



Universität Hamburg

Department Economics and Politics

Inflation Inequality in Europe

Roberta Colavecchio

Ulrich Fritsche

Michael Graff

DEP Discussion Papers

Macroeconomics and Finance Series

2/2011

Hamburg, 2011

Inflation Inequality in Europe[§]

Roberta Colavecchio*

Ulrich Fritsche**

Michael Graff^{†‡}

February 23, 2011

Abstract

We analyze cross-household inflation dispersion in Europe using “fictitious” monthly inflation rates for several household categories (grouped according to income levels, household size, socio-economic status, age) for the period from 1997 to 2008. Our analysis is carried out on a panel of 23 up to 27 household-specific inflation rates per country for 15 countries. In the first part of the paper, we employ time series and related non-stationary panel approaches to shed light on cross-country differences in inflation inequality with respect to the number of driving forces in the panel. In particular, we focus on the degree of persistence of the household-specific inflation rates and their the adjustment behaviour towards the inflation rate of a “representative household”. In the second part of the paper, we pool over the full sample of all countries and test if and by how much certain household categories across Europe are more prone to significant inflation differentials and significant differences in the volatility of inflation. Furthermore we search for the presence of clusters with respect to inflation susceptibility. On the national level, we find evidence for the existence of one main driving factor driving the non-stationarity of the panel and evidence for a single co-integration vector. Persistence of deviations, however, is high, and the adjustment speed towards the “representative household” is low. Even if there is no concern about a long-run stable distribution, at least in the short- to medium run deviations tend to last. On the European level, we find small but significant differences (mainly along income levels), we can separate 5 clusters and two main driving forces for the differences in the overall panel. All in all, even if differences are relatively small, they are not negligible and persistent enough to represent a serious matter of debate for economic and social policy.

Keywords: Inflation, Inequality, Heterogeneity, Time Series, Panel

JEL classification: E31, C22, C23

[§]The positions do not necessarily reflect those of other persons in the institutions the authors might be affiliated with. Thanks to Ingrid Grössl and seminar participants at DG-ECFIN for helpful comments. Thanks to Daniel Triet, Artur Tarassow and Phillip Poppitz for outstanding research assistance. All remaining errors are ours.

*University Hamburg, Faculty Economics and Social Sciences, Department Socioeconomics, Welckerstr. 8, D-20354 Hamburg, Roberta.Colavecchio@wiso.uni-hamburg.de

**Corresponding author, University Hamburg, Faculty Economics and Social Sciences, Department Socioeconomics, Welckerstr. 8, D-20354 Hamburg, and KOF Swiss Economic Institute, Department of Management, Technology and Economics (D-MTEC), Eidgenössische Technische Hochschule Zürich (ETHZ) (Federal Institute of Technology Zurich), Weinbergstrasse 35, CH-8092 Zurich, ulrich.fritsche@wiso.uni-hamburg.de

^{†‡}KOF Swiss Economic Institute, Department of Management, Technology and Economics (D-MTEC), Eidgenössische Technische Hochschule Zürich (ETHZ) (Federal Institute of Technology Zurich), Weinbergstrasse 35, CH-8092 Zurich, and Jacobs University, Bremen, grauff@kof.ethz.ch

1 Introduction

Inflation is a macroeconomic phenomenon, and in standard models the consumer price inflation rate is seen as a variable faced by all households. Empirical measures of inflation are consequently based on a price index (typically a consumer price index, CPI) constructed to measure inflation for a “representative” consumer. National consumer price indices therefore measure the “continuously changing cost of the basket of goods and services purchased by [a] ‘typical’ (...) household” (Hobijn and Lagakos, 2005, p. 581). Most European countries use the “harmonized consumer price index” (HICP) these days. During the last couple of years the dispersion of HICP-based inflation rates *across EMU member states* received some attention.¹ Much less attention, however, was devoted to the *cross-household dispersion of inflation rates* in Europe. There are, however, reasons why such kind of inflation inequality across types of households matters.

First of all, poverty reduction and income redistribution measures are mostly aimed at stabilizing real income for the people at the lower income percentiles. For as much as those households face a significantly different consumption pattern – e.g. because Engel’s law applies – and furthermore certain product groups are more prone to price increases and/ or higher volatility of price changes, those households might be hit much harder by price changes (Michael, 1979; Hagemann, 1982; Hobijn and Lagakos, 2005). Second, elderly people often show rather different spending patterns compared to the median household. In aging societies, the relative importance of the elderly continues to increase further (Amble and Stewart, 1994). Third, as savings rates surely differ across age and income groups, inflation rates might differ as well. As households are concerned about their real consumption and savings possibilities, differing inflation rates give raise to a possible amplification of wealth effects in the economy as a whole (Lettau and Ludvigson, 2001; Carroll et al., 2006; Slacalek, 2006).² Fourth, inflationary processes in itself lead to macroeconomic redistributions (Easterly and Fischer, 2001; Blank and Blinder, 1985; Cutler and Katz, 1991; Romer and Romer, 1998). This in turn might amplify inflation inequality across households.

Our paper tries to fill a gap in the literature as – to the best of our knowledge – the question of inflation inequality has not yet been deeply analyzed for a sample of EU/ EMU member states over the recent decade. There is a variety of studies mostly dealing with US and UK experience in the 1970s and 1980s as well as some cross-country comparisons (see section 2 for a detailed literature survey) but – to the best of our knowledge – there is no up-to-date paper dealing with a panel of EU/ EMU countries. In our paper we are going to address a number of questions:

First of all, what are specific properties of individual inflation rates for a variety of household types and what is the relation to a “representative consumer inflation” on a national level. Are deviations persistent? If this is not the case, how long do the deviations last? How large is the volatility? Are different types of households across different countries more prone to systematic differences with respect to the level of inflation and the volatility of inflation in comparison to a “representative” household? Can we identify clusters of household according to socio-economic categories which are prone to (statistically) similar rates of inflation?

To answer these and other related questions, we constructed “fictitious” monthly inflation rates applicable to a number of different households (grouped according to income levels, household size, socio-economic status, age) for the time span from 1997 to 2008 – insofar as the respective consumption basket data were available from Eurostat.³

¹Papers are *inter alia* (Allsopp and Artis, 2003; Altissimo et al., 2006; Campolmi and Faia, 2006; Dullien and Fritsche, 2008, 2009; Dullien and Schwarzer, 2009; Eichengreen, 2007; European Central Bank, 2005; European Commission, 2008; Fritsche et al., 2005; Gros, 2006; Lane, 2006)

²Another relevant argument, which we cannot follow rigorously due to lack of data, goes as follows: since households at the lower end of the income distribution typically show lower savings rates and the substitutability of their consumption goods might be low, they are much harder hit by rising prices.

³Detailed information is provided in the appendix, section 5.

This resulted in a panel of 23 up to 27 inflation rates per country for 15 countries (besides the countries forming the first stage of EMU (EU 12) we included Denmark, Sweden and United Kingdom as control countries). We used a two-fold investigation strategy. In the first part of the empirical analysis, we mainly used time series and related non-stationary panel approaches to shed light on cross-country differences with respect to the number of driving forces in the panel, with respect to the persistence of inflation rates and with respect to the adjustment behaviour towards the “representative” households. We applied a number of tests, namely panel unit root tests – including the PANIC approach – as well as individual cointegration tests. Furthermore we estimated bivariate ECMs as in [Cecchetti and Moessner \(2008\)](#) to analyze the the adjustment speed towards “representative household’s” inflation. In the second part of the empirical investigation, we used the full sample of all countries and tested if and by how much certain types of households were more prone to significant inflation differentials and significant differences in the volatility of inflation. Furthermore we performed cluster analyses to check for systematic similarities.

The main findings of our paper can be summarized as follows: On the national level, we report evidence for the existence of *one* main factor driving the non-stationarity of the panel. We also find evidence for a *single* co-integration vector between individual household inflation rates and a “representative household inflation rate” on the national level. The persistence of deviations from the inflation rate faced by the representative household, however, is high and the adjustment speed towards this “representative inflation rate” is low. Even if there is no concern about a long-run stable distribution, at least in the short- to medium run, deviations tend to be quite lasting. In the full panel, we can find small but significant lasting differences (mainly along income levels) between individual inflation rates and the respective “representative” inflation rate. We can furthermore identify 5 clusters across the household types in the panel, and we find two main driving forces for the differences in the overall panel. All in all, even if differences are found to be quite small in general, they are not negligible and persistent enough to be a serious concern for economic and social policy.

The paper is organized as follows: Section 2 discusses the state of the literature. Section 3 describes the data we used (additional details are provided in section 5). Section 4 is devoted to the methods employed and the presentation of results. Section 5 discusses the results and concludes.

2 Literature Survey

The fact that inflation affects subgroups of consumers in different ways was documented in a number of seminal papers in the late 1970s and early 1980s for the United States. [Michael \(1979\)](#) showed that between 1967 and 1974, US households with low incomes, low levels of education as well older-aged households experienced higher than average inflation. Yet, according to this study, the differences were not persistent, suggesting that “in the long run no particular group of consumers suffers disproportionately from inflation” ([Michael, 1979](#), p. 45).

[Hagemann \(1982\)](#) updated the study of [Michael \(1979\)](#) for the period from 1972 to 1982, i.e. the period of the two oil price shocks. He found that some components of consumption, especially food-at-home, energy as well as medical services, had price increases higher than average, implying that groups of consumers that devote a relatively large share of their expenditure on these items, experienced higher than average inflation. Based on this result, [Hagemann \(1982\)](#) identified a number of population groups partitioned by various socio-economic variables (income, age, family type and size, education, ethnicity as well as location) that experienced group-specific price increases. Though [Hagemann \(1982\)](#) – as [Michael \(1979\)](#) before him – found that *within-group differences are generally more pronounced* than differences in inflation between groups, he also provided evidence for persistence in deviations, i.e. some household

types faced systematically different inflation than others.

Based on the seminal results of Michael (1979) and Hagemann (1982), a few years ago, the US Bureau of Labor Statistics constructed experimental price indices for elderly as well as for poor people. According to that, for elderly people consumer prices rose somewhat faster than the average from 1987 to 1993, which is due to their larger share of expenditure for medical care (Amble and Stewart, 1994), whereas the poor faced very similar trends as the general population (Garner et al., 1996)

More recently, Hobijn and Lagakos (2005) dived under the skin of the CPI and computed group-specific US inflation rates for different parts of the population, e.g. poor vs. non-poor, whites vs. blacks and younger vs. elderly people. Like Amble and Stewart (1994), they found that the cost of living has increased above average for elderly people due to above average price increases for health expenditures. Moreover, poorer households appeared to be negatively affected by increasing prices for petrol, which represents a relatively large share of their total expenditure. Finally, Hobijn and Lagakos (2005) showed that household-specific inflation is characterised by a low degree of persistence. As a result, they argued that the CPI remains a useful measure for the cost of living for all groups, which confirms the earlier conclusion in Michael (1979) and Hagemann (1982).

Idson and Miller (1997) exploited US Consumer Expenditure Surveys reaching back to 1960 and found that household inflation is falling with the level of education. This result appeared to be reasonably robust and is mainly due to the different shares of expenditure for fuel and energy, where price increases have been larger than overall CPI inflation. Two other recent studies by Chiru (2005a,b) compare group-specific inflation rates in Canada between 1992 and 2004, experienced by (a) the top and the bottom household income quintiles and (b) seniors aged 65 and above vs. the rest of the population. The studies indicate that the low-income group was facing slightly higher inflation over this time interval. Yet, a decomposition of relative price changes over time reveals considerable differences. Initially, the low-income group experienced lower inflation. Thereafter, however, the group-specific price increases started to accelerate and exceed those for better-off households. With respect to age, Chiru (2005a,b) finds that seniors were confronted with price increases slightly larger than for the rest of the population.

Apart from the abovementioned analyses related to evidence from the US and Canada, a small number of empirical studies has been conducted for European countries. Livada (1990) focussed on household-specific inflation rates in Greece between 1981 and 1987 and found that well-off single households as well as childless couples experienced the highest inflation during this period. Crawford and Smith (2002) computed group-specific inflation rates for the UK between 1976 and 2000. They argued that headline inflation did not adequately reflect the experience of the majority of households. In particular, over the full period, inflation rates for only $\frac{1}{3}$ of the households fell into a range of 1 percentage point around the average rate, while in 1989, the share was as low as 9 per cent. Moreover, their results imply *persistent differences* in inflation, where non-pensioners, mortgage-payers as well as employed and childless households are affected by above-average inflation. This finding of persistence is in stark contrast to most other studies; it is particularly noteworthy since Crawford and Smith (2002) analysis covers a relatively long time period.

Brewer et al. (2006) conducted a country study on the UK experience. They analysed the distribution of income along with inequality in spending. While their focus is mainly on poverty, Brewer et al. (2006) also report an interesting observation, finding a significant difference between household expenditures and imputed consumption of housing. More specifically, they found that in countries where many retired people live in owner-occupied dwellings (like the UK) with no outstanding mortgages, expenditure for and consumption of housing may differ considerably. This implies that inflation experienced by individuals is related to their life cycle since housing prices are likely to affect the elderly less than other age groups.

In a study about Germany, [Noll and Weick \(2006\)](#) examine data from the 2002 wave of the *German Socioeconomic Panel* (SOEP) to identify some typical characteristics of elderly people. For our purposes, the most notable result is that – unsurprisingly – elderly people are less likely to own a car; on the other hand, seniors are devoting a larger share of their income to health-related expenditures. [Noll and Weick \(2006, 2007\)](#) exploit data from the 1983, 1993, 1998 and 2003 waves of the German Income and Expenditure Survey to analyse income and expenditure patterns. They find that inequality is more pronounced in income than in consumption and report a narrowing gap between income groups as well as between former East and West Germany over time. Still, there remain differences with regard to age, income position and household type. Moreover, Noll and Weick confirm Engel’s law by showing that, in the long run, households that are growing wealthier devote a diminishing share of their expenditure to food, clothing and the like, while housing, transport, communication and expenses related to leisure time gain more weight.

[Rippin \(2006\)](#) also utilises data from the German Income and Expenditure Survey. Drawing on the 1998 and 2003 waves, she finds that group-specific inflation was lowest for families with one and more children, students, persons under the age of 25 as well as for higher income groups. She concludes that this result is mainly driven by relatively low tobacco consumption and the relatively low share of energy in the group-specific consumption baskets as well as by large shares for IT related expenditure. [Rippin \(2006\)](#) emphasizes, however, that these findings may vary considerably across time and space. As a result, it would not be justified to claim that inflation in Germany is a (persistent) group-specific phenomenon.

3 Data

Our analysis aims at exploring the features of the proper changes in the cost of living for each household; hence, at its core lies the concept of a “household-specific inflation rate”. In the appendix (see section 5) we provide the details of our definition of this concept and show how this indicator is related to the definition of inflation based on Eurostat’s Harmonised Index of Consumer Prices (HICP).

We consider a panel of 15 European countries (Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxemburg, the Netherlands, Portugal, Spain, Sweden, United Kingdom), and Euro area.⁴

The data we employ are provided by Eurostat and are drawn from two sources. Data on household expenditures broken down by household characteristics such as income, socio-economic characteristics, size and composition are obtained from the Household Budget Surveys (HBSs). Data on the spending structure on the aggregate level consist in the annual weights for the HICP sub-indices on a national level. Finally, monthly price data are obtained from the HICP series for the good categories according to the Classification of individual consumption by purpose (COICOP), level 2. Further details on the dataset, such as the list of the household characteristics considered in our analysis as well as the list of the COICOP 2 categories, are provided in the appendix.

The data described above are combined to obtain monthly household-specific inflation rates, spanning from January 1997 through December 2008.⁵ This fictitious gauge represents the

⁴Nine of the considered countries have adopted the euro from the start of the currency union, one before the changeover (Greece), and three (Denmark, Sweden and the United Kingdom) still maintain their national currencies up to this date.

⁵Pooling the household-specific inflation data across the 15 countries results in a panel of 53,625 observations, i.e. 143 monthly observations times 25 household categories across 15 countries. As there are no data on household-specific consumption baskets and hence inflation rates for a limited number of categories in Germany, Italy and the Netherlands, we can compute household specific deviations from country inflation for 52,910 observations, which is

change in the price, over the past year, of the goods basket that a household bought a year earlier and its dynamic can be affected by (1) the deviation of household-group specific weights from the average basket (i.e. HICP item weights); (2) the evolution of goods prices via the differing weighting schemes; (3) changes in the average basket over time. We shed some light on the latter issue with the help of Figures 1 and 2. Figure 1 shows the evolution of the structure of aggregate consumption between 1996 and 2008 in each of the countries considered in our analysis, while the scatter plots in Figure 2 depict, for each COICOP 2 category, real GDP per capita for all the countries and all the years on the horizontal axis and the HICP weights on the vertical axis together with a regression fit line.

Figure 1: Weights for the 12 COICOP categories in HICP (1996-2008) in different European countries

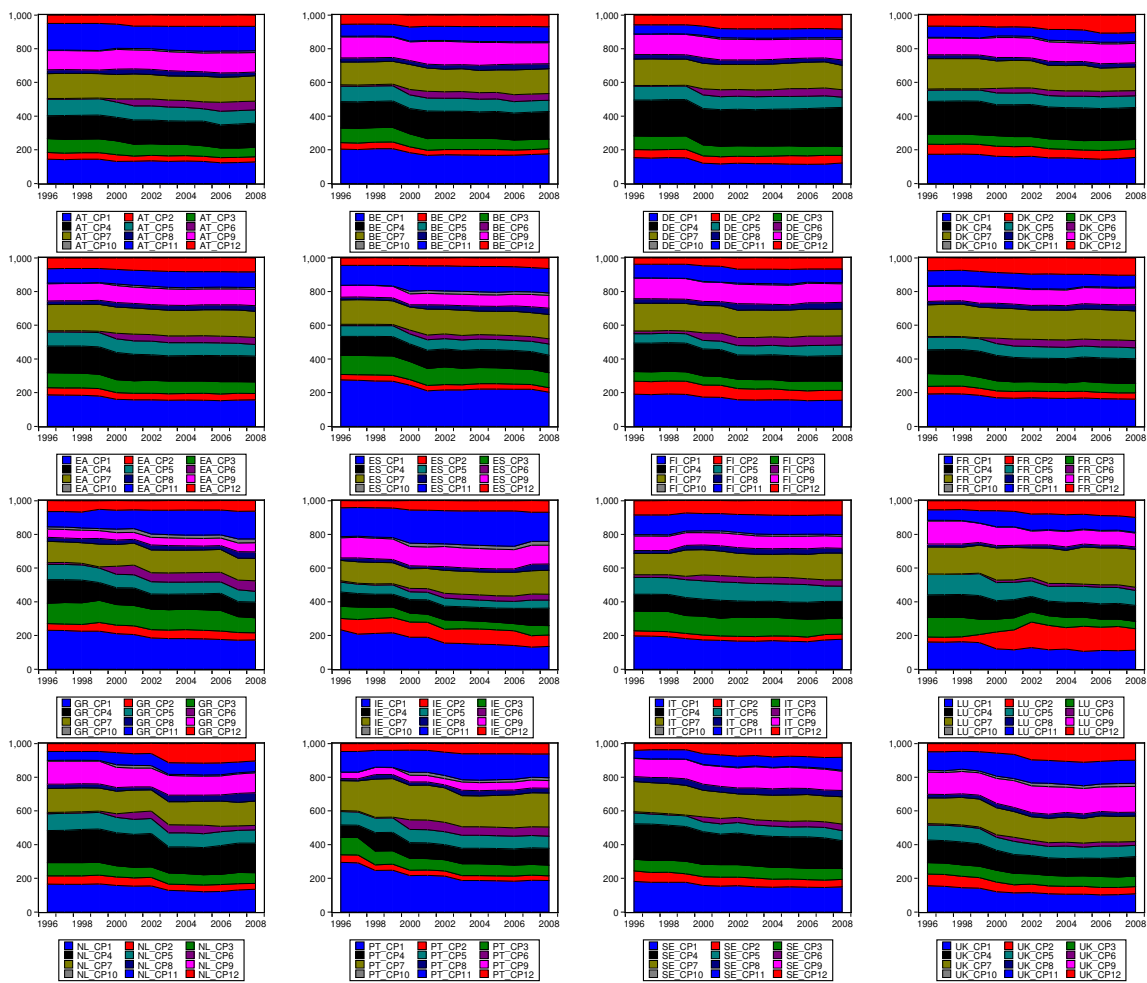
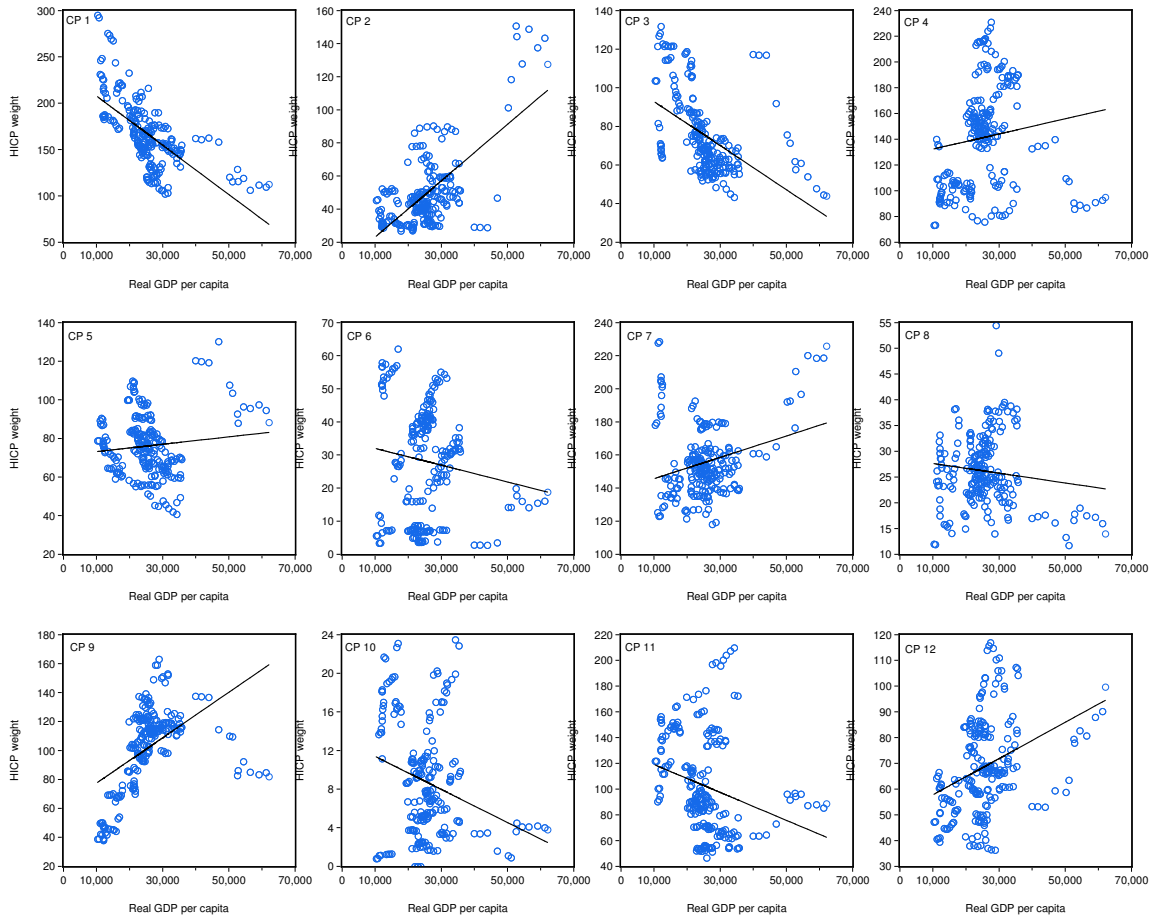


Figure 1 highlights a number of common tendencies in the evolution of the aggregate consumption structure in the countries included in our European panel. First, the shares spent on food (CP01) and alcoholic beverages and tobacco (CP02) are declining all over Europe⁶, as well as the weight of the category “clothing and footwear” (CP03). The decrease in the portion spent on food over the considered time span can be explained in the light of the constant rise in average per capita income experienced by most European countries and by the fact that richer countries tend to consume relatively less on foodstuff than poorer countries, as shown in the first panel in the first row of Figure 2.

slightly less than if we had a full balanced panel, but still an impressive number.

⁶The exception is Luxembourg where the weight of the category CP02 has increased substantially between 1999

Figure 2: Bivariate relationships between the level of economic development (real GDP per capita) and the size of COICOP weights (CP1 to CP12)



Second, the expenditure share for housing, electricity, gas and fuels (CP04) has remained roughly constant, as well as the share spent on transport (CP07). Third, the weight of the category “health” (CP06), although still low on an aggregate level in all European countries, is progressively increasing, with the exception of Greece, Luxembourg and Sweden. Finally, the share spent on hotel and restaurant services (CP11) has increased in Spain, Greece and Portugal, while it has remained broadly unchanged in the majority of the other European countries. The scatter plots in Figure 2 also highlight that richer countries tend to allocate a bigger share of consumption on utilities and housing, recreation and culture and services, while the countries with lower real GDP per capita spend a bigger portion of their income on food and clothes as well as hotels and restaurants.

Throughout the rest of our analysis we often refer to the notion of a “representative” household inflation rate as aggregate measure of price changes, rather than to the HICP inflation. This synthetic gauge is meant to represent the “average/mean” respondent of the HBSs, from whose results we also extract the household-specific inflation rates. This choice has two advantages: first, it allow us to remain consistent with respect to the dataset used in our estimations; second, considering that the HBSs is a rather comprehensive survey, it ensures that our “representative” household is indeed an appropriate proxy of the population, which might not be the case for the HICP. Throughout the considered time span and over the whole panel, the HICP inflation rate and the reference rate are highly correlated and differ only slightly.

and 2002 and has remained larger than in the other European countries ever since.

4 Empirical Analysis

In the course of the paper, we test several hypotheses which in turn define the methods we use. Specifically, we are interested in the following questions:

1. Are the original household-specific inflation rates in general stationary or non-stationary? To test this aspect, we refer to panel unit root tests (see subsection 4.1.1).
2. Are the different household-specific inflation rates driven by one or more common trends? Here we apply the PANIC approach (see Bai and Ng (2001, 2004) for the theory, and the detailed exposition in subsection 4.1.2).
3. Under the aspect of economic-policy making on a national level, a stable relation or mean-reversion between the “representative households inflation rate” and individual inflation rates faced by different types of households, is more relevant than a mean-reversion towards a unknown but assessable common trend. To answer this question we apply panel co-integration tests on a national level (see subsection 4.1.2).
4. To shed further light on convergence properties of the household-specific inflation rates on a national level, we explore two additional aspects. First, we calculate the speed of adjustment of household-specific inflation rates towards the “representative” households inflation. We address this issue by estimating a set of individual error correction models (ECMs) and evaluating the distributions of the estimated loading coefficients (see subsection 4.1.2) in each country. Second, we investigate the persistence of the deviations of the household-specific inflation rates from the inflation faced by the “representative” household.
5. Apart from the investigations on the national level, we formed a huge panel across all countries and all available inflation rates and used a cross-section of household-specific inflation differentials calculated from the pooled data. In particular, we address the following questions (see subsection 4.2):
 - (a) Are there any group-specific inflation rates that differ significantly from the respective (country-specific) overall mean?
 - (b) Are there clusters of households sharing common household specific inflation rate patterns in terms of differences from a reference rate or volatility across Europe?
 - (c) Can we identify common driving processes behind household specific inflation rate patterns across Europe?

4.1 Country-specific time series and panel results

4.1.1 Persistence patterns of inflation rates

First of all, we were interested if all household-specific inflation rates show the same pattern of persistence as measured by the respective unit root properties of the process. Panel unit root tests are the first choice for a data set like ours. Specifically, we applied the following tests: A panel test based on the assumption of a common unit root process using the method proposed in Levin et al. (2002) and a test based on the assumption of individual unit roots using an augmented version of the Dickey and Fuller (1979a) test in a panel version proposed by Maddala and Wu (1999a) and Choi (2001).⁷

⁷The panel unit root tests were performed using EViews 6 and the respective standard settings with regard to lag length (BIC) and bandwidth selection (Newey-West using Bartlett kernel) were taken.

The results are given in Table 1. For the majority of countries – irrespective from the assumption on the deterministic part – the tests fail to reject the hypothesis of a common unit root process. On the other hand, the hypothesis of an individual unit root process is rejected in the overwhelming majority of cases. From that result we can infer that the persistence over time is high in our data set and that there is probably a single common source driving the persistent part in the time series in each country.

4.1.2 Convergence issues

Following the investigation of the stochastic properties of our dataset by means of a set of panel unit root tests, this section explores the issue of convergence of the household-specific inflation rates from a number of different angles. We employ the PANIC approach [Bai and Ng \(2001, 2004\)](#) and panel co-integration tests. Finally, in a country-specific setting, we estimate a set of bivariate ECMs to shed light on the adjustment process.

PANIC approach A useful approach to test for panel unit roots in the presence of either stationary or non-stationary common components is based on a factor representation of the differenced time series in the panel ([Bai and Ng, 2001, 2004](#)). The approach is known by its acronym as PANIC.⁸ The approach allows both idiosyncratic and common components to be integrated of order one, which makes it a very flexible procedure when it comes to test for panel unit roots. Since we investigate growth rates, we assume a model with an intercept but without linear trend. Following the notation of [Bai and Ng \(2004\)](#) our model is given by:

$$X_{it} = c_i + \lambda_i' F_t + e_{it} \quad (1)$$

where X_{it} are $i = 1, \dots, N$ observed growth rates, F_t is an unobserved vector of common factors and e_{it} are unit specific idiosyncratic components. Both F_t and e_{it} are allowed to be I(1). To guarantee consistent estimates of the factors the model has to be estimated in differences, where $x_{it} = \Delta X_{it}$, $f_t = \Delta F_t$ and $z_{it} = \Delta e_{it}$.

In the end, we estimate the following model:

$$x_{it} = \lambda_i' f_t + z_{it} \quad (2)$$

employing the method of principal components. However, we standardize the first differences before estimating in order to avoid possible distortions by volatile series in calculating principal components, see [Bai and Ng \(2001\)](#). In particular, we divide differenced time series by their cross empirical cross-sectional standard deviations. Estimated common factors and idiosyncratic components are then obtained via cumulating for $t = 2, \dots, T$ and $i = 1, \dots, N$. Therefore:

$$\hat{e}_{it} = \sum_{s=2}^t \hat{z}_{is} \quad (3)$$

$$\hat{F}_{it} = \sum_{s=2}^t \hat{f}_s \quad (4)$$

where $\hat{z}_{it} = x_{it} - \lambda_i' \hat{f}_i$ are estimated residuals. [Bai and Ng \(2004\)](#) show that estimated factors and idiosyncratic components are consistent, in particular $T^{-1/2} \hat{e}_{it} = T^{-1/2} e_{it} + o_p(1)$ and $T^{-1/2} \hat{F}_t = T^{-1/2} H F_t + o_p(1)$, where H is a full rank matrix. The rate of convergence is fast enough to leave

⁸Panel Analysis of Nonstationarity in the Idiosyncratic and Common components.

Table 1: Panel unit root tests

Country	Model with constant				Model with constant and trend			
	Levin, Lin and Chu		ADF Fischer		Levin, Lin and Chu		ADF Fischer	
	Statistic	p-value	Statistic	p-value	Statistic	p-value	Statistic	p-value
Austria	-0.188	0.425	64.958	0.107	0.156	0.562	89.010	0.001
Belgium	1.771	0.962	68.670	0.060	1.037	0.850	73.797	0.025
Germany	-1.422	0.077	90.627	0.000	-2.641	0.004	123.573	0.000
Denmark	1.218	0.888	75.578	0.018	2.320	0.990	37.138	0.940
Euro area	-2.604	0.005	113.318	0.000	-1.764	0.039	146.321	0.000
Spain	-4.357	0.000	186.569	0.000	-2.315	0.010	221.422	0.000
Finland	0.171	0.568	63.634	0.129	0.938	0.826	29.916	0.994
France	-0.001	0.500	85.584	0.002	-0.883	0.189	203.373	0.000
Greece	-4.188	0.000	253.416	0.000	-3.972	0.000	190.434	0.000
Ireland	-0.088	0.465	66.958	0.079	4.547	1.000	20.272	1.000
Italy	-0.356	0.361	124.185	0.000	-0.631	0.264	132.557	0.000
Luxembourg	-0.808	0.210	134.337	0.000	5.399	1.000	162.200	0.000
Netherlands	0.058	0.523	36.410	0.890	0.247	0.598	15.937	1.000
Portugal	1.141	0.873	84.199	0.003	3.266	0.999	37.126	0.941
Sweden	-0.419	0.338	108.820	0.000	0.455	0.675	68.345	0.064
United Kingdom	9.320	1.000	10.566	1.000	5.994	1.000	41.808	0.843

Legend: Tests are described in the paper.

the asymptotic distribution of an Augmented Dickey-Fuller-test (ADF-test, see [Dickey and Fuller \(1979b\)](#)) unchanged, if applied to estimated series \hat{F}_t and \hat{e}_{it} . So we can apply any version of the univariate ADF-test as well as pooled unit root tests to estimated factors and idiosyncratic components, respectively. In case of estimated factors we allow for a constant in a test regression and test without any deterministic terms in the panel case of idiosyncratic components.

In our setting, first, we had to determine the number of common factors in the PANIC framework. [Bai and Ng \(2001\)](#) suggest some information criteria to determine the number of factors. We decided to calculate fractions of total variation in the differenced data explained by common factors and set $k = 1$ for further tests on the basis of [table 2](#), because the first factor explains the 97 to 99 percent of the variance of the differenced series in all cases.⁹

Table 2: Determining the number of factors (PANIC approach)

	Variance proportion of $\Delta\pi_{it}$ explained by..	
	First principal component	Second principal component
Austria	0.990	0.006
Belgium	0.991	0.007
Germany	0.987	0.006
Denmark	0.983	0.011
Euro area	0.994	0.005
Spain	0.987	0.009
Finland	0.978	0.018
France	0.993	0.004
Greece	0.984	0.010
Ireland	0.981	0.016
Italy	0.987	0.010
Luxembourg	0.996	0.003
Netherlands	0.983	0.013
Portugal	0.976	0.017
Sweden	0.982	0.014
United Kingdom	0.976	0.017

Second, we decomposed the panels of household-specific inflation rates into the part explained by the common factor and into idiosyncratic components. Our approach is quite similar to the one in [Bai and Ng \(2001\)](#), however, in their case it was applied to a panel of changes in individual goods prices and the common factor was interpreted as a “core inflation”. Here we would interpret the common factor as the inflation rate shared by all types of households, whereas the idiosyncratic components are measures of household-specific parts in their respective inflation rates.

Furthermore, we investigated if the common factor can be seen as the one and only source of non-stationarity (see results in [section 4.1.1](#)) in the panel of household-specific inflation rates. We investigate the issue by testing the non-stationarity properties of the common factors individually for all countries and the properties of the idiosyncratic components in country-specific panels using appropriate panel unit root tests.

The results of the first exercise are given in [Table 3](#).

Applying an ADF-test with a constant, we infer that the hypothesis of a unit root in the common factor can safely be rejected only for Greece and Spain. As a robustness check, we applied the GLS version of the ADF-test as proposed by [Elliott et al. \(1996\)](#). Using 5 % as a threshold, we can reject the null hypothesis for Germany, Denmark, Euro area, Spain, Italy, Luxembourg, Portugal and Sweden. According to this result, there is a significant proportion of non-stationarity remaining in the idiosyncratic components after having controlled for the

⁹We also experimented with $k = 2$ but the loadings of the second factor were always quite small – so the first factor seems to dominate clearly here.

Table 3: PANIC unit root tests (univariate, common factor)

	ADF		GLS-ERS
	Statistic	p-value	Statistic
Austria	-1.985	0.293	-1.880
Belgium	-2.053	0.264	-1.705
Germany	-2.339	0.161	-2.325
Denmark	-2.075	0.255	-2.045
Euro area	-2.679	0.080	-2.389
Spain	-3.212	0.021	-2.799
Finland	-1.994	0.289	-1.388
France	-2.093	0.248	-1.745
Greece	-3.337	0.015	-1.483
Ireland	-2.082	0.252	-1.367
Italy	-2.300	0.173	-2.316
Luxembourg	-2.655	0.085	-2.431
Netherlands	-1.632	0.464	-1.374
Portugal	-2.220	0.200	-2.203
Sweden	-2.511	0.116	-2.343
United Kingdom	0.560	0.988	0.322

Legend: ADF ... Augmented Dickey-Fuller (Dickey and Fuller, 1979a) test with constant. GLS-ERS ... Generalized Least-Squares ADF test with constant using the detrending according to Elliott et al. (1996); critical values for 1, 5, and 10 % significance levels for the GLS-ERS test are -2.581584, -1.943123, and -1.6152 respectively.

common factor. This in turn implies possibly quite persistent or even non-stationary deviations of idiosyncratic parts from the common component.

In the next step, we assessed the non-stationarity properties of the idiosyncratic components. We applied a version of the ADF-test, that combine the p-values from individual unit root tests. This idea has been proposed by Maddala and Wu (1999b) and Choi (2001). As Table 4 reveals, for almost all countries the test does not indicate rejection of the null of non-stationarity, with the remarkable exception of United Kingdom. In sum, we find no evidence that the idiosyncratic components in general are not mean-reverting and do not show exploding or trending variance.

On the basis of the results displayed in Table 4, we could conclude that the panel of household-specific inflation rates in each country seems to be driven by one single factor (not necessarily coinciding with the HICP inflation rate). Moreover, it would appear that the remaining part of the cross-sectional variance in the panel is driven by stationary idiosyncratic components, i.e. the part not explained by the single common factor in each country is mean-reverting with a constant variance. This is good news since it indicates that the individual household inflation rates do not diverge permanently without bounds from the common factor.

Panel co-integration towards the “representative” household inflation In the next step, we test for co-integration between individual household-specific inflation rates and the respective “representative household” inflation rate on national levels. This is a matter of both political and economic relevance because the absence of co-integration implies a lasting or permanent gap between the inflation experience of the “representative” consumer and the inflation rate faced by different households.

Within the panel framework, we first employ a statistic suggested by Kao (1999). This test is constructed on the basis of the Engle and Granger (1987) test in time series framework and consists in an ADF-test statistic applied to residuals generated from (supposedly) long run relationships.

Table 4: PANIC unit root tests (panel, idiosyncratic components)

	Fisher ADF	
	Statistic	p-value
Austria	156.750	0.000
Belgium	115.596	0.000
Germany	119.641	0.000
Denmark	149.614	0.000
Euro area	101.983	0.000
Spain	79.154	0.005
Finland	143.245	0.000
France	141.685	0.000
Greece	75.496	0.011
Ireland	143.834	0.000
Italy	124.886	0.000
Luxembourg	123.973	0.000
Netherlands	120.972	0.000
Portugal	125.819	0.000
Sweden	130.584	0.000
United Kingdom	14.302	1.000

Legend: Fisher ADF ... Pooled ADF-test (assumption of individual unit root processes). Absence of deterministic terms assumed. Probabilites calculated using χ^2 distribution tables.

The results of the [Kao \(1999\)](#) statistics are presented in Table 5. All ADF-test results strongly reject the null hypothesis of no co-integration in all the country panels, suggesting the presence of a co-integrating relationship amongst the household-specific and “representative household” inflation rate. However, since the test of [Kao \(1999\)](#) is residual-based, we also compute the Fisher-type test proposed by [Maddala and Wu \(1999a\)](#) which extends the [Johansen \(1995\)](#) maximum likelihood co-integration test to a panel setting by aggregating the p-values of the individual test statistics.

The test statistic is distributed as χ^2 with degrees of freedom twice the number of cross-section units, i.e. $2N$, under the null hypothesis. We set the lag length to twelve and exclude the presence of a constant term or a trend in the co-integrating relationship. Table 5 reports the results which broadly validate the results of the ADF test statistic. In particular, the Fisher trace tests give additional support to the view that a single co-integrating vector exists in the inflation rate panel of all the considered countries (Austria, Belgium, Denmark, Finland, France, Germany, Greece, Italy, Ireland, Portugal, Spain, Sweden, the Netherlands and the UK and the Euro area) with the exception of Luxembourg, for which the test could not reject stationarity.

Individual adjustment behaviour In the following, we address the issue of convergence from a different perspective: assuming the existence of a stable equilibrium between the household-specific and “representative” household inflation rates, we formulate a set of bivariate ECMs and analyze whether any adjustment process takes place and especially with which speed.¹⁰ In particular, we want to investigate the question whether and how fast the respective household-specific inflation rates adjust towards the inflation rate faced by the “representative” household. As in [Cecchetti and Moessner \(2008\)](#), we use a bivariate error correction model (ECM). The ECM for two variables, y_t and x_t is given by:

$$\Delta y_t = a_0 - \gamma_y(y_{t-1} - bx_{t-1}) + \sum_{j=0}^{n_x} a_{xj} \Delta x_{t-j} + \sum_{j=1}^{n_y} a_{yj} \Delta y_{t-j} + u_{yt} \quad (5)$$

¹⁰The [Johansen \(1995\)](#) tests showed mixed evidence on the co-integration properties between household-specific inflation rates and “representative household” inflation in the fifteen countries under investigation. The results are omitted for the sake of brevity, but are available upon request.

Table 5: Panel cointegration test results

<i>ADF t-Stat.</i>	<i>H0: No cointegration</i>		<i>H0 : r = 0</i>		<i>H0 : r ≤ 1</i>		<i>Country</i>
	<i>Kao(1999)</i>	<i>Fisher Trace-Stat</i> p-value	<i>Maddala and Wu (1999)</i>	<i>Fisher Trace-Stat</i> p-value	<i>Maddala and Wu (1999)</i>	<i># coint rel</i> p-value	
Austria	-11.46	0.00	258.30	0.00	43.49	0.73	1
Belgium	-15.68	0.00	301.50	0.00	18.24	1.00	1
Germany	-12.22	0.00	239.70	0.00	49.08	0.35	1
Denmark	-10.67	0.00	150.40	0.00	18.03	1.00	1
Euro area	-13.31	0.00	208.00	0.00	18.58	1.00	1
Spain	-9.69	0.00	123.20	0.00	12.26	1.00	1
Finland	-8.41	0.00	92.81	0.00	9.11	1.00	1
France	-10.20	0.00	151.00	0.00	11.95	1.00	1
Greece	-11.01	0.00	169.10	0.00	53.45	0.34	1
Ireland	-9.04	0.00	119.60	0.00	37.04	0.91	1
Italy	-13.84	0.00	199.90	0.00	3.85	1.00	1
Luxembourg	-15.70	0.00	272.50	0.00	66.65	0.06	2
Netherlands	-17.98	0.00	299.00	0.00	36.80	0.83	1
Portugal	-9.59	0.00	189.30	0.00	29.70	0.99	1
Sweden	-12.27	0.00	168.50	0.00	42.80	0.75	1
United Kingdom	-3.57	0.00	119.40	0.00	44.46	0.69	1

Legend: Tests are described in the paper.

$$\Delta x_t = b_0 - \gamma_x(y_{t-1} - bx_{t-1}) + \sum_{j=1}^{k_x} b_{xj} \Delta x_{t-j} + \sum_{j=0}^{k_y} b_{yj} \Delta y_{t-j} + u_{xt} \quad (6)$$

where y_t and x_t indicate the household-specific and the “representative household” inflation series, respectively.

In line with the focus of our analysis, we estimated the models under two trend assumptions whose interpretation can be meaningful in terms of inflation rate and price index convergence. In particular, we tested:

1. Model 1: The level data have no deterministic trends, and the co-integrating equations (CE) do not have intercepts;
2. Model 2: The level data have no deterministic trends, and the CE have intercepts.

A distinction which has to be considered in the context of any convergence analysis refers to the distinction between *absolute* and *relative* convergence (Bernard and Durlauf, 1996). The above-mentioned models can be interpreted as representations of absolute and relative convergence of the single household-specific inflation rate towards the “representative” household inflation, respectively. Absolute convergence implies, that the respective inflation rates converge towards the same rate, whereas relative convergence means that the relative distance between the inflation rates is stationary. This distinction has important implications when applied to inflation rates: relative convergence implies, that the purchasing power of each household deteriorates on average with a stable rate, whereas absolute convergence implies a stabilization of the position at a given point.

The speed and the direction of the adjustment process between x_t and y_t are mirrored in the behaviour of the ECM’s loading coefficients, γ_y and γ_x . For example, a high and significant γ implies a fast adjustment of one variable towards the other, while if one of the two γ s is zero, i.e. if $\gamma_x = 0$, the adjustment is only possible via changes in y .¹¹ Finally, estimates of γ s not significantly different from zero, i.e. $\gamma_y = \gamma_x = 0$, indicate that the two variables are not cointegrated and that no long run relationship exists between the two. In our case, significant γ_y s (γ_x s) would indicate that household-specific inflation rates (the “representative” household inflation) adjust towards the “representative” household inflation (household-specific inflation).

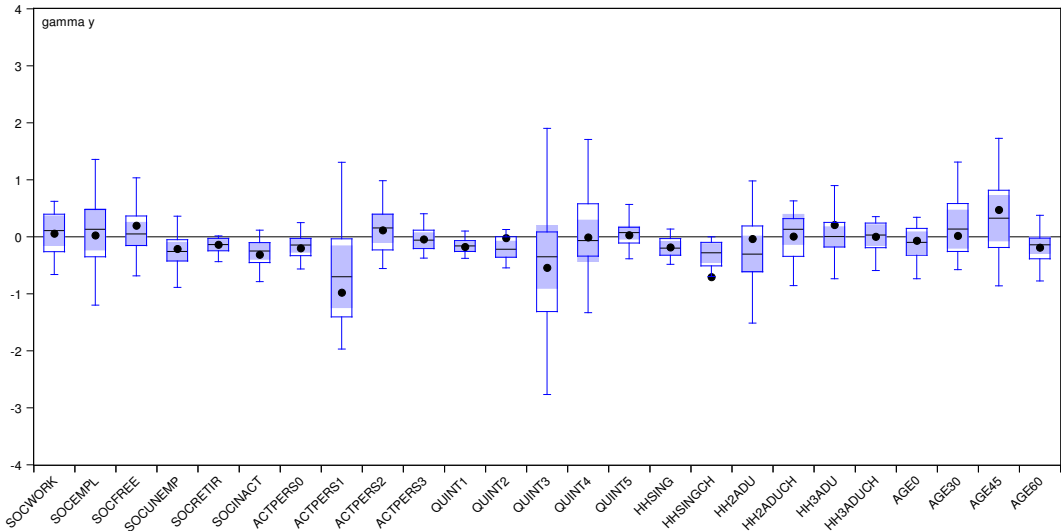
We opted to summarize our estimation results and their significance by means of a graphical illustration. Figure 3 and Figure 4 display the box plots of the γ_y -coefficients for each of the considered socio-economic categories (upper panel) and their respective p-values (lower panel) under the assumption of absolute and relative convergence, respectively. This graphical representation of the distribution of the loading coefficients allows us to assess the “average” direction and speed of the converging (or diverging) behaviour of the household-specific inflation rates with respect to the reference inflation rate.

All in all, our results provide little evidence on the presence of an adjustment process between the inflation rates faced by the each socio-economic category and the inflation faced by the “representative household”; moreover, different deterministic assumptions deliver rather different pictures of the behaviour of the loading coefficients. In particular, under the assumption of absolute convergence (Figure 3), the γ_y -coefficients turned out to be insignificant in virtually all the considered socio-economic categories, with a few exceptions for households featuring unemployed and inactive members, households with no active person in the labour market and households formed by a single component, single parents with dependent children or by a reference person whose age is above 60 years old. For the above-mentioned categories, the household-specific inflation rates show sign of adjustment towards the “representative” household inflation. Moreover, Figure 3 suggests that the inflation rate faced by households including

¹¹In this situation, x is called weakly exogenous.

Figure 3: ECM loading coefficient – Model 1

(a) Point estimates



(b) P-values

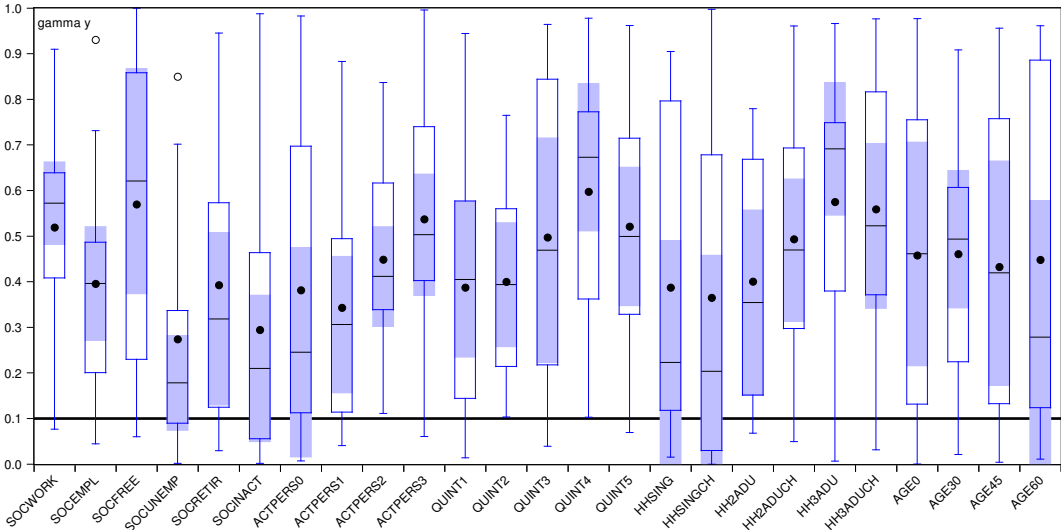
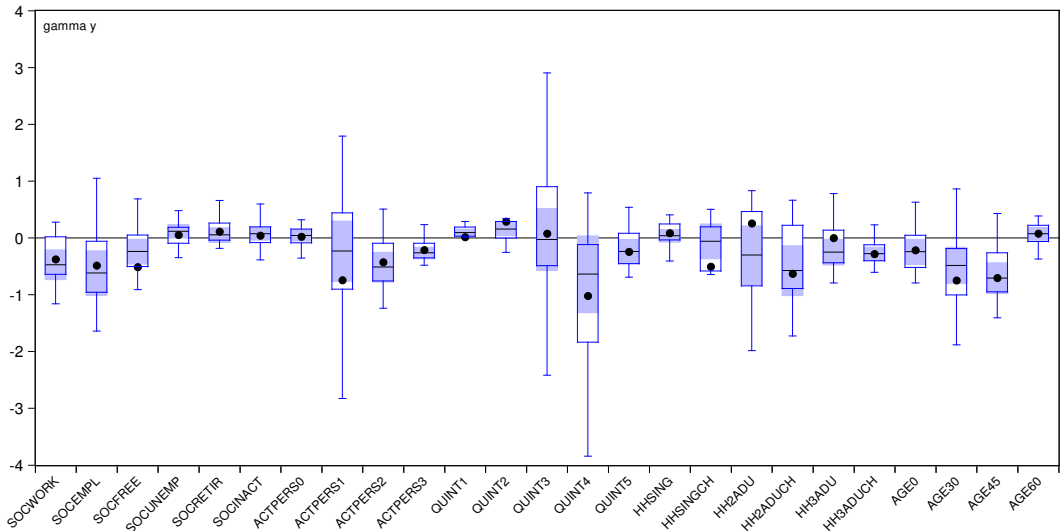
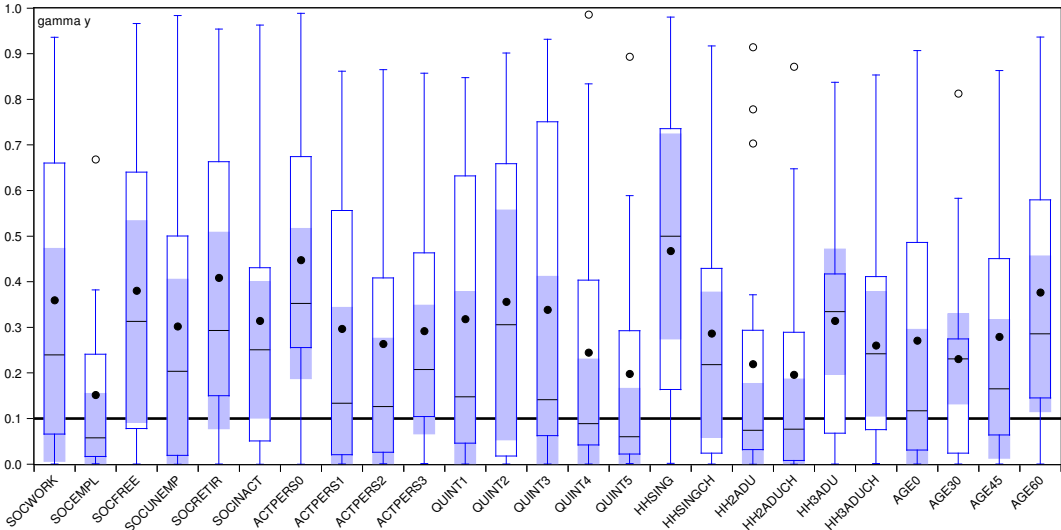


Figure 4: ECM loading coefficient – Model 2

(a) Point estimates



(b) P-values



single parents with dependent children adjusts towards the “representative” household inflation relatively faster than for other categories, such as households featuring unemployed or young (below 30 years old) members, which all tend to deviate quite persistently from the “representative” household inflation rate.

The number of significant loading coefficients increases substantially under the assumption of relative convergence (Figure 4). In particular, evidence of the presence of an adjustment process between household-specific and “representative” household inflation emerges in numerous socio economic categories, where the γ_y are found to be - on average - significant.¹² Figure 4 confirms that households with one active person display, on average, the largest (in absolute value) loading coefficients, together with households belonging to the fourth quartile of the income distribution. In addition to that, the inflation rates faced by households including two adults with dependent children and by households with reference person between 45 and 59 years old also seem to adjust relatively fast towards the reference inflation rate. For the majority of the remaining categories, the adjustment speed towards equilibrium is rather low, indicating a tendency of the household-specific inflations to deviate quite persistently from the “representative household” inflation.

4.2 Pooled Panel Analysis of Inflation Differentials

For the 52,910 observations of our panel, the bivariate correlation of the pooled country-specific headline inflation rates with the household-specific inflation rates amounts to 0.95, which is high, but at the same time still significantly below unity. Nevertheless, the correlation is so close that we can assume a common driving force behind the household specific inflation rates. On the country-level, such an assumption is in line with the results of the PANIC approach (see section 4.1.2).

Statistically, this amounts to the hypothesis that a singly data-generating process dominates the variation in our panel. To illustrate this, we run two principal components extractions, where the variables are the household specific inflation rates; one for the aggregate of the EU-15 countries and the other for the aggregate of the initial 11 Euro area member countries.¹³

The EA principal components extraction covers 22 out of 25 household specific rates.¹⁴ For the EA aggregate, the first component already represents 99.6% of the sample variance, the second component only 0.07%. The finding is very similar for the EU-15 aggregate, where 21 household-specific inflation rates can be computed.¹⁵ The first component picks up 99.2 percent of the sample variance and the second only 0.13%. These are clearly one-dimensional solutions in statistical terms. This finding on our two aggregate levels also holds for all the 15 countries individually.¹⁶ There is one major data generating process reflected by the “representative household” inflation that affects all household categories and without exception represents most of the inflationary variation across time.

Yet, while the inflation generating process appears to be one-dimensional, there still may exist second or lower order inflationary processes affecting more than one household type only.

¹²In particular, this holds for: households where the reference person is a manual or a non-manual worker or unemployed, households featuring up to three active persons, households belonging to the poorest 20 percent or to the richest 60 percent of the population, households including up to two adults with dependent children and households where the age of the reference person is less than thirty years old or between 45 and 59 years old.

¹³Austria, Belgium, Finland, France, Germany, Ireland, Italy, Luxembourg, Netherlands, Portugal, and Spain; henceforth EA.

¹⁴No EA aggregate household-specific inflation rates are available for the self-employed, unemployed and retired categories.

¹⁵Household specific inflation rates for the EU-15 are unavailable for the non-manual worker, unemployed, retired and three or more adults with dependent children categories.

¹⁶The country results are not presented here for space reasons, but they are available from the corresponding author upon request.

These should become visible in the deviations of the household specific inflation rates from the “representative household” inflation in the same country or country group. To assess this possibility, we compute these differences for all observations in the panel.

Let us now proceed to disentangle the variation in the household specific inflation rate in the panel. Table 6 reports the descriptive statistics for this variable.¹⁷

Table 6: Statistics for household specific inflation rates, 15 country panel, 1997m01 to 2008m11

Category	Mean	Median	Minimum	Maximum	S.D.	N
Reference series	2.26	2.09	-1.48	6.58	1.11	52910
All categories	2.36	2.19	-2.12	8.27	1.21	52910
socWork	2.34	2.17	-1.84	6.69	1.18	2145
socEmpl	2.35	2.19	-1.95	6.65	1.20	1859
socFree	2.33	2.16	-1.95	6.75	1.17	2145
socUnemp	2.38	2.23	-1.91	7.72	1.26	2002
socRetir	2.49	2.30	-1.78	8.27	1.28	2002
socInact	2.38	2.19	-1.84	7.80	1.27	2145
actPers0	2.44	2.25	-1.81	8.25	1.28	2145
actPers1	2.35	2.17	-1.90	7.14	1.19	2145
actPers2	2.32	2.16	-1.91	6.51	1.16	2145
actPers3	2.31	2.15	-1.79	6.53	1.16	2145
quint1	2.36	2.19	-1.77	7.74	1.23	2145
quint2	2.36	2.20	-1.75	7.39	1.21	2145
quint3	2.36	2.19	-1.86	7.06	1.20	2145
quint4	2.35	2.19	-1.89	6.89	1.18	2145
quint5	2.33	2.17	-1.99	6.72	1.17	2145
hhSing	2.43	2.23	-1.99	8.21	1.31	2145
hhSingCh	2.32	2.16	-1.93	7.62	1.20	2145
hh2Adu	2.37	2.18	-1.90	7.15	1.21	2145
hh2AduCh	2.31	2.16	-1.87	6.64	1.16	2145
hh3Adu	2.35	2.19	-1.77	6.82	1.17	2145
hh3AduCh	2.29	2.16	-1.71	6.52	1.17	2002
age0_29	2.32	2.16	-2.12	6.94	1.20	2145
age30_44	2.32	2.15	-1.87	6.62	1.17	2145
age45_59	2.34	2.17	-1.85	6.84	1.17	2145
age60_	2.43	2.26	-1.81	8.12	1.26	2145

The evolution of the household specific inflation rates through time, averaged across the 15 countries in the panel, is shown in Figure 5. The evolution of the deviations of household-type-specific inflation from the mean-adjusted country headline inflation rates, averaged across the 15 countries in the panel, is shown in Figure 6. A histogram with the distribution of the deviation variable across the panel is shown in Figure 7.

On the basis of this panel, we shall now investigate the following questions:

1. Are there any group specific inflation rates that differ significantly from the overall mean?
2. Are there clusters of households sharing common household specific inflation rates?
3. Can we identify common driving processes behind household specific inflation rates?

¹⁷To ease comparison of the magnitudes, we refer to those 52,910 observations only, where our 15 national inflation reference series do not have any missing values. Notice that the arithmetic mean of headline = “representative household” inflation across the 52,910 observations of the panel is 2.260%, whereas the mean of all group specific rates across the panel amounts to 2.357%. The slightly different arithmetic means are due to the implicit uniform weights across household types that do not exactly reflect their importance in the “representative household” inflation. Though the difference is minor, it leads to a non-zero arithmetic mean for the household specific inflation rate differentials. Thus, the expected value of this difference for any household type, under the assumption of only random deviations from the “representative household” inflation, is not zero. To control for this, we compute a panel mean-adjusted household type specific inflation rate as well as a panel mean-adjusted household type specific difference from national inflation with the same variance as the original difference, but a mean of zero. In what follows, we shall refer to the panel mean-adjusted variables only.

Figure 5: Household specific inflation rates, pooled data, 1997m01 to 2008m11 (n = 52,910)

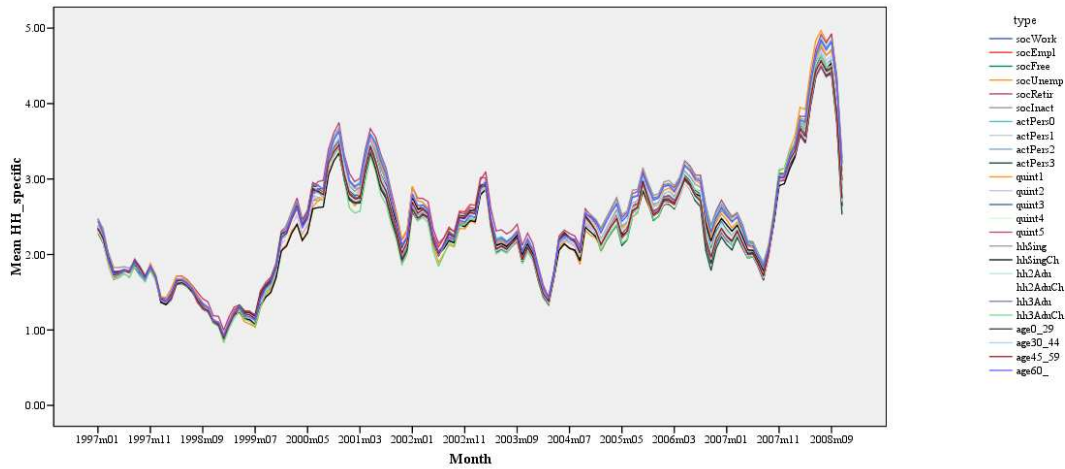


Figure 6: Deviations of household specific inflation rates from country means, pooled data, 1997m01 to 2008m11 (n = 52,910)

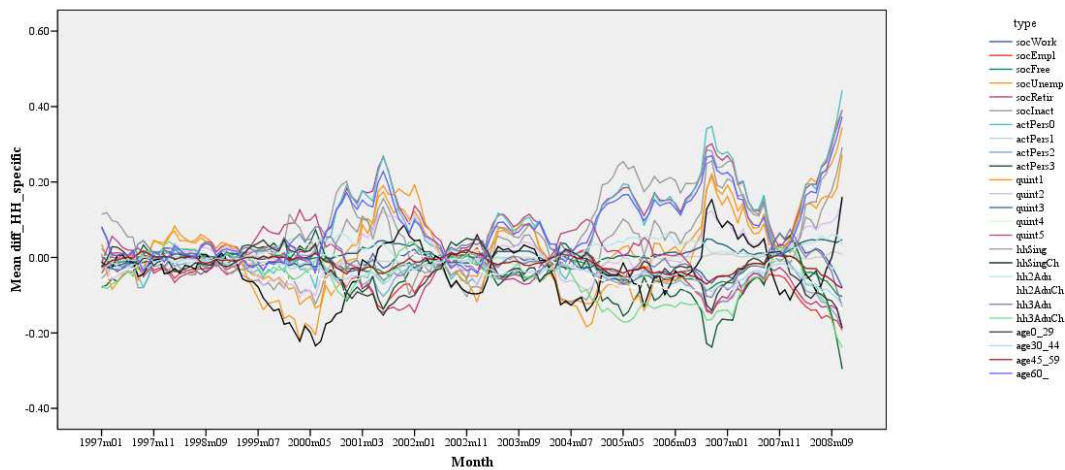
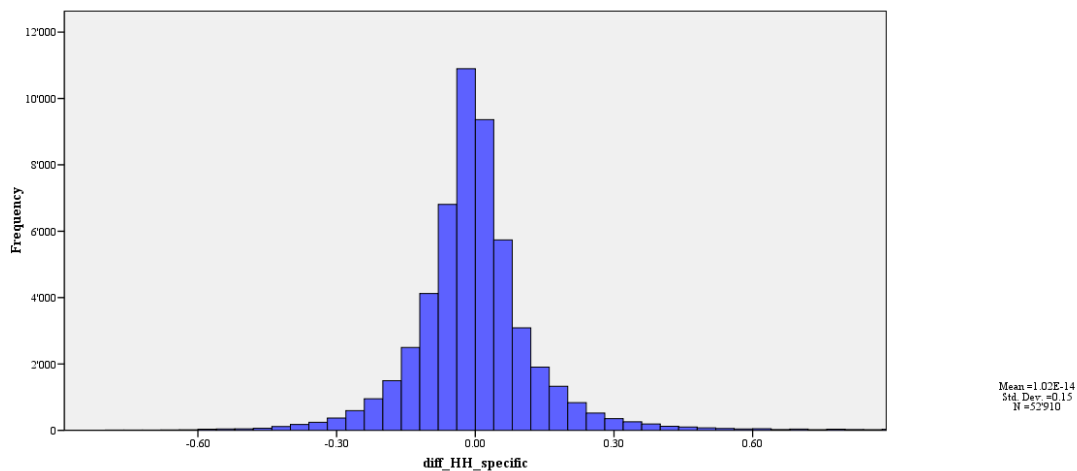


Figure 7: Histogram: deviations of household specific inflation rates from country means, pooled data, 1997m01 to 2008m11 (n = 52,910)



4.2.1 Are there any group specific inflation rates that differ significantly from the overall mean?

The issue whether group specific inflation rates differ significantly from the overall mean is addressed referring to the deviation of household-type-specific inflation from the mean-adjusted country headline inflation rates ($\Delta^{HH}_{\text{specific}}$). To this end, we run 25 independent t-tests (one for each household category) for the difference of the category mean values from zero ($H_0 : \text{mean} = 0$). The results are shown in Table 7. Accordingly, the null hypothesis can be rejected on the 1-percent level for 23 out of 25 household categories. Only *quint1* and *hh3Adu* (italics in the table) fail to pass conventional significance levels up to 0.05 for the deviation from the country specific HICP to be different from zero.

Table 7: $\Delta^{HH}_{\text{specific}}$, arithmetic mean by category (n=52910), t-test ($H_0 : \text{mean} = 0$)

Category	Mean	Std. Dev.	t	p	N
hh3AduCh	-0.05	0.16	-14.95	< 0.001	2002
socEmpl	-0.04	0.09	-21.38	< 0.001	1859
actPers3	-0.04	0.17	-11.56	< 0.001	2145
hh2AduCh	-0.04	0.08	-22.13	< 0.001	2145
hhSingCh	-0.04	0.15	-12.00	< 0.001	2145
actPers2	-0.04	0.09	-20.45	< 0.001	2145
age30_44	-0.03	0.06	-24.20	< 0.001	2145
age0_29	-0.03	0.12	-12.39	< 0.001	2145
socFree	-0.03	0.09	-13.31	< 0.001	2145
quint5	-0.02	0.11	-8.82	< 0.001	2145
age45_59	-0.02	0.06	-13.17	< 0.001	2145
socWork	-0.01	0.08	-7.37	< 0.001	2145
actPers1	-0.01	0.05	-7.76	< 0.001	2145
quint4	-0.01	0.04	-8.53	< 0.001	2145
<i>hh3Adu</i>	<i>-0.01</i>	<i>0.13</i>	<i>-1.82</i>	<i>0.068</i>	2145
<i>quint1</i>	<i>0.01</i>	<i>0.17</i>	<i>1.43</i>	<i>0.153</i>	2145
quint3	0.01	0.04	6.54	< 0.001	2145
quint2	0.01	0.10	4.10	< 0.001	2145
hh2Adu	0.01	0.09	6.55	< 0.001	2145
socInact	0.02	0.23	4.49	< 0.001	2145
socUnemp	0.04	0.18	8.63	< 0.001	2002
age60_	0.08	0.19	19.33	< 0.001	2145
hhSing	0.08	0.26	14.06	< 0.001	2145
actPers0	0.08	0.25	15.03	< 0.001	2145
socRetir	0.09	0.23	17.96	< 0.001	2002
Total	0.00	0.15			52910

Interestingly, the household types on the low end, i.e. the ones with lower than average inflation¹⁸, can typically be expected to be economically better off than the households experiencing significantly higher than average inflation¹⁹. In particular, the latter group comprises all housed types that are by definition explicitly not earning employment incomes and are hence especially prone to lead socially marginalized lives.²⁰ In terms of magnitudes, inflation for households at the lower end is up to about 0.05 percentage points lower than the country average, and about up to 0.09 percentage points higher at the upper end of the distribution. This amounts to about 2.5% and 4% of accumulated inflation over the sample period, respectively, which is not massive, yet economically considerable.

Another way to address this question is to regress $\Delta^{HH}_{\text{specific}}$ through the origin on 25 dummy

¹⁸ *hh3AduCh, socEmpl, actPers3, hh2AduCh, hhSingCh, actPers2, age30_44, age0_29, socFree, quint5, age45_59, socWork, actPers1, quint4*; sorted in ascendant order

¹⁹ *quint3, quint2, hh2Adu, socInact, socUnemp, age60_, hhSing, actPers0, socRetir*

²⁰ An exception to this observation is the *hhSingCh* category, where we would expect single mothers living on transfer incomes to dominate. In our dataset, this category however tends to be submitted to similar inflation levels as the better off households.

variables D_i for the household categories, so that

$$\Delta_{i,j,t}^{HH_{\text{specific}}} = \sum \beta_i D_i + \epsilon_{i,j,t} \quad (7)$$

where i denotes the 25 household categories, j the 15 countries, t the 143 monthly observations and $\epsilon_{i,j,t}$ the 52,910 residuals. The results are summarized in Table 8. By construction, the point estimates for the dummy variable coefficients, β_i , are the same as the group specific means of $\Delta^{HH_{\text{specific}}}$ reported in Table 7. But now we are dealing with partial correlations, so that the significance tests are not the same as in a univariate analysis. Indeed, apart from *hh3Adu* and *quint1*, which again do not pass the conventional 5% level, the panel regression shows three household types (*actPers1*, *quint3* and *quint4*) for which the p -values now exceed 0.01. Nevertheless, they are still below 0.05, so that the results from the univariate t -tests are confirmed in qualitative terms.

Table 8: OLS regression through the origin, dependent variable: $\Delta^{HH_{\text{specific}}}$, $n = 52910$, $R^2 = 0.28$

Category	β	t	p
hh3AduCh	-0.054	-16.76	< 0.001
socEmpl	-0.044	-13.31	< 0.001
actPers3	-0.043	-13.94	< 0.001
hh2AduCh	-0.04	-12.9	< 0.001
hhSingCh	-0.039	-12.68	< 0.001
actPers2	-0.038	-12.35	< 0.001
age0_29	-0.033	-10.53	< 0.001
age30_44	-0.033	-10.77	< 0.001
socFree	-0.025	-8.08	< 0.001
quint5	-0.021	-6.64	< 0.001
age45_59	-0.016	-5.2	< 0.001
socWork	-0.012	-3.89	< 0.001
actPers1	-0.008	-2.51	0.012
quint4	-0.008	-2.47	0.013
<i>hh3Adu</i>	<i>-0.005</i>	<i>-1.58</i>	<i>0.114</i>
<i>quint1</i>	<i>0.005</i>	<i>1.69</i>	<i>0.09</i>
quint3	0.006	2	0.045
quint2	0.009	2.75	0.006
hh2Adu	0.013	4.11	< 0.001
socInact	0.022	7.182	< 0.001
socUnemp	0.035	10.91	< 0.001
age60_	0.078	25.2	< 0.001
hhSing	0.08	25.63	< 0.001
actPers0	0.081	25.97	< 0.001
socRetir	0.09	28.01	< 0.001

A further advantage of the panel setup is that it allows to control for country fixed effects on $\Delta^{HH_{\text{specific}}}$. Adding a vector of 14 country dummy variables D_j to the regression,²¹ so that

$$\Delta_{i,j,t}^{HH_{\text{specific}}} = \sum \beta_i D_i + \sum \beta_j D_j + \epsilon_{i,j,t} \quad (8)$$

guarantees that only the within-country variance of $\Delta^{HH_{\text{specific}}}$ is reflected by the coefficients for D_i , thereby eliminating all possible contamination stemming from differences of D_i in levels across countries.²² And indeed, the F -test for joint significance of the country fixed effects yields

²¹Note that one out of 15 country dummy variables has to be excluded from the regression, which would be overdetermined otherwise. Our choice is Belgium, where the country average of $\Delta^{HH_{\text{specific}}}$ is closest to zero.

²²Differences of pooled $\Delta^{HH_{\text{specific}}}$ in levels across countries have to be expected, as the country mean of the 25 household specific inflation rates cannot be expected to match the country headline inflation rate. To achieve this, the household categories would have to be mutually exclusive (which they are not) and weighted by their share in the “representative household’s” consumption baskets.

$F_{(52,910;14)} = 52.83$, which clearly passes the 1% level, so that omitting the fixed effects implies a possible bias to the regressors of interest. The results of the amended regression are shown in Table 9.

An inspection of the country fixed effects reveals that while 9 out of 14 are clearly insignificant (not even passing the 10% threshold), those referring to Portugal, Denmark and Italy are significantly negative, and those referring to the United Kingdom and Ireland are significantly positive. Accordingly, household types with lower than average inflation are overrepresented in the unweighted average household specific inflation rates in the former group and underrepresented in the latter. Controlling for this leads to some modifications to the point estimates and standard errors of the β_i . In terms of significance, apart from *hh3Adu* and *quint1*, which once more do not pass the conventional 5% level, in the amended panel regression, there are now four household types (*actPers1*, *quint2*, *quint3* and *quint4*) for which the p -values exceed 0.01. While they are still below 0.05 for *actPers1*, *quint2* and *quint4*, the set of D_i regressors that fail to pass any conventional significance threshold now in addition comprises *quint3*. The economic significance of these modifications, however, is practically negligible, as it relates to household types where the difference to country specific headline inflation is minor. At the upper and lower ends of the distribution of household-specific inflation, the findings are virtually unchanged. The rank order of the point estimates for the 15 household types is exactly the same as in Tables 6 and 7, as is their magnitude.²³

Accordingly, even after controlling for country specific factors, we can confirm that over the sample period different household groups face inflation rates that deviate from the country average headline inflation. In particular, the categories which roughly represent the economically better off parts of the population are found to experience inflation rates about 0.05 percentage points lower than the country average headline inflation. On the other hand, the not economically active households face an inflation about 0.09 percentage points higher than the country average.

4.2.2 Are there clusters of households sharing common household specific inflation rates?

Until now, we have been comparing means across the sample period. While this already provided some noteworthy insights into inflation across household types, the period average disregards the dynamics of the inflationary process. Similar arithmetic means may result from similar dynamics, but this is not necessarily the case. That is why we now subject our data to a cluster analysis, directing the focus on the household specific variances on the time axis.

Cluster analyses are methods that decompose a data set into different groups (clusters). The algorithm relies either on distinguishing between different clusters or on the similarity within clusters. In our case, the uniting or distinguishing feature underlying the search for clusters is the dynamics of the inflation experienced by the various household categories, i.e. time series of inflation broken down by household type.

In particular, we should be looking for clusters of households with low longitudinal within-group variance. To this end, we have to resort to aggregates of household types across countries. The panel of 15 countries and 25 household types per country mixes two dimensions, whereas we are now focusing on the household type criterion. Given this, a straightforward choice is to refer to the Euro area (EA) an/or the EU-15 aggregates. Given that the number of household types for the EA is 22, but only 21 for the EU-15, and that the EA can be expected to be more

²³Notice that in the OLS regression, the point estimates of the of D_i regressors exceed their fixed effects counterparts by about 0.001, which implies that the fixed effects on average pick up some excess inflation which is a statistical artifact due to the non-representativeness of the household type breakdown. Equivalently, the average of the country fixed effects is positive, which is largely due to the in comparison pronouncedly positive effect of 0.058 relating to Ireland.

Table 9: Country fixed effects regression through the origin, dependent variable: $\Delta^{HH}_{\text{specific}}$, $n = 52910$, $R^2 = 0.30$

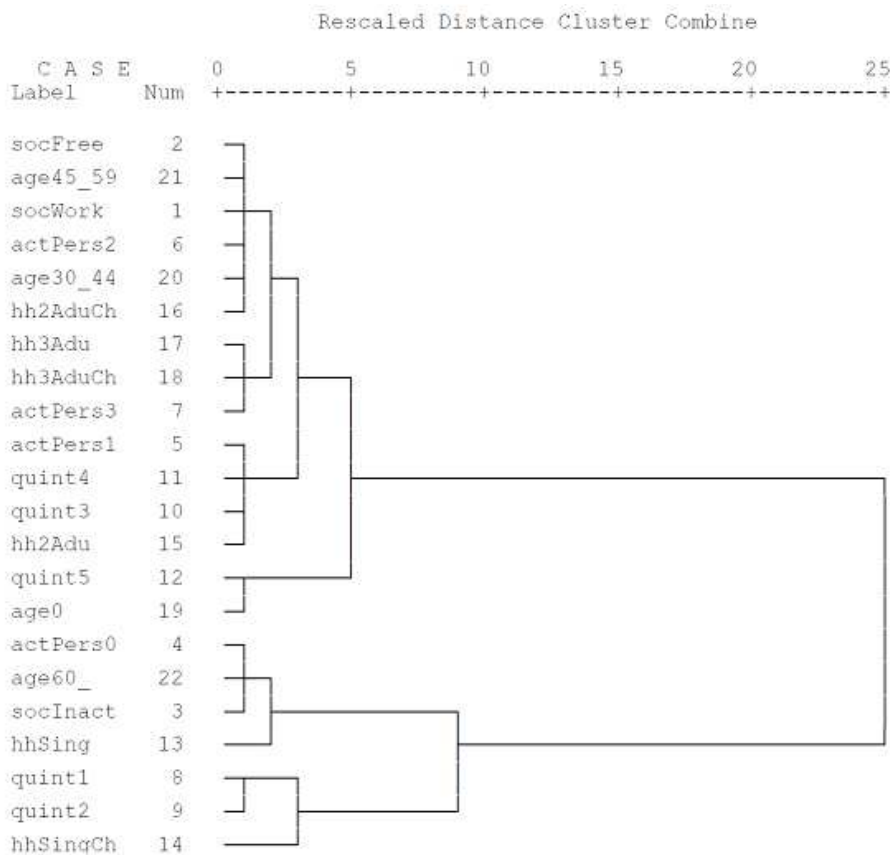
Category	β	t	p
hh3AduCh	-0.06	-13.94	< 0.001
socEmpl	-0.05	-11.51	< 0.001
actPers3	-0.04	-11.46	< 0.001
hh2AduCh	-0.04	-10.62	< 0.001
hhSingCh	-0.04	-10.44	< 0.001
actPers2	-0.04	-10.18	< 0.001
age0_29	-0.03	-8.71	< 0.001
age30_44	-0.03	-8.90	< 0.001
socFree	-0.03	-6.74	< 0.001
quint5	-0.02	-5.57	< 0.001
age45_59	-0.02	-4.42	< 0.001
socWork	-0.01	-3.36	< 0.001
actPers1	-0.01	-2.24	0.025
quint4	-0.01	-2.22	0.027
hh3Adu	-0.01	-1.49	0.135
quint1	0.00	1.14	0.253
quint3	0.01	1.39	0.164
quint2	0.01	2.00	0.046
hh2Adu	0.01	3.09	0.002
socInact	0.02	5.57	< 0.001
socUnemp	0.03	8.64	< 0.001
age60_	0.08	20.09	< 0.001
hhSing	0.08	20.43	< 0.001
actPers0	0.08	20.71	< 0.001
socRetir	0.09	22.55	< 0.001
country_PT	-0.02	-5.13	< 0.001
country_DK	-0.01	-4.25	< 0.001
country_IT	-0.01	-2.56	0.011
country_AT	-0.01	-1.55	0.121
country_FI	-0.01	-1.38	0.168
country_DE	-0.01	-1.37	0.17
country_LU	0.00	-1.16	0.247
country_SE	0.00	-0.60	0.55
country_ES	0.00	-0.25	0.8
country_NL	0.00	-0.40	0.693
country_FR	0.00	0.89	0.373
country_GR	0.00	0.96	0.337
country_UK	0.01	3.34	< 0.001
country_IE	0.06	17.30	< 0.001

homogeneous in terms of prices and inflation than the EU-15, our choice is the EA.²⁴

We determine the clusters by the hierarchical Ward algorithm, applied to the squared Euclidian distance ($\sqrt{\sum (\Delta_{j,p}^{HH_{specific}} - \Delta_{j,q}^{HH_{specific}})^2}$) as measure of similarity, where j denotes the regional aggregate (EA) and household type $p \neq q$, given all pairwise permutations for the 22 household categories available for the EA. Starting from the lowest level of aggregation, this algorithm successively considers all possible pairings and joins household types to clusters, or merges those clusters to higher-level clusters, that result in the minimal increase in total within-groups variance. The algorithm focuses on the within-group homogeneity rather than on the dissimilarity between clusters, and hence is appropriate to explore whether there are clusters of households sharing common household-specific inflation rates.

Figure 8 shows the resulting dendrogram, Table 10 reports the allocation of household types to clusters as we move up in the hierarchy from five clusters to two. We shall examine the cluster structure from the left to right, corresponding to bottom to the top of the hierarchy. Notice that it is customary in cluster analysis to assign higher ordinal numbers as we move down in the hierarchy, i.e. the cluster labeled No. 5 in Table 10 is characterized by the highest within similarity, followed by No. 4, and so forth.²⁵

Figure 8: Cluster analysis Euro area, 1997m01 to 2008m11 (n = 143)



Obviously, the cluster allocation is not random and thus allows identifying groups of household types that share not only the same inflation experience, but also characteristic socio-

²⁴We performed the same analysis on the EU-15 level. The results (not reported for space reasons) show a roughly comparable pattern. They are available from the corresponding author upon request.

²⁵Accordingly, the household types with the most similar inflation time profiles are *quint5* and *age0_29* (cluster No. 5), followed by *quint1*, *quint2*, and *hhSingCh* (cluster No. 4), *actPers1*, *quint3*, *quint4* and *hh2Adu* (cluster No. 3), *socInact*, *actPers0*, *hhSing* and *age60_* (cluster No. 2) and finally *socWork*, *socFree*, *actPers2*, *actPers3*, *hh2AduCh*, *hh3Adu*, *hh3AduCh*, *age30_44* and *age45_59* (cluster No. 1).

Table 10: Cluster membership

Variable	5 Clusters	4 Clusters	3 Clusters	2 Clusters
socWork	1	1	1	1
socFree	1	1	1	1
actPers2	1	1	1	1
actPers3	1	1	1	1
hh2AduCh	1	1	1	1
hh3Adu	1	1	1	1
hh3AduCh	1	1	1	1
age30_44	1	1	1	1
age45_59	1	1	1	1
socInact	2	2	2	2
actPers0	2	2	2	2
hhSing	2	2	2	2
age60_	2	2	2	2
actPers1	3	1	1	1
quint3	3	1	1	1
quint4	3	1	1	1
hh2Adu	3	1	1	1
quint1	4	3	3	2
quint2	4	3	3	2
hhSingCh	4	3	3	2
quint5	5	4	1	1
age0_29	5	4	1	1

economic features leading to the former. Cluster 5 – the *tightest* – comprises the young and rich; we might dub it the “yuppies”. Cluster 4 bundles the low socio-economic status (SES) households. Middle class income earners are sharing the Cluster 3 inflation experience. Cluster 2 mainly consist of the economically inactive and elderly. Finally, cluster 1 – the *loosest* – comprises “classical” role model households with children, mostly middle-aged, actively earning incomes as employees or self employed.

Notably, the clusters can to some degree be associated with a ranking according to the prevailing SES (tentatively, in ascending order: No. 5 → No. 3 → No. 1 → No. 2 → No. 4). Moving up the hierarchy implies lumping together household types that are increasingly dissimilar in terms of the inflation dynamics experienced during the sample period. As Table 10 shows, the four cluster solution merges the “middle class” cluster with the “classical” household types. Reducing the number of clusters to three adds the “yuppie” cluster to the former merger. With only two clusters, the low SES cluster is merged with the socially inactive/elderly cluster. Accordingly, the top-level dichotomization draws a dividing line between the low SES and socially inactive/ elderly households (clusters No. 2 and 5 down the hierarchy) on the one side, and the rest of the population on the other. Thus, similarity in experienced inflation dynamics tends to correspond to similarity in SES.

The answer to the question whether there are clusters of households sharing common household specific inflation rates, is hence affirmative. This allows us to link the findings from the cluster analysis with the main results from the previous section. In particular, in section 4.2.1 we showed that, over the considered time span, lower SES and otherwise socially marginalized households were exposed to higher average inflation than more elevated SES households. On the basis of the analysis carried out in this section, we can conclude that clusters of similar SES display similar dynamics: households within the same cluster experience similar deviations between their own inflation and the average process.

4.2.3 Can we identify common driving processes behind household specific inflation rates?

In the previous sections, we found that lower SES and otherwise socially marginalized households were typically exposed to higher average inflation than higher SES households, and similarity in SES tended to correspond to similarity in experienced inflation dynamics. In the following, we address our third research question and we seek to identify common driving processes behind household-specific inflation rates. The cluster analysis indicates that there are indeed several distinctive processes, but to identify a quantitative representation of them, we have to resort to another statistical method.

Our starting point is the conjecture that the cross-dimensional variance of the observed variable $\Delta_{i,j,t}^{HH_{\text{specific}}}$ can be traced back to a limited number of non-measurable – “latent” – variables. Clearly, this suggests factor or principal component analyses as appropriate methods. We refer to the standard method – principal component analysis – which among all factor-analytic methods is the one that requires least assumptions about the covariance structure of the data. Principal component analysis is a method to reduce a data to a low number of dimensions. In particular, a principal component (PC) is a synthetic variable that results from a linear combination of observed variables. The starting point is a matrix of k variables that can be expected to be related to each other (correlated), and n observations. In our pooled sample, n corresponds to 143 monthly observations and k to the pooled 25 household types (i) in 15 countries (j), so that (with five series missing) $k = 370$.

Each variable $\Delta_1^{HH_{\text{specific}}}, \dots, \Delta_k^{HH_{\text{specific}}}$ can exactly be expressed as a linear combination of k PCs H_1, \dots, H_k . For the x -th variable, observed at the y -th case, we get:

$$\Delta_{x,y}^{HH_{\text{specific}}} = a_{x,1}H_{1,y} + a_{x,2}H_{2,y} + \dots + a_{x,k}H_{k,y} \quad (9)$$

for $i = 1, \dots, k$ and $j = 1, \dots, n$. The algorithm now determines what share of the overall variance of the k observed variables can be reproduced with $z < k$ PCs,

$$\Delta_{x,y}^{HH_{\text{specific}}} = a_{x,1}H_{1,y} + a_{x,2}H_{2,y} + \dots + a_{x,r}H_{z,y} + R_{x,y} \quad (10)$$

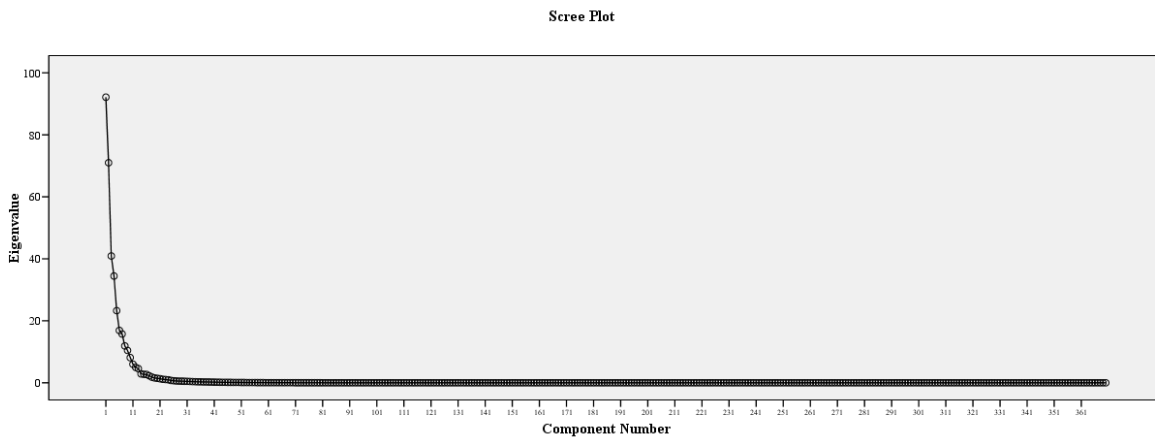
where $R_{x,y}$ stands for the unexplained part when reducing the linear combination to r PCs observed at the y -th case of $\Delta_x^{HH_{\text{specific}}}$. The components are subsequently determined by ordinary least squares minimizing $R_{x,y}$. The loadings $a_{x,1}, \dots, a_{x,r}$ correspond to regression coefficients which would result from the multiple regression of $\Delta_x^{HH_{\text{specific}}}$ on the PCs.

How many PCs are required to reproduce the data? The eigenvalue-rule provides a non-arbitrary rule for the number of components to be extracted: As the number of potential components is equal to the number of variables k , and since the sum of the explanatory contributions of all potential PCs amounts to 100%, an explanatory contribution below $(100/k)\%$ (corresponding to an eigenvalue lower than unity) implies that this component contributes less to the explanation of the overall variance than an average variable.

Submitting our panel to a PC analysis yields $z = 23$ components with eigenvalues equal to or exceeding 1, which is only a fraction of 6 percent of the $k = 370$ inflation time series. The standard scree plot (Figure 9) shows that the first five components stand out in terms of their variance share, followed by another six or so components that are distinguishable from the “scree”. The explanatory power of the components hence rapidly declines once more than a handful of factors are extracted.

Furthermore, PC extractions resulting in more than one component are not unique in that they can be rotated without affecting $R_{x,y}$, and there are various rotation algorithms that lead

Figure 9: PC scree plot, 370 Δ_i^{HH}, j series, 1997m01 to 2008m11 (n = 143)



to different results. The loading matrix and, accordingly, the PCs hence depend on the rotation algorithm.

Given this, we choose a standard orthogonal rotation (*varimax*) that minimizes the number of variables with high loadings on each component, which eases the interpretation of the factors. In a second step, we relax the orthogonality condition (*promax*). The comparison of the alternative results will serve as an (informal) robustness check.²⁶ A surprisingly clear pattern emerges. After both *varimax* or *promax* rotation, exclusively the first and second component reveal high loadings with $\Delta^{HH}_{\text{specific}}$ from more than a single country. Moreover, the subsequent components show high loadings with variables from one country each. This is exclusively the case after the orthogonal rotation, and overwhelmingly so, when the rotated components are allowed to correlate. Accordingly, the first two components – and only these two – reflect transnational household type specific inflation processes; the remaining 21 components that meet the eigenvalue criterion reflect country rather than household specific inflation dynamics.

After the orthogonal rotation, the first component reproduces 18% of the total variance, and the second 13%, so that the transnational variance amounts to 31%. The less restrictive *promax* solution yields a first component reflecting 80% of the total variance, and a second accounting for 52%.²⁷ Thus, while country specific processes are important factors in explaining $\Delta^{HH}_{\text{specific}}$, two transnational processes stand out.

Let us now look at the two components reflecting these processes. They are plotted in Figure 10, where PC1_ *varimax*, PC1_ *promax* and PC2_ *varimax*, PC2_ *promax* denote the first and second PCs after *varimax* and *promax* rotations, respectively.

Obviously, the choice of rotation matters, but not so much to change the picture as a whole, so that we feel assured that our results are fairly robust regarding the rotation algorithm.

What is left to be done is to find an interpretation for the two processes reflected in Figure 10. One option is to resort to data not incorporated in our panel. In particular, one would be looking for times series which are a priori susceptible to reflect the data generating processes above, such as transnational economic developments or shocks, price movements or institutional phenomena.²⁸ The other option is to relate to the data already in our panel and try to find interpretations for correlations with the two components. This is what we shall do now. To this

²⁶Due to the length of the respective table, we decided to make the detailed results available only on request from the corresponding author.

²⁷Notice that variance shares of non-orthogonal factors cannot be added to cumulative explained variance.

²⁸For reasons of space, we leave this exercise for a future paper.

Figure 10: First and second PCs, 370 $\Delta_{i,j}^{HH_{\text{specific}}}$ series, 1997m01-2008m11 ($n = 143$), *varimax* and *promax* rotated



end, we take a closer look at those variables loading high in absolute terms on the first two components. They are put together in Table 11.

Obviously, the first PC can be interpreted along lines already familiar from our previous analyses. It is positively associated with household categories characterized by lower SES and/or social exclusion, and negatively with household categories characterized by higher SES and/or social inclusion. Accordingly, the process reflected by the first PC extracted from the panel reflects conditions that are likely to be the more unfavorable in terms of deviation of experienced inflation relative to headline inflation, the lower the SES of a household or its degree of inclusion.

Is there an equally straightforward interpretation for the second PC? Given the findings in table 11, the common theme behind the second PC is also quite obvious. The positive scorers are mostly households with children, they fall in the age brackets that are likely to raise children, and they are economically active. A negative association is found for economically inactive households including the elderly. Interestingly, this PC is far less associated with the more direct measures for SES or high versus low income. The household specific inflation process apparently reflected by this PC mainly affects household in their child rearing phase of the life cycle (the “battlers”).

To sum up, from the PC analyses we can conclude that, during the sample period, two transnational processes dominated the numerous idiosyncratic country-specific processes in reflecting the household specific dynamics of inflation. In particular, first and strongest process affects lower SES and socially marginalized households versus the better off household types, while the second process discriminates between households with children versus those without.

5 Conclusion

In the paper we tell one story – but from different perspectives. This reflects the fact that the stories we tell depend on the questions we ask. On the national level, we find evidence for the existence of one main driving factor driving the non-stationarity of the panel and find evidence for a single co-integration vector (see section 4.1.2). This is good news as it implies that on the national level individual household’s inflation rates do not diverge from the “representative rate” in the long-run. However, the persistence of deviations is rather high and therefore the

Table 11: Variables with high absolute loadings on first and second PC

First PC		Second PC	
Varimax rotation	Promax rotation	Varimax rotation	Promax rotation
Loadings ≥ 0.7			
DK_diff_hhSingCh	BE_diff_hh3Adu	BE_diff_actPers2	BE_diff_actPers2
DK_diff_socInact	BE_diff_socInact	BE_diff_actPers3	BE_diff_actPers3
FI_diff_actPers0	DE_diff_quint2	BE_diff_age30_44	BE_diff_hh2AduCh
FI_diff_age60_	DK_diff_hhSingCh	BE_diff_hh2AduCh	IT_diff_actPers1
FI_diff_hhSing	DK_diff_socInact	IT_diff_actPers1	IT_diff_actPers2
FI_diff_hhSingCh	ES_diff_actPers1	IT_diff_actPers2	IT_diff_actPers3
FI_diff_quint1	FI_diff_actPers0	IT_diff_actPers3	IT_diff_age30_44
FI_diff_quint2	FI_diff_age60_	IT_diff_age30_44	IT_diff_age45_59
FI_diff_socRetir	FI_diff_hhSing	IT_diff_age45_59	IT_diff_hh2AduCh
FI_diff_socUnemp	FI_diff_hhSingCh	IT_diff_hh2AduCh	IT_diff_hh3AduCh
FR_diff_quint1	FI_diff_quint1	IT_diff_hh3AduCh	IT_diff_hhSingCh
FR_diff_quint2	FI_diff_quint2	IT_diff_hhSingCh	IT_diff_SocWork
IT_diff_quint1	FI_diff_quint3	IT_diff_SocWork	LU_diff_age30_44
IT_diff_quint2	FI_diff_socRetir	LU_diff_age30_44	LU_diff_age45_59
IT_diff_quint3	FI_diff_socUnemp	LU_diff_hh2AduCh	LU_diff_hh2AduCh
SE_diff_actPers0	FR_diff_quint1		
SE_diff_actPers1	FR_diff_quint2		
SE_diff_age60_	IT_diff_quint1		
SE_diff_hhSing	IT_diff_quint2		
SE_diff_hhSingCh	IT_diff_quint3		
SE_diff_quint1	LU_diff_quint1		
SE_diff_quint2	LU_diff_quint2		
SE_diff_quint3	NL_diff_socFree		
SE_diff_socInact	SE_diff_actPers0		
SE_diff_socRetir	SE_diff_actPers1		
SE_diff_socUnemp	SE_diff_age60_		
	SE_diff_hhSing		
	SE_diff_hhSingCh		
	SE_diff_quint1		
	SE_diff_quint2		
	SE_diff_quint3		
	SE_diff_socInact		
	SE_diff_socRetir		
	SE_diff_socUnemp		

adjustment speed towards the “representative household” is low. From a policy perspective, this means that even if there is no concern about a long-run stable distribution of inflation rates, over a short- to medium term horizon, deviations tend to be lasting.

On the aggregate level, we can find small but significant differences in the deviations of household-specific inflation rates from the reference rate – mainly along income and education levels. We can separate five clusters and we identify two main driving forces for the differences in the overall panel. These “driving forces” are related to low-income households and households with children. All in all, even if differences in the deviations of household-specific inflation rates from the reference rate are small in general, they are not negligible and persistent enough to be a serious topic of economic and social policy. Uncomfortably, our results suggest that some of the economically more vulnerable parts of the population may be subject to group-specific inflation dynamics resulting in higher-than-average inflation. To the extent that the cumulative effects wipe out purchasing power of the economically disadvantaged, welfare payments aiming at providing the subsistence level of income must be monitored carefully to avoid letting the recipients slide into absolute poverty.

Further research should concentrate on the quality of data. We approximated the distribution of different types of households in a unweighted manner. This is of course not the only way to deal with the data. We could weight the households in the panel according to their income level to get a more appropriate view on what is going on if the data were available (which was not the case). Further research should focus on micro-data to identify the driving factors behind differences more clearly. Furthermore, techniques like the σ -convergence test by [Quah \(1997\)](#) as used in [Hobijn and Lagakos \(2005\)](#) could be applied if micro-data were available.

References

- Allsopp, C. and M. Artis**, “The Assessment: EMU, Four Years On,” *Oxford Review of Economic Policy*, 2003, 19 (1), 1–29.
- Altissimo, F., M. Ehrmann, and Frank Smets**, “Inflation persistence and price setting behaviour in the Euro area. A summary of the IPN evidence.,” Occasional Paper Series 46, European Central Bank 2006.
- Amble, Nathan and Kenneth J. Stewart**, “Experimental Price Index for Elderly Consumers,” *Monthly Labor Review*, May 1994, 117 (5), 11–16.
- Bai, J. and S. Ng**, “A PANIC attack on unit roots and cointegration,” *Econometrica*, 2004, 72, 1127–1177.
- Bai, Juchan and Serena Ng**, “A PANIC Attack on Unit Roots and Cointegration,” *Boston College Working Paper in Economics*, December 2001, 519.
- Bernard, A. B. and S. N. Durlauf**, “Interpreting tests of the convergence hypothesis,” *Journal of Econometrics*, 1996, 71, 161–173.
- Blank, Rebecca M. and Alan M. Blinder**, “Macroeconomics, Income Distribution, and Poverty?,” Technical Report, NBER 1985.
- Brewer, Mike, Alissa Goodman, and Andrew Leicester**, *Household Spending in Britain - What Can It Teach Us About Poverty?*, 1 ed., Bristol: The Policy Press, April 2006.
- Campolmi, A. and E. Faia**, “Cyclical inflation divergence and different labor market institutions in the EMU.,” Working Paper Series 619, European Central Bank 2006.
- Carroll, Christopher D., Misuzu Otsuka, and Jiri Slacalek**, “What Is the Wealth Effect on Consumption? A New Approach,” mimeo, Johns Hopkins University 2006.
- Cecchetti, S. and R. Moessner**, “Commodity prices and inflation dynamics,” *BIS Quarterly Review*, December 2008, 34 (4), 55–66.
- Chiru, Radu**, “Does Inflation Vary With Income?,” *Statistics Canada Analytical Paper*, June 2005, Catalogue no. 11-621-MIE – No. 030.
- , “Is Inflation Higher for Seniors?,” *Statistics Canada Analytical Paper*, May 2005, Catalogue no. 11-621-MIE – No. 027.
- Choi, In**, “Unit Root Tests for Panel Data,” *Journal for International Money and Finance*, April 2001, 20 (2), 249–272.
- Crawford, Ian and Zöe Smith**, “Distributional Aspects of Inflation,” *IFS (Institute for Fiscal Studies) Commentary*, June 2002, 90.
- Cutler, David M. and Lawrence F. Katz**, “Macroeconomic Performance and the Disadvantaged,” *Brookings Papers on Economic Activity*, 1991, 22 (1991-2), 1–74.
- Dickey, D.A. and W.A. Fuller**, “Distribution of the Estimators for Autoregressive Time Series with a Unit Root,” *Journal of the American Statistical Association*, 1979, 74, 427–431.
- Dickey, David A. and Wayne A. Fuller**, “Distribution of the Estimators for Autoregressive Time Series With a Unit Root,” *Journal of the American Statistical Association*, June 1979, 74 (366), 427–431.
- Dullien, S. and U. Fritsche**, “How bad is divergence in the euro zone? Lessons from the United States and Germany,” *Journal of Post Keynesian Economics*, 2009, 31, 431–459.
- Dullien, Sebastian and Daniela Schwarzer**, “Bringing Macroeconomics into the EU Budget Debate: Why and How?,” *Journal of Common Market Studies*, 2009, 47 (1), 153–174.
- and **Ulrich Fritsche**, “Does the Dispersion of Unit Labor Cost Dynamics in the EMU Imply Long-run Divergence? Results from a Comparison with the United States of America and Germany.,” *Journal of International Economics and Economic Policy*, November 2008, 5 (3), 269–295.
- Easterly, William and Stanley Fischer**, “Inflation and the Poor,” *Journal of Money, Credit and Banking*, May 2001, 33 (2), 160–78.
- Eichengreen, B.**, “The Breakup of the Euro Area,” NBER Working Paper 13393, NBER 2007.

- Elliott, Graham, Thomas J. Rothenberg, and James H. Stock**, “Efficient Tests for an Autoregressive Root,” *Econometrica*, 1996, 64, 813–836.
- Engle, R. and C. W. Granger**, “Co-integration and Error Correction: Representation, Estimation, and Testing,” *Econometrica*, 1987, 55, 251–276.
- European Central Bank**, “Inflation Persistence and Price Setting Behaviour in the Euro Area,” report 2005. available at <http://www.ecb.int/home/pdf/research/inflationpersistencepricesettingreport.pdf>.
- European Commission**, “EMU@10: successes and challenges after 10 years of Economic and Monetary Union,” *European Economy* 2 2008.
- Fritsche, U., C. Logeay, K. Lommatzsch, K. Rietzler, S. Stephan, R. Zwiener, C. Kiziltepe, and Ch. Proano Acosta**, “Auswirkungen von länderspezifischen Differenzen in der Lohn-, Preisniveau und Produktivitätsentwicklung auf Wachstum und Beschäftigung in den Ländern des Euroraums,” Politikberatung kompakt 08/2005, Deutsches Institut für Wirtschaftsforschung (DIW Berlin) 2005.
- Garner, Thesia I., David S. Johnson, and Mary F. Kokoski**, “An Experimental Consumer Price Index for the Poor,” *Monthly Labor Review*, September 1996, 119 (9), 32–42.
- Gros, D.**, “Will EMU survive 2010?,” Technical Report, Centre for European Policy Studies 2006.
- Hagemann, Robert P.**, “The Variability of Inflation Rates across Household Types,” *Journal of Money, Credit and Banking*, November 1982, 14 (4 (1)), 494–510.
- Hobijn, Bart and David Lagakos**, “Inflation Inequality in the United States,” *Review of Income and Wealth*, December 2005, 51 (4), 581–606.
- Idson, Todd and Cynthia Miller**, “The Implications of Demographic-Specific Inflation Rates for Trends in Real Educational Wage Differentials,” *Journal of Business and Economic Statistics*, October 1997, 15 (4), 464–469.
- Johansen, S.**, *Likelihood-based Inference in Cointegrated Vector Autoregressive Models*, Oxford: Oxford University Press, 1995.
- Kao, C.**, “Spurious Regression and Residual-Based Tests for Cointegration in Panel Data,” *Journal of Econometrics*, 1999, 90, 1–44.
- Lane, Ph.**, “The real effects of EMU,” Discussion Paper Series 5536, CEPR 2006.
- Lettau, Martin and Sydney Ludvigson**, “Consumption, Aggregate Wealth, and Expected Stock Returns,” *Journal of Finance*, 2001, 56 (3), 815–849.
- Levin, A., C.-F. Lin, and C.-S. Chu**, “Unit root tests in panel data: Asymptotic and finite sample properties,” *Journal of Econometrics*, 2002, 108, 1–24.
- Livada, Alexandra**, “The Distribution of Household Inflation Rates: The Greek Experience,” *Bulletin of Economic Research*, July 1990, 42 (3), 175–196.
- Maddala, G. S. and S. Wu**, “A Comparative Study of Unit Root Tests with Panel Data and A New Simple Test,” *Oxford Bulletin of Economics and Statistics*, 1999, 61, 631–52.
- **and Shaowen Wu**, “A Comparative Study of Unit Root Tests with Panel Data and a New Simple Test,” *Oxford Bulletin of Economics and Statistics*, November 1999, 61 (Special Issue), 631–652.
- Michael, Robert T.**, “Variation Across Households in the Rate of Inflation,” *Journal of Money, Credit and Banking*, February 1979, 11 (1), 32–46.
- Noll, Heinz-Herbert and Stefan Weick**, *Soziale Ungleichheit, Kulturelle Unterschiede - Verhandlungen des 32. Kongresses der Deutschen Gesellschaft für Soziologie in München 2004*, 1 ed., Vol. Teilband 1, Frankfurt am Main: Campus, August
- **and —**, “Einkommensarmut und Konsumarmut - unterschiedliche Perspektiven und Diagnosen,” *ZUMA Informationsdienst Soziale Indikatoren (ISI)*, January 2007, 37, 1–6.
- Quah, D. T.**, “Empirics for Growth and Distribution: Stratification, Polarization, and Convergence Clubs,” *Journal of Economic Growth*, 1997, 2, 27–59.
- Rippin, Franziska**, “Gibt es gruppenspezifische Inflation? Eine Sensitivitätsanalyse mit Hilfe der Einkommens- und Verbrauchsstichprobe,” Master’s thesis, University of Erfurt 2006.

Romer, Christina D. and David H. Romer, "Monetary policy and the well-being of the poor," *Proceedings*, 1998, pp. 159–201.

Slacalek, J., "What Drives Personal Consumption? The Role of Housing and Financial Wealth," DIW Berlin Discussion Paper 647, DIW Berlin 2006.

Appendix

Construction of Household-Specific Inflation Rates

The inflation rate in period t is defined as the ratio of weighted averages of the percentage price changes of each of the goods categories between period t and a base period in the numerator and between period $t - 1$ and a base period in the denominator. Let $p_{j,t}$ be the price index for good category j at time t , and let $t = b$ denote the base period. Furthermore, let $w_{j,b}$ be the aggregate expenditure share of goods category j in the base period. Using this notation, inflation is defined as follows:

$$\pi_t = \frac{\sum_{j=1}^m w_{j,b} \frac{p_{j,t}}{p_{j,b}}}{\sum_{j=1}^m w_{j,b} \frac{p_{j,t-1}}{p_{j,b}}} - 1 \quad (11)$$

In other words, the inflation rate gauges the percentage change in the price of the base-period goods basket between $t - 1$ and t . Nonetheless, the updates of the base period and of the expenditure weights are rather infrequent, which is the main source of a substitution bias in the index. This means that an inflation rate measured as described above does not properly account for people substituting goods that become relatively cheaper for more expensive goods. In order to minimize this drawback our inflation rates are calculated as chain-weighted indices, i.e. updating the expenditure weights in every time period, rather than use weights from some base period. By setting $b = t - 1$ in (11), we obtain an alternative measure of inflation

$$\pi_t^I = \sum_{j=1}^m w_{j,t-1} \frac{p_{j,t}}{p_{j,t-1}} - 1 = \sum_{j=1}^m w_{j,t-1} \left(\frac{p_{j,t}}{p_{j,t-1}} - 1 \right) = \sum_{j=1}^m w_{j,t-1} \pi_{j,t} \quad (12)$$

Employing monthly price data that are not seasonally adjusted results in inflation rates featuring seasonal fluctuations. We overcome this issue by considering annual inflation rates, i.e. we compare current prices with those twelve months earlier.²⁹

So far, our definition of household-specific inflation rate does not contain any household-specific dimension. In principle, we would need both household-specific expenditure weights and household-specific price changes. For each household, which we will index by i , we observe its specific expenditure shares, $w_{i,j,t}$ for each of the m goods categories.³⁰ However, the specific prices that households pay for the goods categories are unknown. Therefore, we assumed that all households face the same price increases, $p_{j,t}$, for each goods category. The idea behind

²⁹The methods leads in turn to a negative moving average effect in the residuals. As much as possible we are taking this into consideration when we do our econometric analysis.

³⁰Throughout the time span considered in our analysis, Eurostat collected the household-specific expenditure weights only in $t = 1999$ and $t = 2005$, whereas the usual consumer price index item weights according to the COICOP 2 level, which provides information about the changes in the aggregate (representative, median) basket, are adjusted and published on yearly basis. In order to cope with this missing data problem and obtain yearly household-specific expenditure weights, we tracked the evolution of the consumer price index expenditure weights over time and apply the observed changes to the 1999 weights of the characteristics group, keeping the relative distance between the household-specific baskets and the consumer price index basket constant at the 1999 level.

this assumption is that for any particular goods category at each point in time each household faces the same price increase as all other households, but the expenditure profiles they chose in response to these prices are different. This is a common assumption when constructing group price indices, as in Amble and Stewart (1994) and Garner et al. (1996) Garner et al. (1996). Plugging the household-specific expenditure shares in the annual inflation rate as calculated in (12) we arrive at our definition of a household inflation rate, $\tilde{\pi}_{i,t}$ for household i in month t :

$$\tilde{\pi}_{i,t} = \frac{1}{\sum_{j=1}^m w_{i,j,t-1}^{1999}} \sum_{j=1}^m \pi_{j,t} w_{i,j,t-1}^{1999} \quad (13)$$

Here $\pi_{j,t}$ is the inflation in goods category j over the year preceding month t and $w_{i,j,t-1}$ is household i 's expenditure share on good category j defined as:

$$w_{i,j,t-1}^{1999} = \frac{w_{j,t-1}^{HICP}}{w_{j,1999}^{HICP}} w_{i,j,1999}^{1999} \quad (14)$$

where $w_{j,1999}^{HICP}$ and $w_{j,t-1}^{HICP}$ refer to the HICP weights for item j in 1999 and $(t-1)$, respectively, while $w_{i,j,1999}^{1999}$ indicate the 1999 household-specific expenditure weight for good category j and socio-economic category i .

The data are drawn from two sources. Data on household expenditures are obtained from the Household Budget Surveys (HBSs). The HBSs are national surveys whose purpose is to give a picture of living conditions of private households by looking at their total consumption expenditure broken down by household characteristics such as income, socio-economic characteristics, size and composition, degree of urbanisation and region.³¹ Two thirds of the EU Member States carry out annual surveys and the remainder have five-yearly or longer intervals between surveys. For this reason, throughout the considered time span the household-specific consumption baskets are available only for 1999 and 2005. Data collection in the HBS involves a combination of (a) interviews, and (b) diaries maintained by households and/or individuals, generally on a daily basis. The basic unit of data collection and analysis in HBSs is the household. A crucial issue in the survey is the identification of the reference person (often the head of the household) whose personal characteristics can be used in the classification and analysis of information on the household. The socio-economic group, occupation and employment status, income, sex and age of the reference person is often used to classify and present results. In our analysis, we considered the following categories of household characteristics: employment status of the reference person (manual workers in industry and services, non-manual workers in industry and services, self-employed, unemployed, retired, inactive population); number of active persons (0, 1, 2, 3 and more); income quintile (1 to 5); type of households (single person, single parent with dependent children, two adults, two adults with dependent children, three or more adults, three or more adults with dependent children); age of reference person (less than 30, 30 to 44 years, 45 to 59 years, 60 years and older).

Data on the spending structure on the aggregate level consist in the annual weights for the HICP sub-indices on a national level. They represent the aggregate expenditure on any goods category covered by the HICP, expressed as a proportion of the total expenditure on all goods within the HICP coverage. Monthly price data are obtained from the HICP series for the good categories according to the Classification of individual consumption by purpose (COICOP), level 2³², which includes: Food, Alcohol and Tobacco, Clothing, Utilities, Household Equipment,

³¹Due to lack of data availability, we discarded the categories “degree of urbanization” and “household’s primary income source” from our analysis.

³²More disaggregated data are not available for all EU15 countries.

Health, Transport, Communications, Recreation and Culture, Education, Hotels and Restaurants, and Miscellaneous.

To keep the headers of the time series short, we use a system of descriptors where the first part (SOC, ACT, QUINT, HH, ...) refers to the household categories we use, whereas the second part refers to subcategories. A complete overview of all time series, country abbreviations and a list of descriptors can be found in Tables 12 to 14.

Table 12: Description of COICOP Categories

Category	Description
cp1	Food, and non-alcoholic beverages
cp2	Alcoholic beverages and tobacco
cp3	Clothing and footwear
cp4	Housing, water, electricity, gas and other fuels
cp5	Furnishings, household equipment and maintenance of house
cp6	Health
cp7	Transport
cp8	Communication
cp9	Recreation and culture
cp10	Education
cp11	Hotels, cafes and restaurants
cp12	Miscellaneous goods and services

Table 13: Country Codes

Code	Country
AT	Austria
BE	Belgium
DE	Germany
DK	Denmark
EA	Euro Area
ES	Spain
FI	Finland
FR	France
GR	Greece
IE	Ireland
IT	Italy
LU	Luxemburg
NL	Netherlands
PT	Portugal
SE	Sweden
UK	United Kingdom

Table 14: Identifiers for Socio-economic characteristics

Consumption structure...		Descriptor	
		level 1	level 2
by employment status	manual worker	SOC	WORK
	non-manual worker		EMPL
	self-employed		FREE
	unemployed		UNEMP
	retired		RETIR
	inactive		INACT
by number of active persons	zero	ACT	0
	one		1
	two		2
	three and more		3
by income quintile	first	QUINT	1
	second		2
	third		3
	fourth		4
	fifth		5
by household type	single person	HH	SING
	single parent with dependent children		SINGCH
	two adults		2ADU
	two adults with dependent children		2ADUCH
	three or more adults		3ADU
	three or more adults w. dep. children		3ADUCH
by age of reference person	less than 30		0_29
	30 to 44 years		30_44
	45 to 59 years		45_59
	60 years and older		60_