RELATIVE PRICE SHOCKS AND INEQUALITY: EVIDENCE FROM ITALY

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Leonardo Ciambezi
Alessandro Pietropaoli

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Relative Price Shocks and Inequality: Evidence from Italy

Leonardo Ciambezi · Alessandro Pietropaoli

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Abstract Is inflation equal for all? Combining Italian Household Budget Survey (HBS), Survey on Household Income and Wealth (SHIW) and Harmonised Index of Consumer Prices (HICP) data, we investigate the heterogeneity of Italian households' inflation experiences over the period 2015-2023, conditional on their income and other observable characteristics. Following several years of distributional inflation neutrality, we find that the price surge that began in mid-2021 especially increased the cost of living of poorer households and more fragile socio-demographic groups, contributing therefore to increase overall inequality. After peaking in the second half of 2022, the aggregate inflation rate sharply declined in 2023 and so did the differential exposure of Italian households. In addition, by mapping each of the 480 HBS items into 90 ECOICOP 3- and 4-digit level categories, we show that between 2021 and 2022 more than 20% of the measured differential inflation between the top and the bottom income deciles comes from more granular information and would remain hidden by merely relying on 2-digit product-price data. Finally, the comparison over time between Laspeyres and Paasche average inflation rates reveals that while the two indices have generally coincided during normal times, the Paasche index-based inflation rate has consistently been higher than the Laspeyres measure since inflation began to rise. This puzzling result highlights the exceptional nature of the recent inflationary context - mostly driven by

Leonardo Ciambezi
CNRS GREDEG, Université Côte d'Azur, Nice
Institute of Economics and l'Embeds, Scuola Superiore Sant'Anna, Pisa, Italy
ORCID: 0009-0006-1553-4584
E-mail: leonardo.ciambezi@santannapisa.it

Alessandro Pietropaoli (corresponding author)
CNRS GREDEG, Université Côte d'Azur, Nice
Territorial Research Network, Bank of Italy, L'Aquila, Italy
ORCID: 0000-0003-0279-2737
E-mail: alessandro.pietropaoli@bancaditalia.it

energy price shocks - where income effects rather than substitution effects seem to have prevailed across Italian households.

Keywords Household-specific inflation rates · Energy price shocks · Inflation inequality · Italy

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1 Introduction

Price inflation is traditionally considered an aggregate variable. Any price index commonly built and used by national statistical services, such as the Harmonised Index of Consumer Prices (HICP), is thought to be a measure of the cost of a large bundle of products purchased by a single representative household. Unfortunately, such representative household does not exist. Once one realises that the basket actually purchased by each household may differ from the HICP basket, it becomes clear that each household may experience an inflation that is very different from the official rate. Therefore, measuring inflation through an aggregate index, while natural and appealing, may be misleading because it eliminates the heterogeneity in household consumption patterns and cost of living. An immediate implication of inflation heterogeneity across households is that price changes may contribute to increase overall inequality not only from the revenue side, by depressing real wages, but also from the consumption side. This would be the case whenever the prices of goods and services that are consumed relatively more by lower income households increase faster than prices on average. The so-called *consumption transmission channel* goes unnoticed when using a single aggregate consumer price index.

In this paper, combining information from the Household Budget Surveys (HBS) and Surveys on Household Income and Wealth (SHIW) on annual household expenditure decisions and income with the monthly updated Harmonised Index of Consumer Prices (HICP), we aim to investigate the distribution of inflation rates across Italian households over the period 2015-2023 and to highlight the most recent developments. As price consumer indices are usually viewed, even in the public debate, as a measure of the cost of living, focusing on a single index rather than on the distribution may provide a fundamentally flawed picture of how living conditions actually evolve across the population. Our main purpose is to assess to what extent household-specific inflation rates have been diverging from the aggregate rate and whether some income and social groups have been more severely affected by the latest price shocks. We show that until early 2021, during a period characterised by extremely low general price growth, dispersion across the household-specific inflation distribution has been negligible, and the aggregate inflation index has provided a good measure of the inflation exposure of every household. However, following the sharp increase in energy and food prices, poorer households have been exposed to a much heavier increase in the cost of their consumption bundle relative to the richer, with the bottom income decile exposed to an inflation rate that was more than double that experienced by the households at the top of the income distribution.

The first request for group-specific price indices dates back to Arrow (1958), when he argued that the poorest were likely to have different consumption patterns relative to the richest. However, it is since late '90s that the growing availability of rich micro data on household spending decisions and disaggregated price dynamics has allowed researchers to evaluate whether traditional

aggregate inflation indices are good measures of inflation for everyone (e.g., Garner et al., 1996; Crawford and Smith, 2002).
One of the earliest works on the topic has been Crawford and Smith (2002) who studied the evolution of the Retail Price Index (RPI) for the UK over the period 1976-2000 and concluded that the average price level had not been a good guide to the actual inflation experienced by individual households. They emphasised that the representativeness of the average rate, measured as the percentage of households close to the mean, tended to decrease as inflation increased. Furthermore, they showed that over the whole period, specific subpopulations such as non pensioners, mortgagors, employed and childless households had faced higher than average inflation. A few years later, Hobijn and Lagakos (2005) measured the degree of inflation inequality across US households over the period 1987-2001 and provided evidence for substantial differences in individual inflation experiences. They found that the increase in the cost of living was on average higher for elderly and, interestingly, that the cost of living for the poorest was most sensitive to the historically large fluctuations in gasoline prices.

Nevertheless, in the low-inflation economy of the 2000s, when the degree of dispersion of individual inflation rates used to be quite low, aggregate price indices provided a good approximation of the cost of living for the whole population. As a result, studying the inequality impact of household-specific inflation rates became less appealing. One of the few exceptions has been the paper by Gürer and Weichenrieder (2020), that studied the distributional effects of the heterogeneity in expenditure shares and relative price changes in a sample of 25 European countries over the period 2001-2015. They showed that the consumption bundles of poorer households have, on average, become more expensive than those of richer households in almost all the countries, with very few exceptions.
However, the debate on inflation inequality and its consequences has recently been revitalised by the abrupt rise in inflation experienced throughout the EU and USA between 2021 and 2022. Furthermore, the latest price increases have more intensely affected particular consumption categories such as electricity, gas and food, which have traditionally represented a larger share of lower income household expenditures. This circumstance may have contributed to increase the dispersion of individual inflation rates around the official consumer price index. Then, after two decades of subdued price growth, there has been renewed interest, over the past few years, in investigating the distributional implications of inflation (e.g., Curci et al., 2022; Basso et al., 2023; Gros and Shamsfakhr, 2023). Our work fits exactly in this strand of research and it contributes to the existing literature in several ways.

First, to our knowledge, no other studies have focused on the distributional aspects of inflation in Italy over the years leading up to the recent energy crisis. Our analysis fills this gap by extending the investigation beyond the period covered by Gürer and Weichenrieder (2020), which examined household-specific inflation distribution in several European countries, including Italy, up to 2015. Furthermore, studies analysing the latest national inflation inequality dynamics and their implications for economic policy, either rely on markedly different both theoretical and empirical techniques or address the phenomenon from quite distinct perspectives. For instance, Curci et al. (2022) used microsimulation tools to quantify the extent to which Italian government measures have mitigated the distributional consequences of the recent inflationary surge. Corsello and Riggi (2023) set up a dynamic stochastic general equilibrium two-agent model with imported energy to explore the role of monetary policy in the transmission of price shocks and its redistributional impact in the presence of heterogeneous consumption patterns. Finally, Infante et al. (2024) is likely the closest work to ours, as it also adopts a microeconomic perspective to assess the distributional consequences of recent inflation dynamics. By employing a methodology similar to the Distributional Wealth Accounts developed at the European level, they assess the impact of 2022 inflation surge on Italian households' financial wealth along the joint distribution of income and wealth. The authors centre exclusively on the so called *portfolio composition transmission channel* of inflationary redistribution. Our work, which also explores the determinants and characteristics of inflation inequality in Italy at the micro level, complements their analysis by shifting the focus on the *consumption transmission channel* of relative price changes. Low-income households are particularly vulnerable to high inflation episodes not only due to the composition of their assets and liabilities, but also because their consumption baskets are more sensitive to sudden price increases, as our study demonstrates. Furthermore, unlike all the aforementioned studies, we do not limit our analysis to the inflation gap across income groups and leveraging the rich information from Italian Household Budget Surveys, we test whether observable features other than income (e.g., homeownership, place of residence, age, professional status or education) have also played a role in shaping inflation exposures across Italian households between 2015 and 2023.

Second, it is well-known in the inflation inequality literature that exploiting highly disaggregated product-price data is crucial to capture the full extent of inflation heterogeneity across the population (Jaravel, 2021). However, traditional empirical research, which relies on survey data and is mainly concerned with differences in spending patterns and price variations *between* categories and not *within*, has often been forced to work with at most 2-digit category data because of the lack of more detailed information (Hobijn and Lagakos, 2005; Gürer and Weichenrieder, 2020; Basso et al., 2023). To handle more granular product-price data than typically found in standard literature, we leverage the richer detail of Eurostat HBS. This allows us to partition the over 480 goods and services from the national HBS up to 90 expenditure classes given by a combination of 3- and 4-digit products for which price data are available in the Italian HICP. We show that ignoring such additional information, we would seriously underestimate the measured differential inflation between the bottom and top deciles of the Italian household income distribution by more than 20%

during the core years of the recent energy crisis (2021-2022).

Third, the current work has also implications for Consumer Price Index theory, as it highlights how different ways of aggregating household consumption bundles can give back distinct pictures of price dynamics whenever the variability of inflation, both individual and aggregate, becomes relevant. In similar scenarios, we show that aggregating households by assigning to each of them a weight proportional to their total expenditure, the so-called *plutocratic* weighted average of individual price indices, leads to significant underestimation of the inflation experienced by lower income deciles and it makes an inadequate cost of living indicator for the large majority of households. More generally, our study puts into question the adequacy of any aggregate price index, both *plutocratic* and *democratic*, at least in a context of highly rising prices and sharp relative price fluctuations, when individual inflation experiences can widely differ across the income distribution, as they did very recently. This last evidence calls for a more widespread adoption of group-specific price indices to inform policymakers whenever significant inflationary pressures are in place.

Finally, an additional contribution stems from the comparison between Laspeyres and Paasche average inflation rates, which are the most commonly used price indices to compute inflation for a bundle of k goods and services, available across two different periods.[1] The two statistical indices ultimately differ because of the way they deal with the product-substitution decisions taken by rational consumers, which are supposed to optimally react to relative price changes across products (see Section 2). This is why comparing their evolution, both through normal times and during the recent energy crisis years, allows us to appreciate the empirical relevance of the theoretical substitution effect. In particular, the Laspeyres index using expenditure shares from the previous period, before relative prices change, it does not allow households to substitute products become relatively more expensive with products now relatively cheaper and so it tends to overstate true inflation. On the other hand, the Paasche index relying on current consumption shares, after relative prices change, it implies that substitution is fully occurred and so it would tend to understate true inflation. We compute both inflation measures until December 2022 and we show that they have essentially coincided between 2015 and 2021, over a period characterised by negligible price fluctuations and consequently by little household consumption substitution. However, since early 2022 right when overall inflation started to grow, the two indices began to diverge, but contrary to theoretical predictions, the Paasche index-based inflation rate, supposed to be the *lower* bound of the cost of living, has consistently been higher than the Laspeyres index-based inflation rate over the whole year. This puzzling result can be understood by considering the exceptional nature of the recent inflationary shock. Even though both gas and electricity prices have more than doubled over the 2022, their relative weights on household consumption

[1] See Diewert (1993) for a survey of the early history of price index research.

bundles have actually increased since both energy goods are necessities and their demand is known to be particularly rigid to sudden unanticipated price shocks. In other words, in the recent inflationary context driven by energy price fluctuations, income effects rather than substitution effects seem to have prevailed across Italian households.

The remainder of the paper is organised as follows. Section 2 details the data and the methodology used in our empirical analysis. Section 3 extensively discusses all the results through specific subsections. Section 4 summarises and concludes.

2 Data and methodology

Computing household-specific inflation rates requires two complementary pieces of information: on the one hand, we need micro data on expenditure decisions for a representative sample of Italian households and on the other, updated series of price data for a sufficiently disaggregated set of goods and services.

We obtain the first piece of information by exploiting the Household Budget Surveys (HBS) yearly conducted by the Italian National Institute of Statistics (Istat) since 1968, with the aim of collecting information on the expenditure of resident households on goods and services that are exclusively used for domestic and consumption purposes. Over time, two deep changes have been introduced in every stage of the survey process, first in 1997 and then in 2014. In 1997, the survey was first restructured to improve the quality of information and align with European standards. To this end, new detailed questionnaires, such as the "*Libretto degli acquisti*", "*Riepilogo delle spese familiari*" and "*Taccuino degli autoconsumi*" were introduced to capture comprehensive expenditure data; the sample size was expanded up to about 24000 respondents to increase the representativeness of the survey and the European Classification of Individual Consumption by Purpose (ECOICOP) was firstly adopted to harmonise data collection with other European countries. Then, in 2014, the survey experienced another significant overhaul. In particular, the sampling design was renewed to improve the representativeness of diverse households types and regions; the interviews period was extended to cover the entire year providing a more complete view of household expenditures across different seasons and data collection was updated by means of modern techniques like Computer-Assisted Personal Interviewing (CAPI) and self-completed diaries. Furthermore, the expenditure categories were expanded and refined to capture a wider range of goods and services, by including more specific sub-categories for items like technology, leisure activities and health services (Freguja and Romano, 2015). Consequently, time comparisons between recent and pre-2014 estimates can be made only by using *ad hoc* series reconstructed by Istat. In order to rely on higher quality data and since we are mainly interested in the latest price dynamics, we choose to limit our analysis to the period 2015-2023.

The survey is conducted every year on a cross-sectional basis on a very large sample of Italian households, ranging in our study from a minimum of 15013 in 2015 to a maximum of 28608 in 2021. The questionnaire is based on the harmonised international classification of expenditure voices (ECOICOP), over 480 categories of goods and services, to ensure international comparability and it represents the main informative base for the various consumer price indices and for the official estimates of relative and absolute poverty in Italy.

Because the HBS lacks information on prices, we need to resort to a second data source, i.e., the Harmonised Index of Consumer Prices (HICP) which is monthly calculated by Istat, according to EU regulations, through a chained Laspeyres formula in which both the consumption bundle and the weighting system are annually updated. Since one of the purposes of the HBS is to calculate the weights for the HICP, the disaggregation of consumption expenditure categories is, at least in principle, identical in the two datasets. Then, mapping price information into consumption decisions is a trivial procedure once one constructs a bridging table between expenditure and price categories. We obtain the full 5-digit ECOICOP categorisation by matching the variable nomenclatures from the Istat HBS with the corresponding 5-digit expenditure categories officially reported in the Eurostat HBS. Then, we eventually partition the over 480 categories of goods and services included in the Italian HBS to 90 expenditure classes given by a combination of 3- and 4-digit products for which price data are actually available in the Istat HICP.[2]

Since (Engel, 1857), it is well-established that households with different incomes purchase different consumption bundles, i.e., poorer households spend an higher fraction of their income on necessities, while the richest assign a larger share of their resources to luxuries. Then, if the prices of necessities increase faster than the aggregate price index, lower income households end up facing a higher level of inflation than the one computed at the country level. The same logic applies to all those socio-demographic groups that may differ from each other because of their consumption patterns. It becomes clear that an aggregate consumer price index cannot, by construction, capture the heterogeneous impact that substantial changes in relative prices might have on the own inflation experience. This is why computing household-specific price indices is actually needed.
There are two common ways to allow for household heterogeneity when computing inflation, i.e., either by using group-specific homothetic price indices or by relying on non-homothetic cost of living indices (Jaravel, 2021). In our analysis, we adopt the former approach, which utilises standard price indices while accommodating differences in inflation rates across households by simply assuming homothetic preferences for each socio-demographic group (e.g., McGranahan and Paulson, 2005; Broda and Romalis, 2009; Argente et al., 2020).

[2] The full mapping table between the Household Budget Survey 2021 expenditure codes and ECOICOP 2013 classification can be found in the online appendix and in our Household-specific inflation rates for Italy 2015-2023 online repository..

This method naturally builds on the cost of living indices typically computed by statistical agencies to account for heterogeneity between groups. Importantly, it does not require any specific assumption about the functional form of the utility functions. Indeed, with homothetic preferences, all households within the same group have identical consumption shares and experience the same inflation rate, which conveniently does not depend on the utility level.[3] In contrast, the use of non-homothetic utility functions allows both expenditure shares and price indices to vary with utility levels and so non-homothetic cost of living measures end up nesting homothetic price indices as special cases. However, this approach requires the development of an *ad hoc* theoretical framework including convenient restrictions about household preferences to preliminarily estimate utility parameters (e.g., Atkin et al., 2024; Hochmuth et al., 2022).

The most commonly used price indices to compute inflation for a bundle of k goods and services, available at both $t-1$ and t, are the Laspeyres and Paasche indices:

$$1 + \pi_{t-1,t}^{Laspeyres,h} = \frac{\sum_k q_{k,t-1}^h \times p_{k,t}}{\sum_k q_{k,t-1}^h \times p_{k,t-1}} = \sum_k s_{k,t-1}^h \times \frac{p_{k,t}}{p_{k,t-1}} \tag{1}$$

$$1 + \pi_{t-1,t}^{Paasche,h} = \frac{\sum_k q_{k,t}^h \times p_{k,t}}{\sum_k q_{k,t}^h \times p_{k,t-1}} = \sum_k s_{k,t}^h \times \frac{p_{k,t}}{p_{k,t-1}} \tag{2}$$

where h indicates household groups (e.g., income deciles), $p_{k,t}$ is the price of product k at time t, $q_{k,t}^h$ is the quantity purchased by group h of product k in t and $s_{k,t}^h$ is the period t expenditure share of group h on product k. In principle, inflation can vary across households due to heterogeneity both in the expenditure shares and in the prices paid. However, without scanner data, it is not possible to take into account the effects that differences in quality and variety of the k products may have on the prices actually paid by each household. In the survey data we use, the assumption is that all households face the same price for the same good, it follows that differences in household-specific inflation rates will exclusively emerge because of different between-groups consumption patterns and not from within-category price changes.[4]

The two statistical indices deal differently with the product-substitution decisions taken by rational consumers that are supposed to optimally react to relative price changes across products. The Laspeyres index (equation 1) uses expenditure shares at the previous period $t-1$, before relative prices change, it does not allow households to substitute and so it tends to overstate true inflation. This is why the Laspeyres index is usually regarded as the *upper* bound of the cost of living. The Paasche index (equation 2) uses consumption shares at the current period t, after relative prices change, it implies that

[3] The goal of any price index is to measure how the expenditure required to maintain a certain level of utility U changes over time.

[4] Given the exceptional nature of the latest price shocks, we are not worried about this data limitation and within-industry effects are beyond the scope of our analysis.

substitution has fully occurred and so it tends to understate true inflation. This is why the Paasche index is usually regarded as the *lower* bound of the cost of living (Schultze, 2003).
Since Italian Household Budget Surveys are conducted every year, it is possible to track annual shifts in household consumption patterns and both inflation measures can be easily calculated. In our main analysis, we use group-specific Laspeyres indices to leverage all available information and appreciate the reduction in the inflation inequality that began in early 2023. However, we also compute monthly individual Paasche inflation rates up to December 2022 to compare the dynamics of the two indices between 2015 and 2022.

Unfortunately, the Italian HBS does not collect any direct measure of household income. Since our primary purpose is to analyse the heterogeneity in inflation exposures among poorer and richer consumers, it is essential to recover reliable information about Italian households' income distribution from alternative data sources. To this end, we rely on the Survey on Household Income and Wealth (SHIW), conducted on a two yearly-basis by the Bank of Italy since 1965 to gather detailed data on the savings and incomes of the Italian population. In particular, we are interested in household net disposable income, defined by the Bank of Italy as the sum of all household members' incomes after taxes. This measure includes salaries, wages and other forms of compensation, along with pensions and retirement income, self-employment earnings and property income derived from real estate and financial assets. We are well aware that capital income tends to be underreported in the SHIW compared to official macroeconomic aggregates. For instance, Neri and Zizza (2010) document some degree of misreporting in certain income components, particularly those related to financial assets and self-employment earnings. This discrepancy may affect the representativeness of higher-income households in the sample. However, this limitation does not undermine the robustness of our results. We show in Appendix A that our findings remain consistent when equivalent non-durable consumption is used as a proxy for household living standards instead of equivalent disposable income. To integrate consumption and income data, we employ a statistical matching procedure (D'Orazio, 2006), which produces a synthetic dataset combining the HBS and SHIW information while preserving the joint distribution and correlation structures of the original datasets. The details on this procedure are outlined in Appendix B. Once income data are effectively imputed to each sample household, we equivalise disposable income by dividing it by the square root of the number of household components.[5] The resulting vector of equivalent disposable incomes is then divided into ten groups, with the size of each decile determined by the cumulative survey weights. By accounting for weights, rather than simply splitting the sample into equally sized groups, we ensure that income deciles are actually representative of the entire household population. After assigning each household to its respective

[5] In Appendix C we show that our results are robust to the adoption of alternative equivalence scales.

income decile, we compute the weighted average of household-specific inflation rates within each decile to construct time series of inflation rates specific to each income decile.[6]

3 Results

In what follows, the main results of our analysis are conveniently summarised and extensively discussed through specific subsections.

3.1 The distribution of household and country inflation rates

So far, we have stressed the importance of computing household inflation rates since the cost of living growth may substantially differ across the population. Then, it is possible to aggregate such sample household-specific price indices to obtain an inflation measure for the entire country in line with the official Harmonised Index of Consumer Prices.
Indeed, since Prais (1959) it is well-known that the standard consumer price indices computed by most statistical agencies can be seen as a weighted average of individual price indices, where the contribution of each household to determine the aggregate index is proportional to its expenditure (Ley, 2005). In other words, more relevance is usually given to the inflation experienced by those households spending more, which are likely to be the richest ones, hence the definition of *plutocratic* index:

$$\Pi_{t-1,t}^{Plutocratic} = w^h \times \frac{S_{t-1}^h}{S_{t-1}} \times \sum_{h=1}^{H} \pi_{t-1,t}^h \tag{3}$$

where h indicates the individual household, $\frac{S_{t-1}^h}{S_{t-1}}$ is the weight of household h total expenditure over national expenditure at time $t-1$ and $\pi_{t-1,t}^h$ is the household-specific Laspeyres inflation rate as previously described.An analogous relation between individual inflation rates and the country price index would obviously hold for household-specific Paasche indices as well. Finally, the aggregate price index is rescaled by applying the population weight w^h associated with each of the H sample households as a measure of their population representativeness.
Aggregation methods other than the plutocratic scheme are also possible, such as the *democratic* index, which assigns the same weight to each household, according to the principle of "one household-one vote":

$$\Pi_{t-1,t}^{Democratic} = w^h \times \frac{1}{H} \times \sum_{h=1}^{H} \pi_{t-1,t}^h \tag{4}$$

[6] The dataset used in the current analysis is publicly available in the previously mentioned Household-specific inflation rates for Italy 2015-2023 online repository.

where the notation is the same as above.
By comparing (3) and (4) and recalling how household inflation rates are computed (see equation 1), it is straightforward to realise that under certain conditions the two alternative indices would actually coincide:

- each household ($h = 1, ..., H$) consumes exactly the same amount S^h_{t-1};
- the expenditure share of each household on all goods and services is identical, i.e. $s^h_{k,t-1} = \frac{s_{k,t-1}}{H}, \forall k = 1, ..., K$ and $\forall h = 1, ..., H$;
- the relative price changes $\frac{p_{k,t}}{p_{k,t-1}}$ are the same for all consumption products ($k = 1, ..., K$).

However, the more the actual situation differs from the above conditions, the greater is the difference - known as *plutocratic bias* - between the two price indices. In principle, neither approach is formally superior and so the choice often depends on the use that has to be made of the consumer price index. On the one hand, plutocratic indices are better suited for both national accounting and monetary policy purposes since they are appropriate indicators of overall macroeconomic conditions as they weight each dollar of expenditure equally, in accordance with the principle of "one dollar-one vote" (Martin (2022)). On the other hand, democratic indices are assumed to be more representative since they weight poorer and richer households equally (Bandyopadhyay and Ramaswami (2022)) and they may be preferable when constructing an indicator of consumer experiences (Astin and Leyland (2015)) or addressing welfare policy questions as they track the average price change across households rather than across dollars of expenditure.

Figure 1 shows the evolution of inflation rates over the entire period for both the bottom and top income deciles of the representative sample of Italian households, together with the weighted-sample democratic and plutocratic indices, as well as the Harmonised Index of Consumer Prices officially computed by ISTAT.
Both our in-sample aggregate inflation measures and the official HICP has closely tracked one another until early 2021, with only minor deviations occurring sporadically. From that point onward, the national price index has primarily aligned with the inflation experienced by higher-income households, resulting in lower inflation estimates compared to our aggregated sample indices during the energy crisis. This trend is consistent with the fact that the HICP, in its essence, is a plutocratic index. Discrepancies between inflation measures derived from household budget survey data and those based on national accounts are to be expected, given fundamental differences in data sources, coverage and methodologies.[7] These distinctions underscore why a direct comparison

[7] Specifically, our plutocratic index is built on HBS data, which, although detailed in capturing household-level consumption, may not perfectly correspond with the broader, economy-wide data used for calculating the HICP (Mostacci, 2004; D'Acunto, 2006). The key distinction lies in the weighting: our plutocratic index uses weights based on the aggregation of HBS consumption patterns, while the HICP derives its weights from the final household consumption item from national accounts , which can diverge, particularly during periods

between the official HICP and our survey-based inflation measures may be inappropriate, especially during periods of pronounced price volatility, such as the recent energy crisis.

From 2015 to early 2021, during a period when price growth has been constantly very low, both the plutocratic and democratic indices have followed an extremely close evolution, with very small monthly deviations between the two inflation measures, ranging from −0.13 to 0.33 percentage points. Furthermore, the poorest- and the richest-specific inflation rates have been very close to each other and to the aggregate inflation indices, as well. Between 2015 and 2020, the top 10% of the population has experienced an average inflation equal to 0.37%, which is slightly higher than the inflation faced by the poorest income decile (0.3%). The evidence that inflation has not been traditionally pro-rich in Italy, unlike in the rest of Europe, is in line with the conclusions reached by Gürer and Weichenrieder (2020). They compute household-specific price indices for a sample of 25 European countries over the period 2001-2015 and find that the increase in the cost of living has been, on average, higher for the poorest across almost all the countries, with Portugal and Italy as notable exceptions.

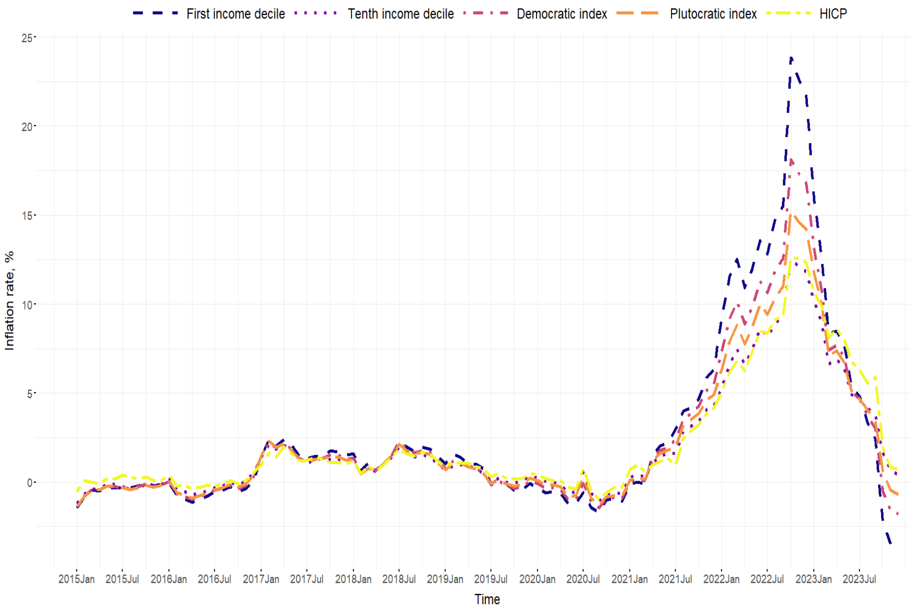

Fig. 1 Bottom and top decile-specific inflation rates, democratic consumer price index, plutocratic consumer price index and Istat HICP (2015-2023).

of significant inflationary shocks. Additionally, the HICP methodology may incorporate smoothing techniques to mitigate short-term price spikes or adjust for seasonal fluctuations, which have been particularly pronounced over the past years.

The picture completely changes starting from early 2021, following the supply-chain disruptions due to the 2020 global pandemic and later the energy crisis caused by the outbreak of the Ukrainian war in February 2022. Figure 2 focuses on these very recent price dynamics and looks at the specific inflation rates experienced by each income decile.

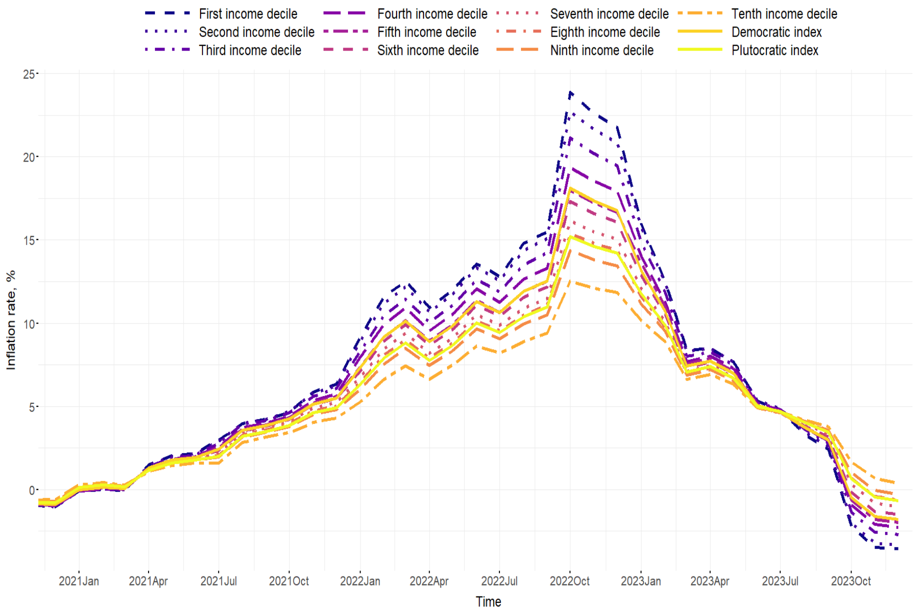

Fig. 2 Decile-specific inflation rates, democratic consumer price index, plutocratic consumer price index (2021-2023).

Figure 2 reveals the major limitation of using traditional aggregate indices of consumer prices. During periods of low and stable inflation, such as from January 2015 to March 2021, a single synthetic measure has provided an appropriate description of the inflation faced by Italian households on average. However, the representativeness of any aggregate index tends to decrease as overall inflation begins to rise, as observed since April 2021. In particular, the plutocratic index has done a better job in tracking inflation for the higher income deciles and it has performed worse in tracking the evolution of the cost of living for the poorer.[8] Between 2021 and 2022, at the heart of the energy crisis, the plutocratic measure has actually been representative of the inflation experienced by the higher income half of the population (6.31% and 6.32%, respectively), while it has diverged from the average price increase faced by

[8] Muellbauer (1974) examines which household's consumption shares most closely match the aggregate plutocratic weights used in the UK CPI and finds it corresponds to a household at the 71st percentile of the expenditure distribution. Similarly, for the USA in 1990, Deaton (1998) estimates that such household occupies the 75th percentile. Thus, the "representative" plutocratic consumer seems to be inclined towards likely richer groups of the population.

the median household (8.2%) by around 2 percentage points. Similarly, the democratic index, equal to 7.25% over the same period, even though more representative of the average price dynamics since the expenditure pattern of each household counts in equal extent in determining the aggregate index, it has also suffered from the same drawback. Over the two core energy crisis years, the bottom income decile has seen the price of its consumption bundle increase by 9%, while the basket of goods and services purchased by the richest decile has become only 5.4% more expensive. The maximum gap between the inflation levels faced by these income groups, 11.3 percentage points, has been reached in October 2022. Since the beginning of 2023, as the country inflation rate declined, so did the differential exposure of Italian households and by August, we went back to the pro-poor inflation dynamics observed during the pre-crisis period.

The preliminary graphical analysis has shown in a very intuitive way how aggregate price indices, both plutocratic and democratic, have turned out to be good guides to the actual inflation experienced by individual households during normal times, but they have proven to be little instructive when inflation rates have been more widely dispersed throughout the population, as recently happened. In similar scenarios, relying on group-specific price indices seems to be required in order to take accurate policy decisions.

3.2 Overestimating or underestimating household-specific inflation rates?

A careful reader may argue that we are actually overestimating the inflation experienced by individual households because we are computing the price growth of individual expenditure bundles by applying a Laspeyres price index. Following an inflationary shock, relative prices change and rational economic agents are supposed to adjust their consumption choices by substituting products that become relatively more expensive with products that are now relatively cheaper. A Laspeyres index using expenditure shares from the previous period, before relative prices change, does not allow rational households to substitute and so it would tend to overstate true inflation. On the other hand, the alternative Paasche index, which relies on current consumption shares, after relative prices change, implies that rational consumers have fully substituted and so it would tend to understate true inflation.

With the available data, we can compute both monthly price indices at the household level up to December 2022. This allows us to compare their evolution both during normal times and throughout the recent energy crisis. By doing so, we can determine whether the two cost of living measures have diverged on average and to what extent Italian households have actually resorted to substitution in response to the latest relative price changes.

Figure 3 shows the evolution of both the Laspeyres and Paasche average household inflation rates throughout the entire period. Until the end of 2021, the two indices have generally coincided. This circumstance should not be surprising, as until the recent energy crisis, price dynamics had always been subdued and there was no reason to expect any shift in household consumption decisions in response to negligible price effects. However, since early 2022 right when overall inflation started to grow, the two price indices began to diverge, but contrary to theoretical predictions, the Paasche index-based inflation rate, supposed to be the *lower* bound of the cost of living, has consistently been higher than the Laspeyres index-based inflation rate, usually regarded as the *upper* bound of the cost of living, over the whole year. This, at first glance, puzzling result may be solved by considering the exceptional nature of the inflationary shock recently faced by the Italian population, which has been mostly driven by the manyfold price increase of very few and peculiar goods, i.e energy goods.[9]

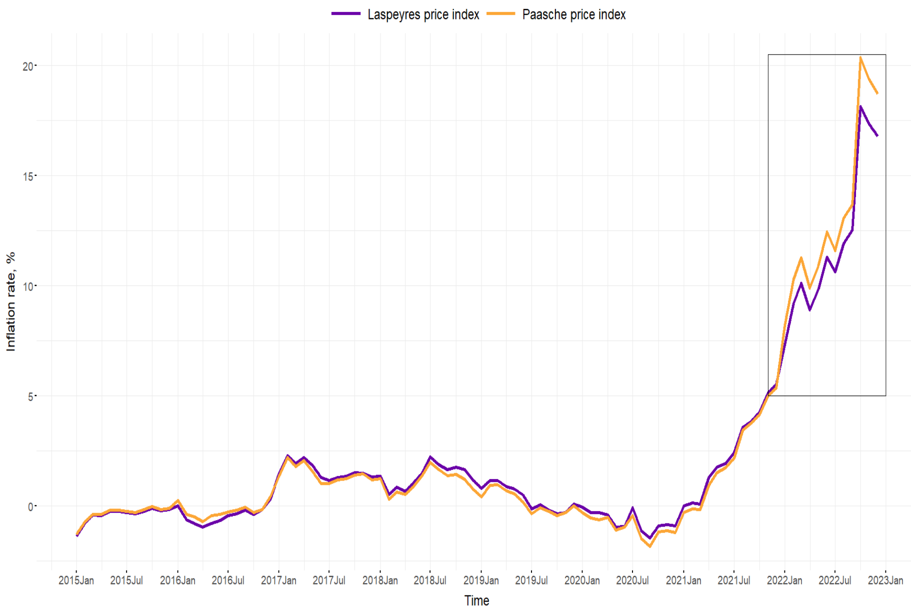

Fig. 3 Laspeyres (purple) and Paasche (orange) democratic inflation rates (2015-2022).

Then, in order to shed light on this empirical puzzle, we investigate how Italian households have adjusted their consumption behaviour in response to the

[9] For interested readers, Appendix D displays the evolution of both the Laspeyres and Paasche price indices by income decile between 2021 and 2022. Notably, the Paasche index-based inflation rate has been higher than the Laspeyres counterpart across all income deciles since early 2022, with this trend being particularly pronounced among lower income deciles.

recent inflationary shock. In the left panel of Figure 4, we plot the consumption share variations versus the price changes for all expenditure categories over the period 2021-2022. The relationship between changes in quantities and changes in prices appears to be oddly upwards, i.e. a larger price increase between 2021 and 2022 is associated with a larger share in the 2022 consumption bundle for a generic good x. This counterintuitive evidence actually explains why the Paasche price index has been larger than the Laspeyres price index over the whole year. Interestingly, when we exclude the two north-east outliers, i.e. gas (0452) and electricity (0451), the relationship between price changes and expenditure share variations turns out to be slightly downwards, in line with the theoretical substitution effect prediction (see Appendix E).

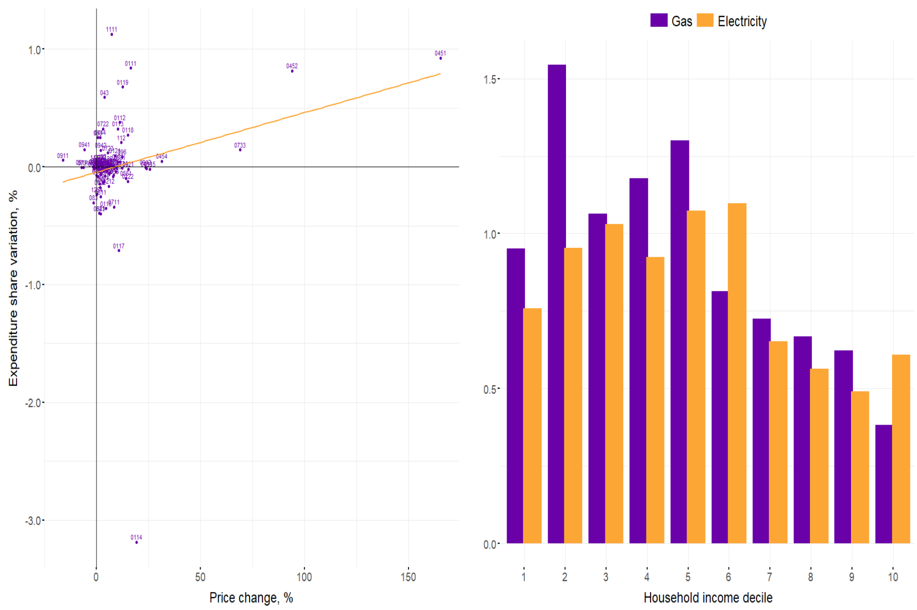

Fig. 4 *Left panel*: **Consumption share variations and price changes (2021-2022)**. *Right panel*: **Consumption share variations of gas and electricity by income decile (2021-2022)**.

To understand better what is behind this unexpected consumer behaviour, the right panel of Figure 4 draws the consumption share variations of both energy goods for all income deciles between 2021 and 2022. Despite both gas and electricity prices have more than doubled over 2022, their relative weights on household consumption bundles have actually increased. This evidence is robust across the entire population and is especially significant for the lower deciles of the income distribution. The observed consumption dynamics is likely explained because both gas and electricity are necessities rather than luxury goods, making their demand particularly rigid in response to sudden, unanticipated price shocks.There exists a sizeable literature documenting that the short-term elasticity of household energy consumption is generally very low and that households usually take several years to adapt their behaviour to energy price shocks (e.g, Boonekamp, 2007; Lijesen, 2007; Zhu et al., 2018).

To sum up, the recent abrupt inflationary episode seems to have caused, at least temporarily, a relatively small drop in the consumption of energy goods and a larger reduction in the consumption of luxury goods with the net effect of increasing the relative importance of gas and electricity on household expenditure bundles. In other words, in the recent inflationary context driven by energy price shocks, income effects rather than substitution effects seem to have prevailed across Italian households.
Although we do not find any evidence of substitution effects from energy goods to other expenditure categories, it may still be possible that households have revised their consumption choices in response to inflation dynamics, but that substitution has occurred *within* product categories rather than *between*. Instead of shifting consumption from expenditure categories whose prices were increasing above average to others whose prices were rising less than average, households may have chosen to purchase, for each given expenditure category, products of lower quality and lower variety. Unfortunately, because of the lack of detailed micro proprietary data, we cannot rule out this scenario. As far as between category substitution is concerned, we find no supporting evidence, even in the face of sharply increasing energy prices.

3.3 Disaggregation matters: a simple decomposition of the bottom-top inflation differential

Before analysing the main drivers of recent inflation inequality dynamics, we would like to emphasise the importance of using highly disaggregated data when studying the heterogeneous impact of relative price growth across the population. This is especially important during periods of high inflation, when the dispersion in the rates among households tends to increase. In such scenarios, relying on broad price categories may obscure a significant portion of the inflation inequality existing across various household groups.

The differential inflation between any two socio-demographic categories can be, indeed, decomposed into a *between* and a *within* component. The *between* component corresponds to the differential inflation that would prevail if households differed only in terms of their expenditure shares across product categories and faced the same inflation within each product category. The *within* component corresponds to the differential inflation that would prevail if households differed only in terms of the inflation rate they faced within a product category and had the same expenditure shares across categories. Then, for any category of products G, the differential inflation between two household groups, e.g., the top and bottom income deciles, can be decomposed as proposed by Diewert

(1976):

$$\pi^R - \pi^P = \sum_G s_G^R \pi_G^R - \sum_G s_G^P \pi_G^P = \underbrace{\sum_G s_G^R \pi_G - \sum_G s_G^P \pi_G}_{Between} + \underbrace{\sum_G \overline{s_G}(\pi_G^R - \pi_G^P)}_{Within} \quad (5)$$

where s_G^i is the expenditure share of household group i on product category G and π_G^i the inflation faced by household group i on product category G. π_G and $\overline{s_G}$ are the average inflation rate and the average expenditure share for product category G, respectively.

Unfortunately, most of the traditional empirical works investigating the distributional consequences of inflation have been forced to rely on relatively coarse consumption decision-product price information.[10] This data limitation often leads to a biased measure of the inflation dispersion across households, as most of the variation in consumption actually lies *within* large categories rather than *between* (Jaravel, 2019).
For this reason, a recent body of research exploiting the higher granularity of scanner data is quickly growing (e.g., Kaplan and Schulhofer-Wohl, 2017; Faber and Fally, 2022); because of data availability, most of these studies focus on USA inflation inequality-related episodes.
It is important to note that scrutinising within-industry price effects is beyond the scope of our work. Additionally, relying on proprietary data is not essential for our analysis, as such data cover only part of households' expenditure baskets and would not provide any additional insights into energy price dynamics, which have been at the heart of the recent inflation surge in most advanced economies. However, to minimise the typical aggregation limitations of working with survey data, we have chosen to match HBS and ECOICOP national data in a way to exploit all the available information. By leveraging the richer detail of the Eurostat HBS classification, we have eventually managed to gather up to 90 consumption categories which fall into either 3- or 4- digit price levels.

In what follows, we illustrate in an intuitive way the aggregation bias that using only 2-digit price-product information would have introduced in our estimates of the inflation differential between the richest and poorest Italian households throughout the energy crisis.
The left panel of Figure 5 plots the evolution, between 2021 and 2022, of the inflation differences between the top and bottom income deciles of the Italian population for varying levels of ECOICOP aggregation (12 and 90 consumption

[10] For example, Hobijn and Lagakos (2005) study the distributional consequences of relative price changes in the U.S. by exploiting only 19 product categories; Gürer and Weichenrieder (2020) investigate inflation inequality in a sample of 25 EU countries by leveraging just 30 expenditure categories; Crawford and Smith (2002) analyse the differences in the inflation rates experienced by different households in the UK by using 69 categories; Basso et al. (2023) estimate household-specific inflation rates at 2-digit level from 2006-2021 in Spain, they only exploit 4-digit level information when they study the most recent inflation surge.

categories, respectively). It emerges that relying solely on the standard 2-digit expenditure classification would have significantly underestimated inflation inequality during the recent energy crisis, with the largest measurement bias reaching −2.2 p.p. in October 2022.

The right panel of Figure 5 shows, instead, the average decile-specific inflation rates for the period 2021-2022 calculated using the two different levels of expenditure disaggregation. If we would limit our analysis to the standard 12 macro consumption categories, the average inflation faced by each household income decile would be consistently underestimated. This bias would be particularly significant for the poorest segments of the population, with the second income decile experiencing a bias of −0.85 percentage points. The only exception would be the richest decile, whose inflation would be overestimated by 0.46 percentage points. Then, when measured at the 3- and 4- digit levels of disaggregation ($N = 90$), the full differential inflation between the top and bottom household income deciles turns out to be equal to 3.6 percentage points. However, when considering only the *between* component at the 2-digit level ($N = 12$), the estimated inflation inequality falls down to 2.8 percentage points. This implies that not accounting for the *within* component, captured by the more granular 3- and 4- digit product information, would underestimate the measured inflation inequality by almost one fourth throughout the energy crisis.

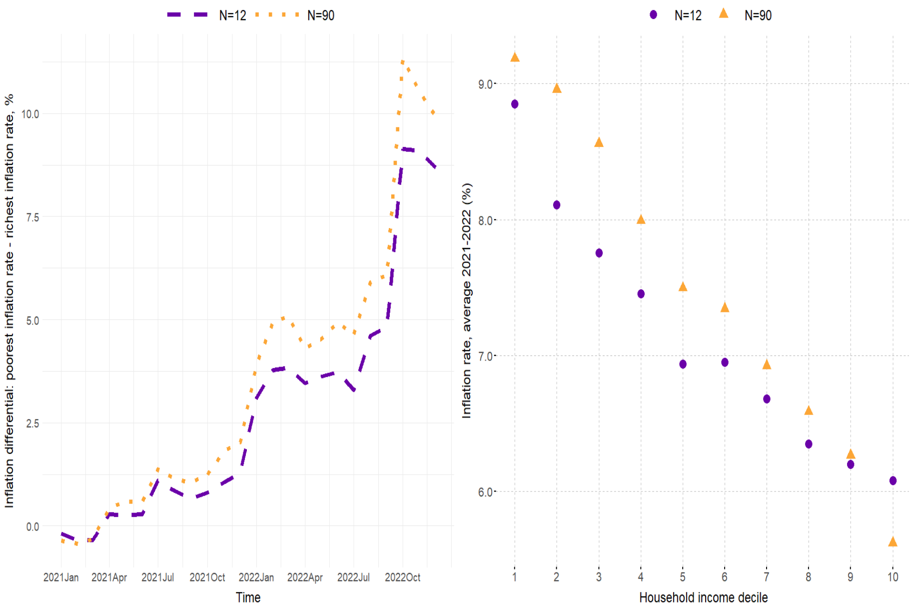

Fig. 5 *Left panel:* **Monthly top-bottom differential inflation by different consumption categories disaggregation (2021-2022)**. *Right panel:* **Average decile-specific inflation rates by different consumption categories disaggregation (2021-2022)**.

3.4 Drivers of Inflation Inequality

It should now be clear that heterogeneous inflation experiences across income and social groups mechanically emerge whenever relative prices change substantially since expenditure shares usually vary across households.

Figure 6 aims to show which kind of goods and services lie behind the recent surge in inflation inequality by plotting the price variation of all 90 consumption categories together with the difference in expenditure shares between the poorest and the richest over the period 2021-2022.[11]

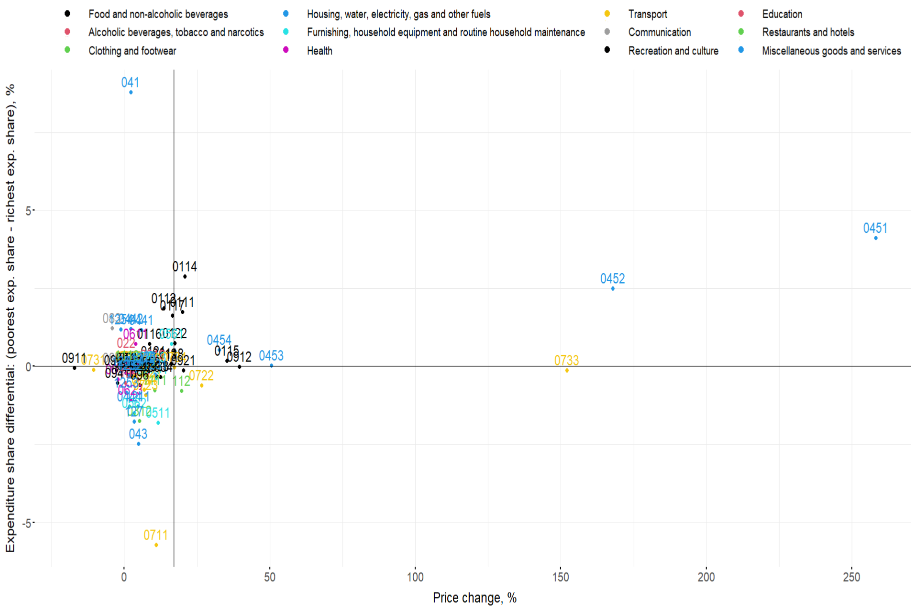

Fig. 6 Expenditure share differentials and price changes (2021-2022). *Notes*: A numerically ordered listing of the category codes can be found in Appendix G. The x-axis represents the average aggregate inflation between 2021 and 2022. The y-axis measures the expenditure share differentials between the poorest and the richest deciles. Products above (below) the x-axis are more (less) consumed by the bottom 10% of Italian households.

[11] Appendix F presents analogous scatter plots that illustrate the price variation of all 90 consumption categories together with the differences in expenditure shares among various socio-demographic household groups other than income deciles.

After several years of distributional neutrality, the differential inflation between the bottom and top income deciles became substantial, averaging about 3.5 percentage points between 2021 and 2022. Figure 6 clearly shows why the consumption basket purchased by the poorest became more expensive relative to that of the richest. The energy crisis following the outbreak of the Ukrainian war led to abrupt increases in both electricity (0451) and gas (0452) prices by 258% and 168%, respectively. Expenditure shares on energy goods are traditionally the main difference across income group consumption patterns. In particular, the bottom income decile used to devote an higher fraction of its total expenditure to both electricity (+4.1%) and gas (+2.5%) relative to the top decile. Therefore, the large energy price shocks made quite mechanically the poorest to face a much higher increase in the cost of their consumption basket relative to the richest.
Few more things are worth mentioning. First, the rents (041), which have exhibited the highest expenditure share differential (+8.7%) for the bottom income decile, have partially limited inflation inequality since their price has grown (2.3%) well below the official price index (17%). Furthermore, it is interesting to note that most of the products mainly consumed by the richest (e.g., domestic and household services, garments, hospital services, hairdressing salons and personal grooming establishments, etc.) were concentrated in the third quadrant, indicating that their prices have increased less than average between 2021 and 2022.

To highlight this last circumstance, Figure 7 shows the unweighted fraction of expenditure above or below the Harmonised Index of Consumer Prices for all income deciles. Over the period 2021-2022, in addition to the crucial relevance of the expenditure on electricity and gas, slightly less than 45% of the consumption basket of the bottom income decile has been exposed to a price increase above the HICP, but at the same time the richest have only seen around 30% of their bundle's price increasing faster than average.
Then, although energy price shocks have clearly played a primary role in determining the magnitude of the very recent inflation inequality episodes, other factors - such as very different consumption patterns across income groups - have contributed as well.

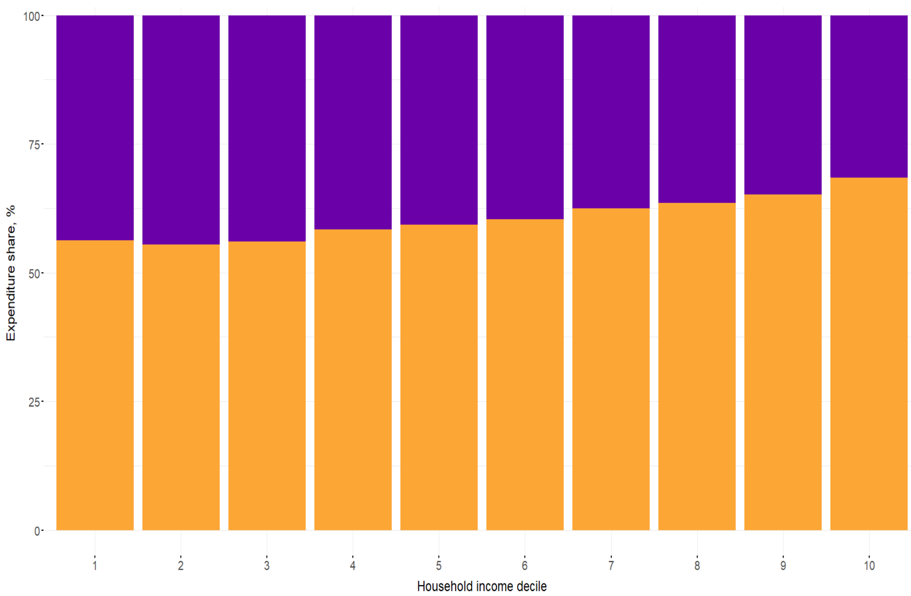

Fig. 7 Expenditure shares above or below the HICP by decile (2021-2022). *Notes*: Expenditure shares represented in purple (orange) had a price increase above (below) the Harmonised Index of Consumer Prices between 2021 and 2022.

3.5 Multivariate regression approach

Relative price changes may have a distributional impact not only between income groups, but also across different social categories. A multivariate regression approach, where the dependent variable is the household-specific inflation rate and the explanatory variables are a set of socio-demographic observable characteristics, is a good way to capture systematic differences in inflation experiences across household types.

We run OLS regressions for each available year and on the pooling of all the yearly cross-sections with the addition of a full set of time dummies. All the estimates are reported in Table 1. Each individual regressor refers to the highest earner in the household and any coefficient has to be interpreted relative to the corresponding reference category.[12] Some interesting regularities emerge.

[12] The reference categories in the multivariate regression are the following: Tenant (for Homeowner), North (for Center and South), Man (for Woman), Under 34 years old (for Adult(34$<$age$<$64) and Over 65 years old), Italian (for Foreigner), Undergraduate or less (for Graduate and postgraduate), Primary sector (for Secondary sector and Tertiary sector), White collar (for Blue collar and Self-employed) and Employed (for Non-employed).

	2015 (1)	2016 (2)	2017 (3)	2018 (4)	2019 (5)	2020 (6)	2021 (7)	2022 (8)	2023 (9)	Pooled (10)
Intercept	−1.47***	−1.36***	2.26***	1.96***	0.23***	−2.43***	3.90***	24.74***	3.99***	1.32***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.06)	(0.14)	(0.13)	(0.03)
Homeowner	−0.27***	−0.24***	0.36***	0.25***	−0.02***	−0.34***	0.78***	3.01***	0.61***	0.65***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.03)	(0.01)
Center	−0.01	−0.05***	0.20***	0.13***	0.02***	0.02***	0.05***	0.18***	0.02	0.06***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.02)	(0.01)
South	0.02***	−0.01	0.09***	0.14***	0.03***	0.05***	0.22***	0.95***	0.20***	0.23***
	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)	(0.03)	(0.02)	(0.01)
Log(equivalent income)	0.13***	0.14***	−0.13***	−0.10***	0.01***	0.27***	−0.30***	−2.24***	0.06***	−0.36***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.02)	(0.02)	(0.00)
Woman	0.27***	0.07***	−0.08***	−0.12***	0.03***	0.09***	−0.03**	0.33***	0.07***	0.07***
	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)
Adult (34<age<64)	0.11***	0.05***	−0.05***	−0.08***	0.02**	0.07***	−0.05***	0.02	−0.02	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.04)	(0.04)	(0.01)
Over 65 years old	0.44***	0.14***	−0.04***	−0.05***	0.05***	0.10***	0.07***	0.77***	−0.02	0.20***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.05)	(0.05)	(0.01)
Foreigner	0.32***	0.11***	−0.07***	−0.17***	−0.02**	0.14***	−0.33***	−0.08	0.32***	0.05***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.05)	(0.04)	(0.01)
Graduate and postgraduate	−0.01	0.05***	−0.01	−0.07***	0.01	0.02**	−0.09***	−0.22***	−0.09***	−0.10***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.03)	(0.01)
Secondary sector	−0.18***	−0.03***	−0.04***	−0.03***	−0.04***	−0.11***	0.02	−0.58***	−0.23***	−0.11***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.05)	(0.04)	(0.01)
Tertiary sector	−0.13***	−0.01*	−0.04***	−0.06***	−0.05***	−0.07***	−0.04*	−0.65***	−0.27***	−0.11***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.05)	(0.04)	(0.01)
Blue collar	0.07***	−0.06***	0.06***	0.08***	0.00	−0.03***	0.17***	0.77***	0.13***	0.17***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.02)	(0.01)
Self-employed	−0.01	−0.07***	0.06***	0.12***	0.03***	−0.07***	0.20***	0.94***	0.08***	0.20***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.02)	(0.01)
Non-employed	0.19***	0.05***	−0.00	0.00	0.04***	0.04***	−0.05***	0.83***	0.20***	0.17***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.03)	(0.01)
2015	-	-	-	-	-	-	-	-	-	0.04***
										(0.01)
2016	-	-	-	-	-	-	-	-	-	2.13***
										(0.01)
2017	-	-	-	-	-	-	-	-	-	1.88***
										(0.01)
2018	-	-	-	-	-	-	-	-	-	0.89***
										(0.01)
2019	-	-	-	-	-	-	-	-	-	−0.14***
										(0.01)
2020	-	-	-	-	-	-	-	-	-	2.98***
										(0.01)
2021	-	-	-	-	-	-	-	-	-	12.15***
										(0.01)
2022	-	-	-	-	-	-	-	-	-	5.47***
										(0.01)
R^2	0.08	0.03	0.04	0.04	0.00	0.03	0.03	0.13	0.00	0.59
Adj. R^2	0.08	0.03	0.04	0.04	0.00	0.03	0.03	0.13	0.00	0.59
Num. obs.	185472	166548	171072	186000	201276	206424	285456	320544	315576	2038368

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table 1 Socio-demographic characteristics and household-specific inflation - regression estimates.

The regression estimates confirm our main conclusion, i.e., higher income households have been experiencing lower inflation recently. In particular, the *log(equivalent income)* coefficient in column (8) is negative and very large (−2.24), it is also statistically significant at 1% level of confidence.

The pooled OLS regression exhibits a quite high R^2 because of the inclusion of a full set of year dummies which are always highly significant. At the same time, the low R^2 of the year-by-year regressions suggest that a significant portion in the variability of household-specific inflation rates takes place within socio-demographic groups, as well. Then, plotting the estimated coefficients for the most relevant household attributes and for each year is a helpful way to appreciate not only the level but also the changes over time of the relationship between individual characteristics and specific inflation experiences.

The top-left panel of Figure 8, for instance, shows the regression marginal effects of the dummy associated with being a homeowner relative to being a tenant on the household inflation rate experienced across the years. In line with our previous discussion, even though slightly counterintuitive at first glance, being a homeowner rather than a renter appears, *ceteris paribus*, to have been positively correlated with higher inflation exposure especially over the last years. In a recent work, Gros and Shamsfakhr (2023) have shown that rents have provided a partial offset for higher energy prices across the euro area on average, as they use to exhibit lagged inflation. Since rents in Italy have experienced extremely low growth (close to 0) since 2015, this is why, homeowners have used to face higher inflation on average once all the other socio-demographic characteristics are held constant.

From our regression analysis, a geographical inflation pattern clearly emerges as well. Households living in the Center and especially in the South (top-right panel of Figure 8) have seen, on average, their consumption bundle price increase faster than that of households living in the North, once we control for their standards of living. This evidence has been particularly strong in 2022, at the hearth of the energy price crisis. We run the same regression by including regional dummies in place of geographic macro-area dummies as a robustness check (Appendix H). The results are substantially identical (regional dummies themselves are not displayed for the sake of legibility). In Appendix I, we provide further insights into the recent regional heterogeneity of inflation, arising because of different household consumption patterns at the regional level, as HICP is the same for all regions.

Furthermore, the multivariate correlations seem to suggest that the consumption basket of the elderly has been, *ceteris paribus*, consistently more expensive than the bundle typically purchased by younger people, on average, over most years (bottom-left panel of Figure 8). In the life-cycle consumption literature, expenditure behaviour during retirement is a highly investigated topic (see Hurst, 2008; Aguiar and Hurst, 2013, for some references), but the sign of the association between age and inflation exposure is not clear *a priori*. For example, Crawford and Smith (2002) find that UK households whose head was of pensionable age experienced slightly lower inflation overall; in contrast, Hobijn and Lagakos (2005) conclude that the cost of living increases were generally higher for elderly people, in the USA, in large part because of their health care expenditures. Interestingly, the recent evidence by Basso et al. (2023) who investigate inflation dynamics in Spain between 2006 and 2021, introducing controls for age as well, supports our estimates.

Finally, the bottom-right panel of Figure 8 plots the regression marginal effects on household inflation experience, specifically due to the head of the household being a blue-collar worker. It results that such households have, on average, been exposed to higher inflation compared to households with a white-collar professional as the head, after accounting for all other socio-demographic attributes. This trend has been particularly evident over the past few years. Similar evidence (not shown) is observed when comparing the evolution of the price of the consumption bundle typically purchased by household with a self-employed head to those with a professional head.

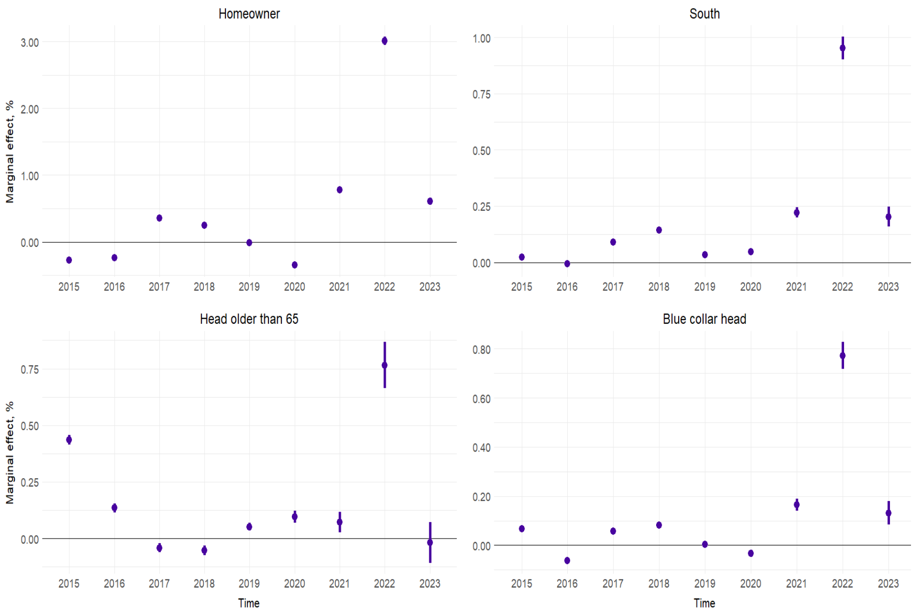

Fig. 8 Marginal effects of specific socio-demographic characteristics on the household inflation rate (2015-2023). *Top-let panel*: **dummy variable "homeowner"**. *Top-right panel*: **living in the "South"**. *Bottom-left panel*: **head older than 65**. *Bottom-right panel*: **head being a blue-collar worker**.

To wrap up this section, we find helpful to collect the single contributions of each household characteristic to inflation exposure in 2022, since most of the heterogeneity in inflation experiences across income and social groups has especially emerged over that year. Then, Figure 9 shows the estimated marginal effects of each income and socio-demographic attribute in 2022, while holding all other covariates constant.

It appears clear that differences in living standards have been crucial in determining household differential inflation, i.e. households with higher levels of income have faced lower individual inflation rates over the year. However, being a homeowner, a circumstance usually positively correlated with personal income, has been associated with higher inflation exposure in 2022. Then, mostly due to their sluggish nature, the rent dynamics seems to have at least partially counterbalanced the inflationary pressure of energy price shocks. This effect is likely to reverse over the next few years as rent prices will progressively embed the 2021-2022 inflation. Other socio-demographic characteristics that have contributed to spread inflation experiences across households at the hearth of the energy crisis have been geographical residence, age and professional position (e.g., blue-collars and self-employed have been exposed, on average, to higher inflation than white-collar workers over the year).

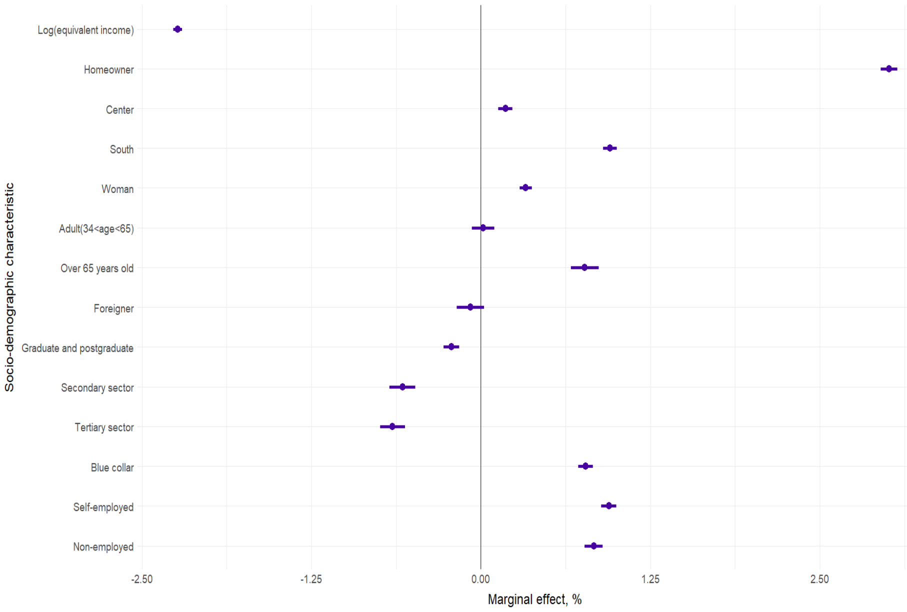

Fig. 9 Marginal effects of all socio-demographic characteristics on the household inflation rate (2022).

4 Concluding remarks

Since expenditure shares usually vary across households, substantial relative price changes may imply significant distributional consequences across the population. By construction, an aggregate price index, which measures the changing cost of a large consumption basket purchased by the representative household, cannot capture the differential effect that large price shocks may have across households purchasing their own consumption bundle.
Combining the Household Budget Survey (HBS) and the Harmonised Index of Consumer Prices (HICP) data from Istat, we build a novel dataset including up to 90 expenditure categories, a combination of 3- and 4-digit products, for which price information is available. Then, we compute household-specific price indices to investigate the distribution of inflation rates across Italian households between 2015 and 2023 and to assess the heterogeneous impact of the latest energy price shocks across income and social groups.

Our analysis suggests that until early 2021, a period when price growth has been constantly subdued, heterogeneity in household-specific inflation rates has been extremely low and aggregate price indices have been sufficiently representative of living costs for the entire population. However, the picture has drastically changed over the past few years. Following the food supply-chain disruptions due to the 2020 global pandemic and especially the energy crisis caused by the outbreak of the Ukrainian war in February 2022, the differential inflation between the bottom and top income deciles progressively widened to reach the maximum gap (11.3 percentage points) in October 2022. During this period, the plutocratic aggregate price index has quite closely tracked the inflation experience of the higher income half of the population but has underestimated the average price increase faced by the median household by around 2 percentage points. The main drivers of recent inflation inequality dynamics have clearly been the staggering price increases of both electricity and gas, which represent a relatively higher share of lower income decile expenditure bundles, but also quite generally different consumption patterns across income groups have contributed to exacerbate the differential inflation exposure. On the other hand, the rents, which poorer households typically devote a larger fraction of their income, have provided a partial offset for higher energy prices because of their sluggish nature. By means of a multivariate regression approach, we also show that relative price changes had a distributional impact not just between income groups, but also across different social categories. In particular, households living in the South, elderly, less educated people, blue-collar workers and non-employed have been exposed on average to higher inflation over the entire period. Few other interesting results emerge from our analysis.
First, by comparing the evolution of both Laspeyres and Paasche price indices until December 2022, we show that the Paasche index-based inflation rate has consistently been higher than the Laspeyres index-based inflation rate over the whole last year. We rationalise this counterintuitive result through the exceptional nature of the latest inflationary shock, which has been mostly driven by the manyfold price increases of energy goods. Both gas and electricity are naturally considered necessities rather than luxury goods and their demand is particularly rigid with respect to any price shock. These features may explain why, in the recent inflationary context, relying on consumption substitution has been almost unfeasible, and income effects rather than substitution effects seem to have prevailed across Italian households. Finally, by relying on a simple between-within decomposition of the bottom-top differential inflation, we stress the relevance of using the most granular data available when studying the heterogeneous impact of price growth across the population. We find that ignoring 3- and 4-digit level information would underrate the specific inflation difference between the extreme income deciles by slightly less than one fourth between 2021 and 2022, at the hearth of the energy crisis.

All in all, our work shows how even in a country such as Italy, where inflation has not been traditionally pro-rich, exceptional circumstances may

cause relative price changes to have serious distributional implications. In similar scenarios, aggregate price indices may not be very accurate tools for both the calculation of the actual cost of living for the great majority of households and the evaluation of several policy measures.
With all this in mind, future research may rely on individual or group-specific price indices to quantify the effectiveness of government interventions on reducing overall inflation together with their distributional impact. It may also be very interesting to replicate our study for countries characterised by historically higher inflation dynamics since the dispersion in the individual rates is likely to be larger and inflation inequality may actually have structural implications.

Appendix A Inflation heterogeneity across the equivalent non-durable expenditure distribution

The success of our statistical matching procedure in preserving key relationships among variables that represent the 'true' underlying population relies on the assumption that the rank of each household in the SHIW consumption distribution accurately reflects its rank in the HBS. In Appendix B, we provide some evidence suggestive of this assumption. Here, we further show that our conclusions about inflation heterogeneity across Italian households remain robust when using a different proxy for living standards.

In the absence of a direct measure of household income, using equivalent non-durable expenditure to rank Italian households from the poorest to the richest may be a second-best solution as suggested by Baldini (2005). While this proxy for households well-being does not always perfectly align with income, which is typically the variable at the core of any welfare analysis, it has the advantage of relying solely on HBS information.
To build this alternative indicator of living standards, for each household we sum the total expenditure on the over 480 goods and services of the survey and the value of imputed rents on home ownership. We finally subtract expenditures on durable goods and on extraordinary maintenance.[13] The household living standards indicator is finally obtained by dividing that amount by an equivalence scale given by the square root of the number of household components. Each year, households are then divided into deciles of non-durable equivalent consumption.

The results remain qualitatively consistent throughout the entire period, aligning with our main specification. Notably, since early 2021, there has been a pronounced increase in inflation heterogeneity across the various consumption

[13] Attributing the expenditure of a durable good exclusively to its purchasing period would make a household appear richer than it truly is in that given year. The correct way of imputing durable good consumption for a measure of household welfare would be estimating the flow of services provided by those goods at each period Amendola and Vecchi (2022). Unfortunately the data available does not allow such exercise, so we opt to exclude durable goods altogether.

deciles (Figure 10). This trend mirrors the inflation inequality observed across the income distribution of Italian households (see Figure 2 for a comparison). Between 2021 and 2022, at the heart of the energy crisis, the inflation experienced by the half of the population with higher spending turned out to be similar to the increase in the cost of living faced by the higher income half of households (6.13% and 6.32%, respectively). If anything, when looking at the consumption distribution rather than the income distribution of the Italian population, the gap between the inflation levels faced by the bottom and top expenditure deciles widens on average, reaching its maximum value of 15.3 percentage points in October 2022.

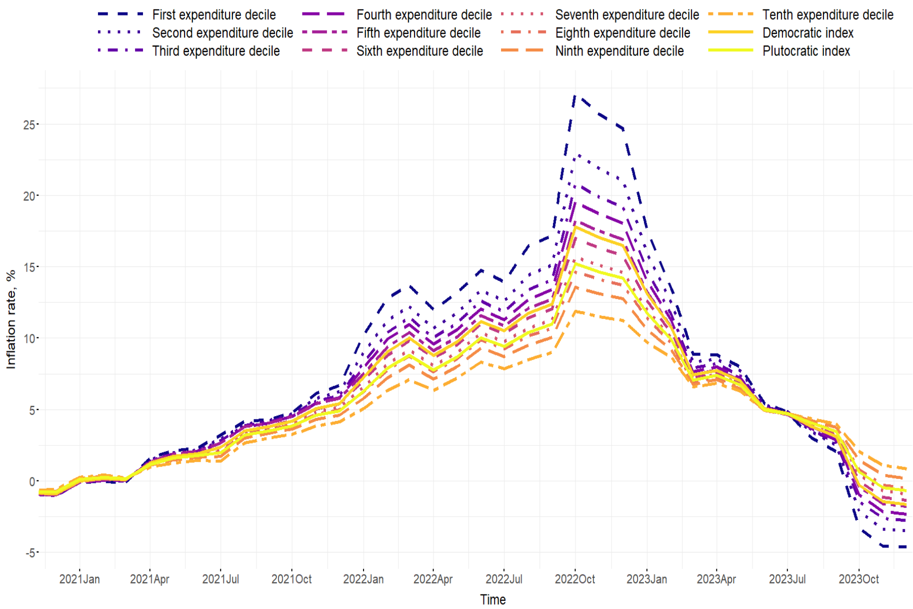

Fig. 10 Decile-specific inflation rates, democratic consumer price index, plutocratic consumer price index (2021-2023). *Notes*: **Households are ranked according their non-durable equivalent consumption distribution.**

Appendix B Matching expenditure and income data from independent sources

We adopt a *statistical matching* methodology to impute income data from households in the SHIW to those in the HBS sample. This approach leverages common information across both data sources to provide joint statistical information on variables and indicators collected through the two surveys. Statistical matching, also known as data fusion, integrates multiple datasets under the assumption that they share information on a set of common variables while also containing unique, non-overlapping variables (D'Orazio, 2006). The process typically involves two main steps. First, appropriate *donation classes* has to be defined as homogeneous subsets of observations based on shared characteristics. Second, each unit from the "recipient" dataset is matched with a unit from the "donor" dataset within the same donation class to form matched pairs. This constrained matching enhances the accuracy of the process.

Donation classes are generally constructed using a few categorical variables common to both datasets. In our case, the SHIW and the HBS share a wide range of socio-demographic variables describing households and their members, such as size, region, education, age and other features. To select the most suitable variables for defining appropriate donation classes, we employ both regression trees and OLS regressions, identifying the observables common to both datasets that exhibit the strongest association with both the matching variable, i.e, the consumption expenditure, and disposable income. Both regression trees and OLS regressions consistently pin down household size and education level of the head as the most relevant predictors. Consequently, we stratify the datasets by these two variables to construct appropriate donation classes.

The second step of the statistical matching procedure involves generating donor-recipient pairs that are sufficiently close with respect to a matching variable common to both datasets. In our case, we use total yearly consumption expenditure, which is available in both surveys. However, it is well-documented that the SHIW underreports actual consumption compared to external sources (Cifaldi and Neri, 2013). During our period of interest, we find that average and median consumption expenditure in the SHIW sample are approximately 20% lower than in the HBS. This discrepancy is expected, as the SHIW survey prioritises collecting detailed income information while only including a few general questions on consumption. To address this issue, we apply a rank hot procedure (Singh et al., 1990), following the approach in D'Orazio (2006). Using the shared matching variable, that is consumption expenditure, households in both datasets are ranked separately based on the values of such variable. The matching is then performed by aligning households in the recipient file (HBS) with households in the donor file (SHIW) according to their position in the empirical cumulative distribution function of the matching variable. This method relies on the assumption that a household's rank in the SHIW consumption distribution is a reliable proxy for its rank in the HBS distribution, despite potential underreporting. Using this ranking, we impute disposable income to each observation in the HBS dataset.

Before evaluating the outcome of our actual matching procedure, it is helpful to briefly describe the two primary distributions of interest: equivalent consumption expenditure from the HBS dataset and the equivalent disposable income from the SHIW dataset.

Figure 11 presents the empirical probability distribution functions of these two variables. To complement the graphical information, Tables 2 and 3 provide a detailed set of descriptive statistics for each decile group.

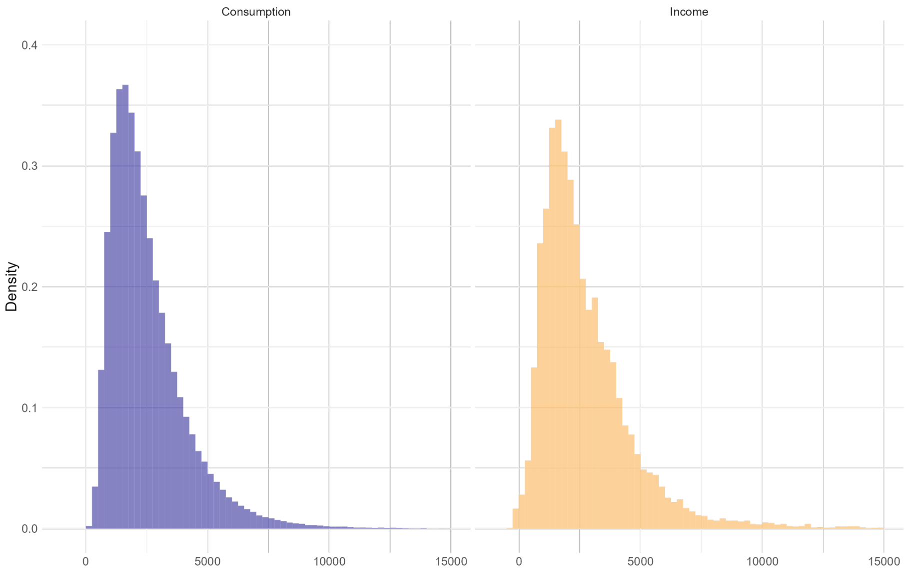

Fig. 11 Empirical probability distribution functions for the HBS total consumption expenditure (left) and the SHIW net disposable income (right). Density on the y axis is scaled by a factor 1000 to improve readability.

The two variables share several similar characteristics, though few notable differences also emerge. Both distributions are right-skewed, with their modes and medians located at relatively lower values compared to their means. Both also exhibit long right tails, indicating that a small proportion of households in each sample have particularly high income or expenditure levels. However, the income distribution features a heavier right tail, reflecting the presence of more extreme outliers among high-income households compared to high-expenditure households. Conversely, the mass of the consumption distribution is more concentrated toward the lower end, suggesting a relatively left-shifted pattern. Additionally, while the support of consumption expenditure is strictly positive, disposable income, as defined and computed by the Bank of Italy, can be negative. Disposable income comprises the sum of all household members' incomes after taxes - including salaries and wages, retirement income, self-employment income - along with transfer payments and income from property and financial assets. This definition clearly allows for the possibility of negative values in a given year.

Decile	Mean	Median	SD	IQR
1	757.41	790.10	171.55	252.46
2	1145.92	1148.67	87.06	150.74
3	1428.86	1428.68	79.37	137.69
4	1702.18	1701.84	79.34	137.89
5	1991.03	1989.49	87.57	151.56
6	2317.72	2315.28	102.20	177.89
7	2709.83	2704.26	127.82	221.31
8	3223.30	3213.47	172.33	296.49
9	3989.00	3960.70	288.96	494.42
10	6146.67	5584.49	1822.57	1697.95

Table 2 Descriptive statistics for monthly household consumption expenditure across deciles, including mean, median, standard deviation (SD), and interquartile range (IQR).

Decile	Mean	Median	SD	IQR
1	611.33	686.67	376.05	331.49
2	1119.08	1103.72	106.20	175.51
3	1448.99	1450.57	86.46	142.35
4	1751.53	1750.46	91.17	153.57
5	2075.89	2069.14	97.59	159.19
6	2460.07	2445.60	124.88	218.82
7	2956.33	2959.63	153.83	266.59
8	3548.64	3537.47	191.86	321.84
9	4385.17	4344.77	333.35	560.28
10	7880.10	6430.74	5064.66	2707.51

Table 3 Descriptive statistics for monthly household net disposable income across deciles, including mean, median, standard deviation (SD), and interquartile range (IQR).

Returning to our matching procedure, we now assess the goodness of the imputation by comparing both the distribution and correlation structures of the original SHIW dataset with those of the fused dataset. Figure 12 illustrates the empirical probability density functions of disposable income for both the original SHIW and the synthetic datasets.

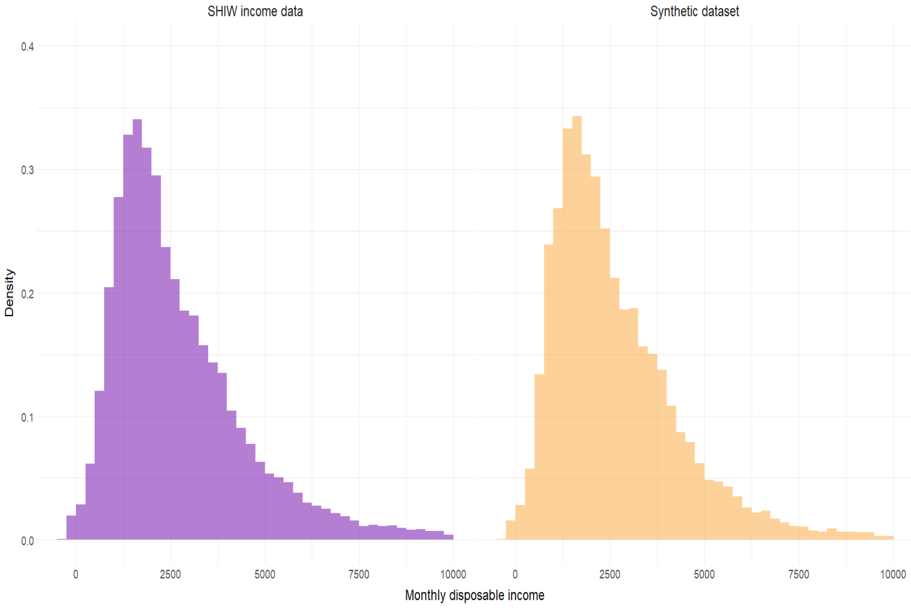

Fig. 12 Empirical probability distribution functions for the original SHIW disposable income (left) and the synthetic dataset (right). Density on the y axis is scaled by a factor 1000 to improve readability.

Table 4 provides a comparison of the key moments of both distributions. Overall, the SHIW and the synthetic income distributions are highly comparable. The sample means differ by approximately 4% and the medians by less than 2%. The two datasets also exhibit strong similarity in higher moments, such as skewness and kurtosis.

Statistic	SHIW Income Data	Synthetic Dataset
Mean	2790.02	2674.75
Median	2273.03	2239.36
Std Deviation	1925.62	1776.43
Skewness	1.57	1.57
Kurtosis	6.77	6.79

Table 4 Sample moments for disposable income in the original SHIW and in the synthetic datasets.

Table 5 evaluates whether the correlation structure between disposable income and other relevant socioeconomic variables is preserved in the fused dataset. The correlation coefficients between income and the considered variables are generally well-maintained, with only minor variations introduced by the matching process. Remarkably, this holds even for variables such as region, gender and occupational sector, which were not directly included in the matching procedure as either matching variables or criteria for constructing appropriate donation classes. This evidence indicates that the matching procedure effectively preserves the integrity of the original data structure, ensuring that the fused dataset retains the key relationships observed in the SHIW.

	SHIW Income Data	**Synthetic Dataset**
Size	0.19	0.27
Macro-Region	-0.14	-0.11
Region	-0.13	-0.11
Expenditure	0.72	0.67
Gender	-0.13	-0.11
Age	-0.05	-0.11
Education	0.35	0.36
Sector	0.07	0.12

Table 5 Correlation between disposable income and a set of socio-demographic variables in the two datasets.

We conclude the analysis of the data fusion outcomes by examining the joint distribution of disposable income and consumption in the synthetic dataset. Figure 13 shows the joint distributions of these two variables, as well as that of their ranks. The latter is particularly relevant for our analysis given the rank-based nature of our matching algorithm. Both scatter plots reveal a strong positive correlation between disposable income and consumption expenditure across units. Pearson's R correlation is equal to 0.67, while Spearman's rank correlation, which measures the correlation of rank distributions, amounts to 0.79. These results consistently highlight a stable and significant association between disposable income and consumption, with the relationship being particularly robust when considering their relative positions within their respective distributions.

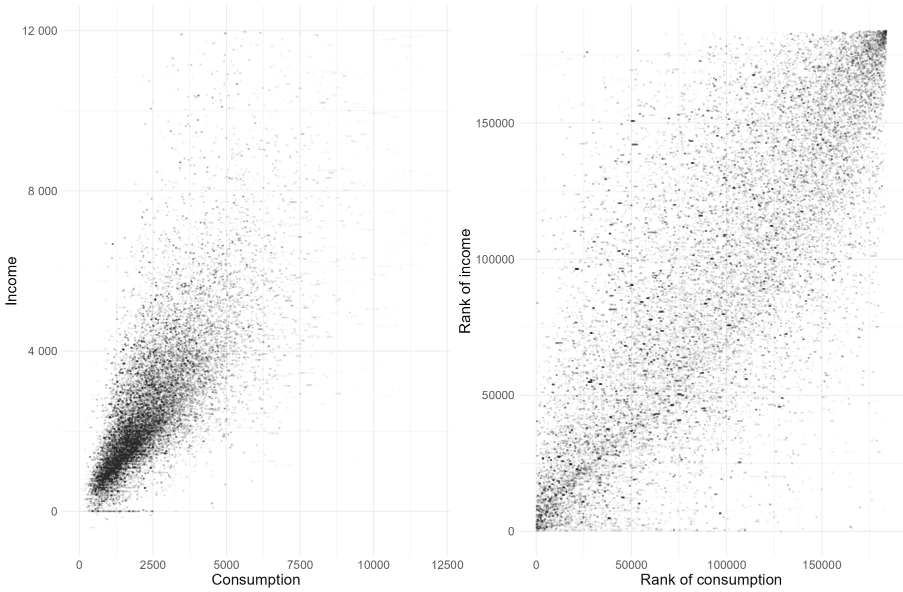

Fig. 13 Joint distribution (left) and joint rank distribution (right) of consumption and income in the synthetic dataset.

Appendix C Robustness check: alternative equivalence scales

In the benchmark specification (see Section 2), we scale back income by the square root of the number of household components. In this section, we test for the adoption of two alternative scales. The OECD equivalence scale (Förster and d'Ercole, 2012) accounts for household size and composition by weighting children and adults differently. On the other hand, the Carbonaro equivalence scale (Carbonaro, 1993), employed by Istat to estimate relative poverty, is based on a log-log estimation of the Engel curve for food expenditure.

Figure14 shows the quantile-quantile plots for differently scaled distributions of disposable income. There is no significant difference between applying the square root and the alternative OECD scales. However, the Carbonaro-scaled distribution exhibits a larger right-side tail compared to the other two, as it does not penalise larger families to the same extent.

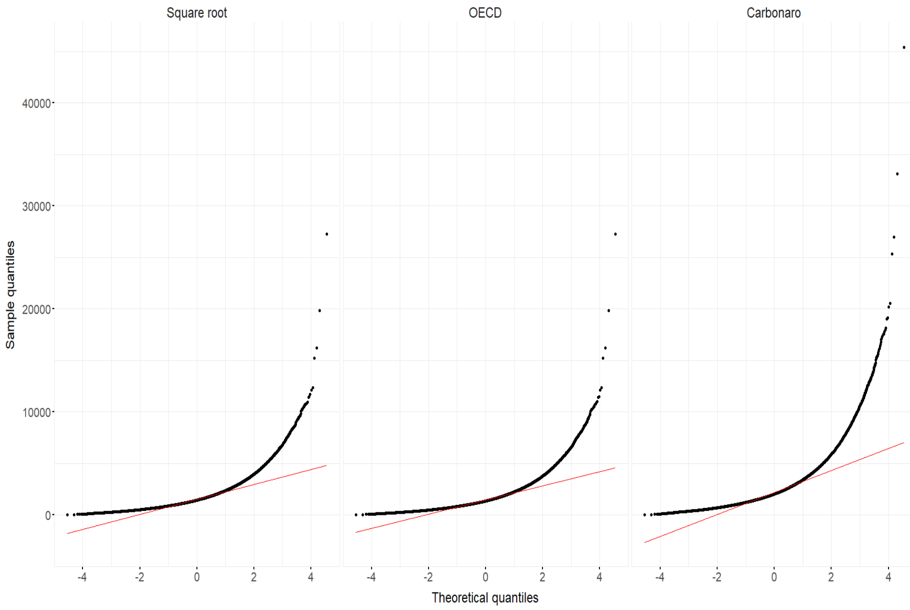

Fig. 14 Quantile-quantile plots for differently scaled distributions of disposable income.

Next, for each household in the sample, we compute the decile of disposable income to which they belong and calculate the rank correlation across the different equivalence scales. The results are displayed in Table 6. We use both the Spearman and Kendall metrics to assess whether two households would be sorted into the same decile according to different equivalence scales. The correlations indicate that the three measures are actually very close in terms of their ordinal association.

Correlation Type	Kendall's Tau	Spearman's Rho
Square Root vs. OECD	0.98	0.94
Square Root vs. Carbonaro	0.96	0.88
OECD vs. Carbonaro	0.97	0.92

Table 6 Kendall and Spearman rank correlations among disposable income deciles (2015-2023).

Finally, Figure 15 shows the household inflation distribution by income decile for the three equivalence scales. No qualitative differences emerge between the alternative scales. In all three cases, the pattern of inflation across deciles is consistent, with the different equivalence scales tracking each other very closely.

All in all, our results appear to be highly robust to the adoption of different equivalence scales.

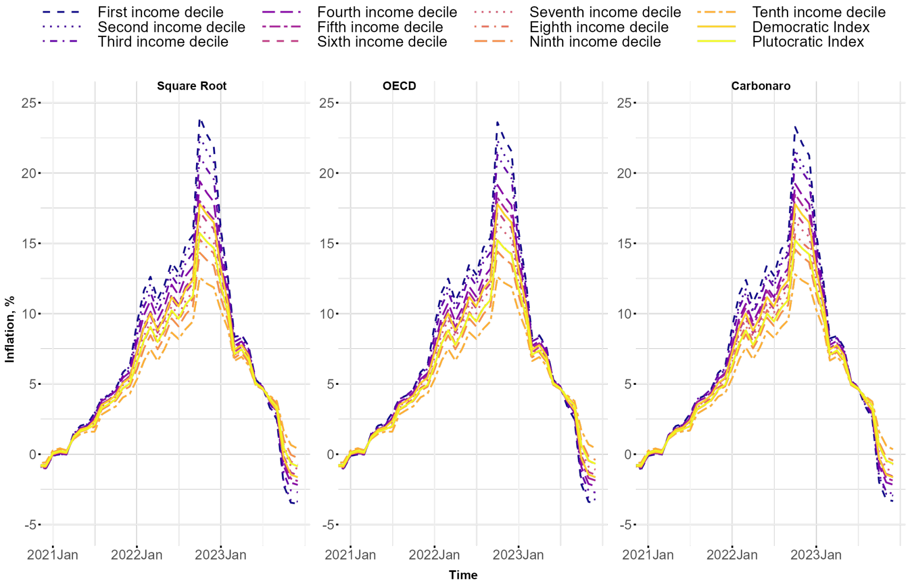

Fig. 15 Inflation rates by expenditure decile for each equivalence scale.

Appendix D Decile-specific Laspeyres and Paasche price indices (2021-2022)

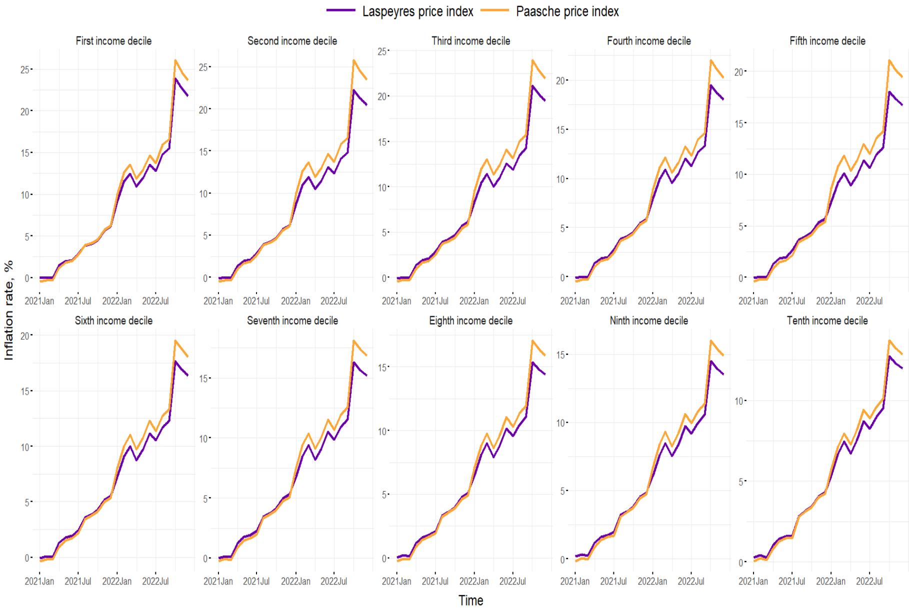

Fig. 16 Decile-specific Laspeyres and Paasche price indices (2021-2022).

Appendix E Consumption share variations and price changes (2021-2022). No outliers.

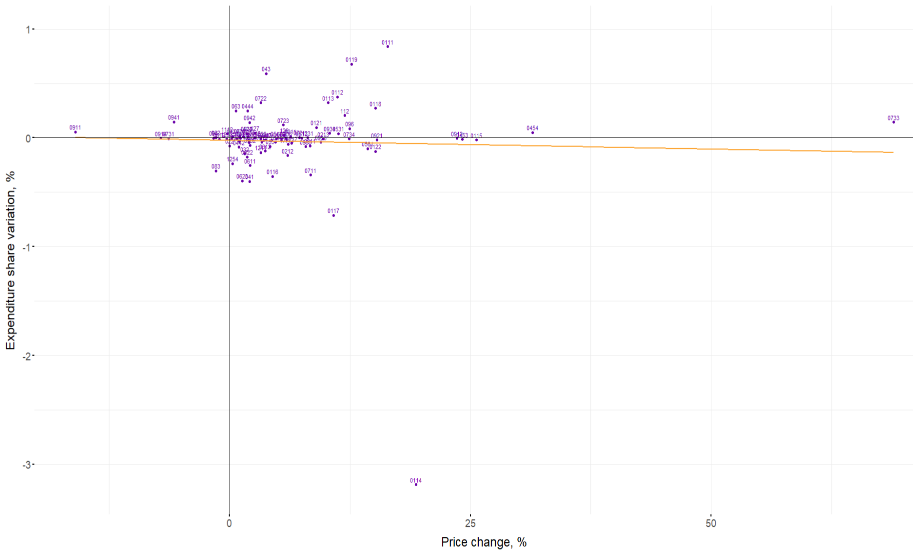

Fig. 17 Consumption share variations and price changes (2021-2022). *Notes:* Gas and electricity have been ruled out.

Appendix F Drivers of inflation inequality (socio-demographic household characteristics)

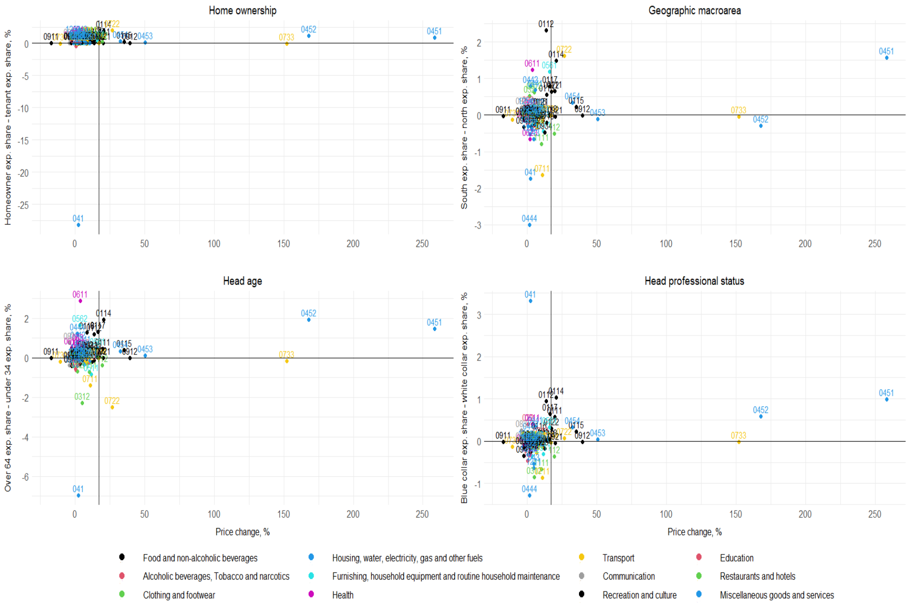

Fig. 18 Expenditure share differentials and price changes (2021-2022). *Notes*: A numerically ordered listing of the category codes can be found in Appendix G. The x-axis represents the average aggregate inflation between 2021 and 2022. The y-axis measures the expenditure share differentials between two different socio-demographic household groups. Products above (below) the x-axis are more (less) consumed by the first household group. *Top-let panel*: **homeowner vs. tenant**. *Top-right panel*: **living in the south vs. living in the north**. *Bottom-left panel*: **head older than 65 vs. head younger than 34**. *Bottom-right panel*: **blue-collar head vs. white-collar head**.

Appendix G Expenditure categories and variable codes (ECOICOP classification)

Variable Code	Expenditure Category	Variable Code	Expenditure Category
0111	Bread and Cereals	0712	Purchase of Motor, Cycles and Bicycles
0112	Meat	0721	Spare Parts and Accessories for Personal Transport Equipment
0113	Fish and Seafood	0722	Fuels and Lubricants for Personal Transport Equipment
0114	Milk, Cheese and Eggs	0723	Maintenance and Repair for Personal Transport Equipment
0115	Oils and Fats	0724	Other Services in Respect of Personal Transport Equipment
0116	Fruit	0731	Passenger Transport by Railway
0117	Vegetables	0732	Passenger Transport by Road
0118	Sugar, Jam, Honey, Chocolate and Confectionery	0733	Passenger Transport by Air
0119	Food Products n.e.c.	0734	Passenger Transport by Sea and Inland Waterway
0121	Coffee, Tea and Cocoa	0735	Combined Transport Passenger
0122	Mineral Waters, Soft Drinks, Fruit and Vegetable Juices	0736	Other Purchased Transport Services
0211	Spirits	081	Postal Services
0212	Wine	082	Telephone and Telefax Equipment and Telephone and Fax Numbers
0213	Beer	083	Telephone and Telefax Services
022	Tobacco	0911	Equipment for Reception, Recording and Reproduction of Sound And Picture
0312	Garments	0912	Photographic and Cinematographic Equipment and Optical Instruments
0313	Other Articles of Clothing and Clothing Accessories	0913	Information Processing Equipment
0314	Cleaning, Repair and Hire of Clothing	0914	Recording Media
032	Footwear	0921	Major Durables for Outdoor and Indoor Recreation Including Musical Instruments
041	Actual Rentals for Housing	0931	Game, Toys and Hobbies
043	Maintenance and Repair of the Dwelling	0932	Equipment for Sport, Camping and Open-air Recreation
0441	Water Supply	0933	Gardens, Plants and Flowers
0442	Refuse Collection	0934	Pets and Related Products Including Veterinary and Other Services for Pets
0443	Sewerage Collection	094	Recreational and Cultural Services
0444	Other Services Relating to the Dwelling n.e.c.	0941	Recreational and Sporting Services
0451	Electricity	0942	Cultural Services
0452	Gas	0951	Books
0453	Liquid Fuels	0952	Newspapers and Periodicals
0454	Solid Fuels	0953	Stationery and Drawing materials
0511	Furniture and Furnishings	096	Package Holidays
0512	Carpets and Other Floor Coverings	10	Education
0513	Repair of Furniture, Furnishings and Floor Coverings	1111	Restaurants, Cafes and the Like
052	Household Textiles	1112	Canteens
0531	Major Household Appliances Whether Electric or not	112	Miscellaneous Goods and Services
0533	Repair of Household Appliances	1211	Hairdressing Salons and Personal Grooming Establishments
054	Glassware, Tableware and Household Utensils	1212	Electric Appliances for Personal Care and Other Appliances, Articles and Products for Personal Care
055	Tools and Equipment for House and Garden	1231	Jewellery, Clocks and Watches
0561	Non-durable Household Goods	1232	Other Personal Effects
0562	Domestic Services and Household Services	124	Social Protection
0611	Pharmaceutical Products	125	Insurance
0612	Other Medical Products and Paramedical Services	1252	Insurance Connected with the Dwelling
0622	Dental Services	1253	Insurance Connected with Health
0623	Medical Services and Paramedical Services	1254	Insurance Connected with Transport
063	Hospital Services	126	Financial Services
0711	Purchase of Motor Cars	127	Other Services

Table 7 Expenditure categories and variable codes.

Appendix H Household-specific inflation with regional dummies - regression estimates

	2015	2016	2017	2018	2019	2020	2021	2022	2023	Pooled
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Intercept	-1.62^{***}	-1.43^{***}	2.25^{***}	1.89^{***}	0.24^{***}	-2.41^{***}	3.88^{***}	24.63^{***}	3.99^{***}	1.30^{***}
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.06)	(0.15)	(0.13)	(0.03)
Homeowner	-0.25^{***}	-0.22^{***}	0.34^{***}	0.24^{***}	-0.01^{**}	-0.32^{***}	0.76^{***}	2.97^{***}	0.61^{***}	0.65^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.03)	(0.01)
Log(equivalent income)	0.13^{***}	0.14^{***}	-0.12^{***}	-0.10^{***}	0.01^{***}	0.27^{***}	-0.29^{***}	-2.22^{***}	0.06^{***}	-0.35^{***}
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.02)	(0.02)	(0.00)
Woman	0.28^{***}	0.08^{***}	-0.09^{***}	-0.12^{***}	0.03^{***}	0.09^{***}	-0.03^{***}	0.31^{***}	0.07^{***}	0.07^{***}
	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)
Adult (34<age<64)	0.10^{***}	0.05^{***}	-0.04^{***}	-0.08^{***}	0.02^{**}	0.07^{***}	-0.05^{***}	-0.01	-0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.04)	(0.04)	(0.01)
Over 65 years old	0.42^{***}	0.12^{***}	-0.03^{***}	-0.06^{***}	0.05^{***}	0.10^{***}	0.07^{***}	0.70^{***}	-0.01	0.19^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.05)	(0.05)	(0.01)
Foreigner	0.33^{***}	0.12^{***}	-0.07^{***}	-0.17^{***}	-0.02^{**}	0.14^{***}	-0.34^{***}	-0.11^{**}	0.32^{***}	0.05^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.05)	(0.04)	(0.01)
Graduate and Postgraduate	-0.02^{***}	0.05^{***}	-0.00	-0.06^{***}	0.01	0.02^{**}	-0.09^{***}	-0.23^{***}	-0.10^{***}	-0.10^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.03)	(0.01)
Secondary Sector	-0.18^{***}	-0.04^{***}	-0.04^{***}	-0.03^{***}	-0.04^{***}	-0.12^{***}	0.02	-0.57^{***}	-0.24^{***}	-0.11^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.05)	(0.04)	(0.01)
Tertiary Sector	-0.14^{***}	-0.04^{***}	-0.03^{***}	-0.05^{***}	-0.05^{***}	-0.10^{***}	-0.01	-0.58^{***}	-0.28^{***}	-0.11^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.05)	(0.04)	(0.01)
Blue Collar	0.07^{***}	-0.06^{***}	0.06^{***}	0.08^{***}	0.01	-0.03^{***}	0.17^{***}	0.77^{***}	0.13^{***}	0.17^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.02)	(0.01)
Self-Employed	0.00	-0.07^{***}	0.06^{***}	0.12^{***}	0.03^{***}	-0.07^{***}	0.20^{***}	0.92^{***}	0.07^{***}	0.19^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.02)	(0.01)
Non-employed dummy2	0.20^{***}	0.06^{***}	-0.01	0.01	0.04^{***}	0.04^{***}	-0.05^{***}	0.86^{***}	0.19^{***}	0.17^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.03)	(0.01)
R^2	0.10	0.04	0.06	0.04	0.00	0.04	0.03	0.13	0.00	0.59
Adj. R	0.10	0.04	0.06	0.04	0.00	0.04	0.03	0.13	0.00	0.59
Num. obs.	185472	166548	171072	186000	201276	206424	285456	320544	315576	2038368

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table 8 Socio-demographic characteristics and household-specific inflation including regional dummies - regression estimates.

Appendix I Inflation rates and inflation inequality at the regional level

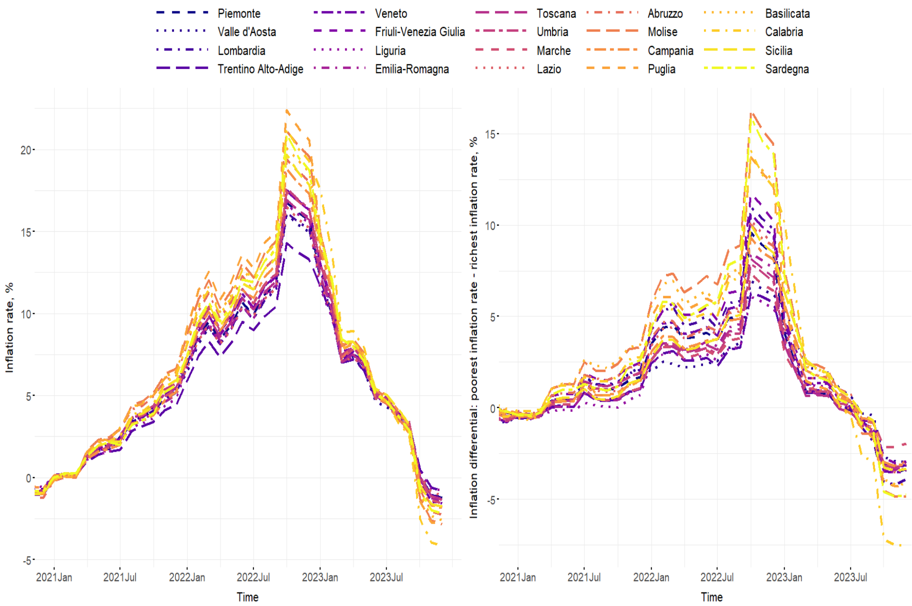

Fig. 19 *Left panel*: **Regional inflation rates (2021-2023).** *Right panel*: **Regional inflation differential between bottom and top deciles (2021-2023)**.

Different household consumption patterns across Italian regions have significantly influenced inflation exposure between 2021 and 2023 (left panel of Figure 19). In particular, average regional inflation has ranged from 5.5% in Trentino-Alto Adige to 7.5% in Puglia, with a standard deviation exceeding 5%. Similar heterogeneity is observed when we consider inflation inequality at the regional level (right panel of Figure 19). The difference in average inflation experienced by the bottom and top income deciles spans from less than 1.2 percentage points in Liguria to more than 3.6 percentage points in Molise.

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