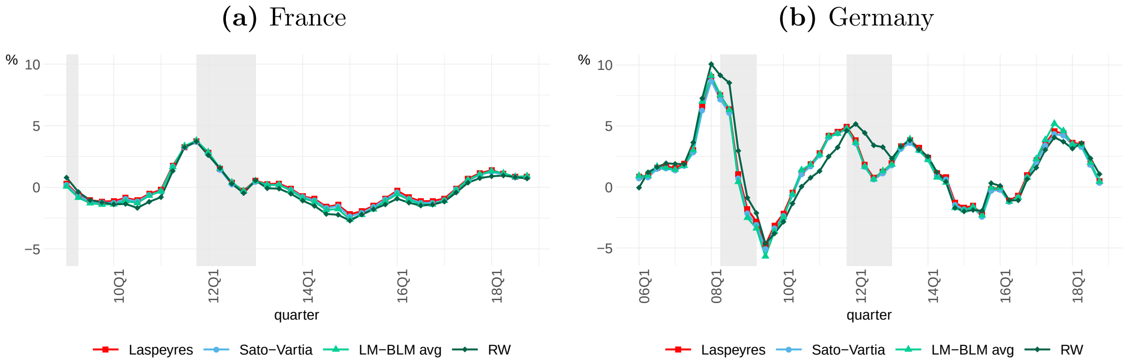
Figure 20: Histogram of the estimated elasticities of substitution (only food)

(a) France **(b)** Germany



Note: The elasticity of substitution is estimated for each household as described in Appendix A.3. The vertical dashed lines denote the medians, 5.37 for France, 4.07 for Germany. The total number of households is 9870 for France, 19107 for Germany. The sample period used for the estimation is 2008q1–2018q4 in both countries.

Figure 21: Medians of COGI vs COLI



Note: Medians of quarterly year-on-year household-level indices. 'Laspeyres' denotes Laspeyres indices $\pi_{hq}^{\boldsymbol{h}}$ as defined in Section 2.2.1. 'Sato-Vartia' denotes the Sato-Vartia index, 'LM-BLM avg' denotes the geometric average of the Lloyd-Moulton and the Backwards Lloyd-Moulton indices π_{hq}^{LLM} and 'RW' denotes the Redding-Weinstein CCV index π_{hq}^{RW} as defined in Section 2.2.3. Goods are restricted to food and beverages. Households that repurchase at least 25 products in both quarters. For further restrictions on the households see Appendix A.3.

A.8 Inflation by Income Group and Expenditure Quartile

The calculation of an aggregate inflation by income group or expenditure quartile requires a decision on how to weight the individual households within the given group. The "democratic" approach weights the inflation rate of each household equally, whereas the "plutocratic" approach weights by expenditure. The former implies that the repurchase of an item is required to be at the household-level, while in the case of the latter the repurchase must take place within the group-level, but not necessarily the same household. In the following we report results for indices calculated by using the democratic approach. We assign each household to an income group/expenditure quartile c based on either the common grid of four income groups (Table 8) or the expenditure quartiles. Let the set $H(cq)$ contain all households which belong to a given group c during quarter q. The inflation rate based on the democratic approach, π_{cq}, takes the arithmetic average of the household-level inflation rates ($\pi_{hq}^{\boldsymbol{h}}$) across the set of households $H(cq)$ belonging to group c in quarter q.

A.8.1 Aggregation of Households by Income Group or Expenditure Quartile

The democratic approach, when inflation for an income group is calculated as an arithmetic average of household-level inflation rates, provides an explicit link from household-level inflation to income-group-level inflation. The downside is, however, that because the repurchase of products is required at the household-level, only products purchased frequently by households enter the basket. This reduces the set of products underlying such a price index in our sample by about one third (Table 16) relative to requiring a repurchase only within the income-group or the expenditure quartile. In the case of the plutocratic approach each income group/expenditure quartile is treated as homogeneous, therefore repurchases are required at the income group/expenditure quartile level.

Table 16: Average number of distinct products per quarter

Repurchase at	Germany	France
income group	84477	86701
expenditure quartile	83806	85150
household	54453	51449

Note: Sample period for Germany: 2006Q1–2018Q4, for France: 2009Q1–2018Q4.

A.8.2 Dispersion

During the common sample period 2008-2018, the annual average Laspeyres inflation rate was approximately 0.06 percentage points higher for the lowest income group than for the highest income group in Germany and 0.23 percentage points higher in France (columns 1-3 of Table 17) based on the democratic income group-level index. Kaplan and Schulhofer-Wohl (2017) report a similar ordering of income groups for the USA (column 4 of Table 17). The US income groups span a wider range, but even a comparison of the lower three US income groups with all four European ones hints at a larger inflation differential in the USA albeit beside a higher level of inflation rates.

Table 17: Annual average inflation rates per income group (%)

income	Laspeyres				Paasche		
group c	DE05	DE	FR	US	DE05	DE	FR
low (1)	1.55	1.41	0.08	3.22	1.10	0.97	-0.22
(2)	1.56	1.43	0.09	3.01	1.07	0.95	-0.22
(3)	1.51	1.37	-0.05	2.75	1.02	0.89	-0.20
(4)	1.50	1.35	-0.15	2.58	1.00	0.86	-0.38
high (5)	-	-	-	2.51	-	-	-

Note: The table compares the annual geometric average of the income-group level inflation rates across all quarters q in the sample, defined as $\bar{\pi}_c = 100\left(\sqrt[Q]{\prod_q \pi_{cq}} - 1\right)$, where Q is the number of quarters in the sample. π_{cq} is the income-group level inflation based on the democratic approach, therefore the repurchase requirement is at the household level. Column "DE05" is based on the full sample period available for Germany (2005-2018). Columns "DE" and "FR" use the common sample period 2008-2018. Income groups in France and Germany are based on the net income of the household per month at defined in Table 8. The results for the USA are taken from Kaplan and Schulhofer-Wohl (2017) and based on household income for a nine-year period ending in the third quarter of 2013.

Regarding the Laspeyres indices, the expenditure quartiles have the same pattern as the income groups (columns 1-3 of Table 18): the bottom quartile has a higher inflation than the top quartile. However the pattern of the Paasche indices differ: in the case of the expenditure quartiles, the top quartiles have higher inflation in both countries. Therefore it seems that, when only frequently purchased products are taken into consideration - as the democratic approach requires repurchase at the household level - the bottom quartiles seem to substitute more.

Table 18: Annual average inflation rates per expenditure quartiles (%)

expenditure quartile c	Laspeyres DE05	Laspeyres DE	Laspeyres FR	Paasche DE05	Paasche DE	Paasche FR
low (1)	1.58	1.41	-0.09	0.96	0.80	-0.37
(2)	1.57	1.43	-0.07	1.03	0.89	-0.33
(3)	1.54	1.41	-0.07	1.09	0.96	-0.30
high (4)	1.44	1.32	-0.07	1.09	0.99	-0.28

Note: The table compares the annual geometric average of the expenditure quartile-level inflation rates across all quarters q in the sample, defined as $\bar{\pi}_c = 100\left(\sqrt[Q]{\prod_q \pi_{cq}} - 1\right)$, where Q is the number of quarters in the sample. π_{cq} is the expenditure-quartile level inflation based on the democratic approach, therefore the repurchase requirement is at the household level. Column "DE05" is based on the full sample period available for Germany (2005-2018). Columns "DE" and "FR" use the common sample period 2008-2018.

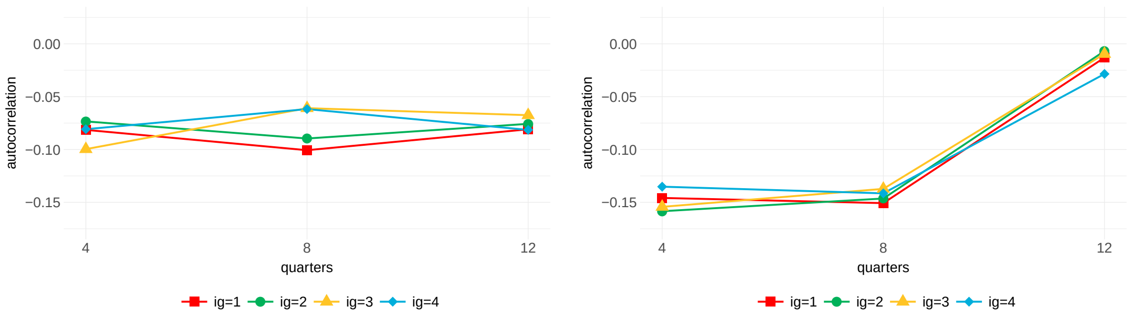
A.8.3 Persistence

The autocorrelation function is negative for both countries across households within income groups. The magnitude of autocorrelation is smaller in France for a one-year lag, but it stays at this magnitude for all lags of the three-year horizon, while for Germany it returns to zero by the end of the third year (Figure 22). A similar pattern holds for the expenditure quartiles (Figure 23).

The cross-sectional correlation across households within income groups with a horizon of one year has a small magnitude and it is mostly negative throughout most of the sample period in both France and Germany (Figure 24). Cross-sectional correlation across households within expenditure quartiles have a similar pattern (Figure 25).

Figure 22: Inflation autocorrelation across households within income groups

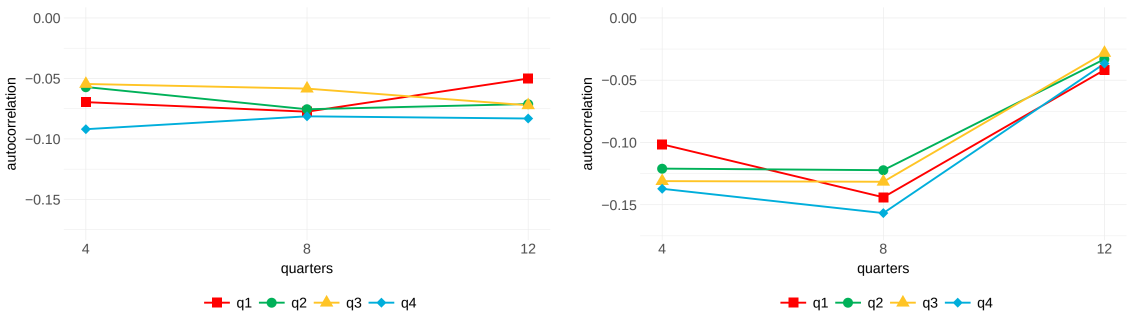
(a) France (b) Germany



Note: The household-specific autocorrelations ρ_h^δ based on $\pi_{hq}^{\boldsymbol{h}}$ as in Section 2.2.1 are grouped by income group and the median is calculated separately for each income group. Income groups are defined in Appendix A.1.3.

Figure 23: Inflation autocorrelation across households within expenditure quartiles

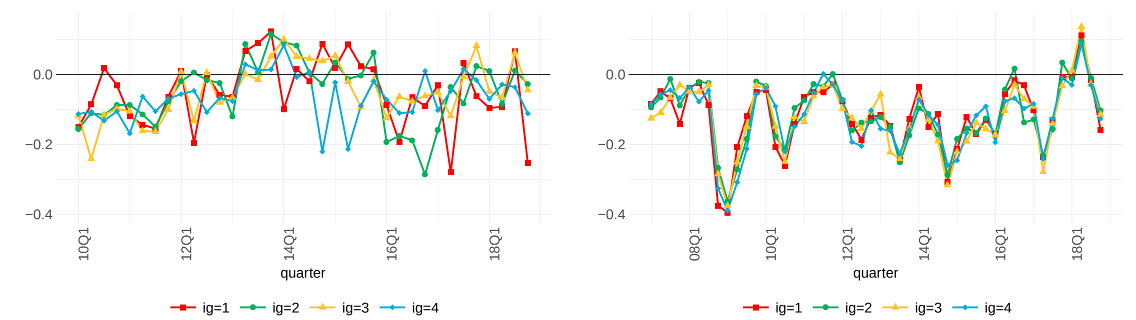
(a) France (b) Germany



Note: The household-specific autocorrelations ρ_h^δ based on $\pi_{hq}^{\boldsymbol{h}}$ as in Section 2.2.1 are grouped by expenditure quartiles and the median is calculated separately for each expenditure quartile. Households are ranked in expenditure quartiles every quarter based on household size-adjusted quarterly expenditures.

Figure 24: Cross-sectional inflation correlation across households within income groups

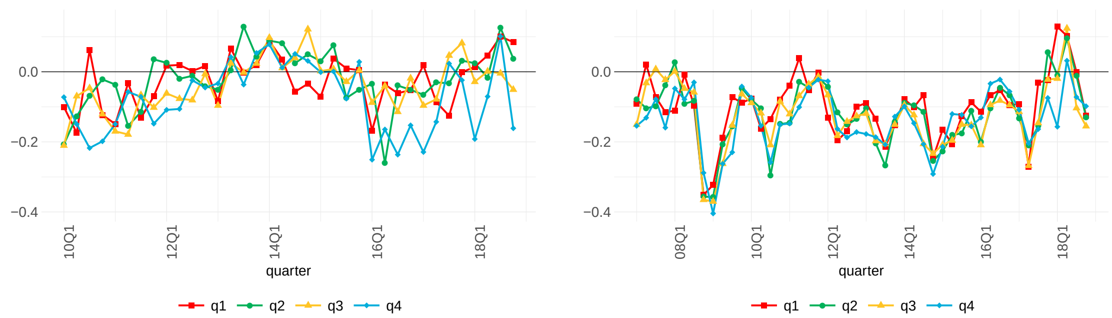
(a) France (b) Germany



Note: Cross-sectional correlation ϱ_q^δ calculated based on $\pi_{hq}^{\boldsymbol{h}}$ as defined in Section 2.2.1 for each income group separately. The lag δ=4. Income groups are defined in Appendix A.1.3.

Figure 25: Cross-sectional inflation correlation across households within expenditure quartiles

(a) France **(b)** Germany



Note: Cross-sectional correlation ϱ_q^{δ} calculated based on $\pi_{hq}^{\boldsymbol{h}}$ as defined in Section 2.2.1 for each expenditure quartile separately. The lag δ=4. Households are ranked in expenditure quartiles every quarter based on household size-adjusted quarterly expenditures.

Acknowledgements

We thank Luca Dedola, Greg Kaplan, Dirk Krüger and the members of the PRISMA network for comments and suggestions.
Any views expressed represent those of the authors and not necessarily those of the European Central Bank or the Eurosystem.

Regina Kiss
Universität Wien, Vienna, Austria; email: regina.kiss@univie.ac.at

Georg Strasser
European Central Bank, Frankfurt am Main, Germany; email: georg.strasser@ecb.europa.eu

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

PDF ISBN 978-92-899-6378-7 ISSN 1725-2806 doi:10.2866/531182 QB-AR-24-015-EN-N