# Projection of household-level consumption expenditures in a macromicro consistent framework

Ulmed Temursho, Matthias Weitzel and Rafael Garaffa

April 2024

## IOpedia Research Paper No. 05



### Projection of household-level consumption expenditures in a macro-micro consistent framework\*

Umed Temursho<sup>a,b,#</sup>, Matthias Weitzel<sup>a</sup>, Rafael Garaffa<sup>a</sup>

<sup>a</sup>European Commission, Joint Reseach Centre (JRC), Seville, Spain <sup>b</sup>IOpedia (www.iopedia.eu), Seville, Spain

April 1, 2024

#### Abstract

This paper presents a new approach for projecting or updating household-level consumption expenditures in line with the existing macro-data (projections) on aggregate consumption and demographic dynamics. Our macro-micro modelling exercises reveal that the use of outdated microdata could lead to an overestimation of direct climate policy costs as well as benefits from compensatory revenue recycling measures. In terms of distributional impacts, using unadjusted microdata may overstate the regressivity of climate policy costs and the progressivity of after-transfer welfare impacts. These results highlight the importance of using fully consistent macro and micro datasets in policy evaluations. The study further emphasizes the value of producing consumer expenditure projections to quantify the relative uncertainties (or robustness) of results in integrated macro-micro modelling, particularly in relation to (un)expected shifts in household consumption patterns, assessment of different policy instruments or scenarios, and comparisons of projected distributional measures, inequality indicators, and other policy-relevant metrics such as energy or transport poverty.

**Keywords**: consumer expenditure projections, consumption structure change, population dynamics, macro-micro modelling, distributional analysis

**JEL classification**: C63, C68, D12, O11, O12

<sup>\*</sup> The information and views set out are those of the authors and do not necessarily reflect the official opinion of the European Commission. This report was prepared under the GD-AMEDI/AMEDI+ projects. We gratefully acknowledge the feedback received from Alessia Fulvimari (EMPL) and Antonio Amores (JRC.B2).

<sup>#</sup> Corresponding author. E-mail: <u>umed.temursho@ec.europa.eu</u>

#### **1** Introduction

To conduct a comprehensive assessment of various policies, it is no longer sufficient to present estimated impacts solely in terms of aggregate measures such as GDP, trade balance, investments, savings, or (un)employment by industry. Given the high priority of social and fairness on the EU policy agenda (e.g. in the context of the green transition towards climate neutrality<sup>1</sup>), it is essential to add to the analysis the distributional impacts of policies. This necessitates integrated macro-micro modelling assessments.

To ensure reliable results, it is crucial that the databases underpinning integrated macromicro modelling are made mutually consistent is some way, which may vary depending on the objectives of a specific (modelling) project. The data used in macro models often come from National Accounts (NA), which are generally comparable across countries and are comprehensive in that they include all forms of economic activities, including shadow economy. This comparability comes from the fact that NA follow a globally harmonized methodology of the System of National Accounts (SNA 2008).<sup>2</sup> On the flip side, NA depict economic behaviour of the average household, overlooking the significance of household heterogeneity. Hence, to study distributional issues, economic modellers are required to additionally use microdata, obtained from social surveys and/or administrative records.

The macro and micro datasets, however, are not easily compatible as they usually use different concepts of income and consumption.<sup>3</sup> These concepts for macro and micro data are defined, respectively, in the SNA and Canberra Group Handbook (UNECE 2011). On the national accounts agenda, the issue of joint use of the macro and micro data for the compilation of policy-relevant statistics for different household groups started in 2009. In particular, the report of the Commission on the Measurement of Economic Performance and Social Progress (Stiglitz et al. 2009) and the Communication of the European Commission "GDP and beyond – Measuring progress in a changing world" (EC 2009) shifted the focus from measuring economic production to measuring household economic well-being within an integrated analysis framework (see also European Commission 2023).

The first serious attempt of reconciling macro and microeconomic data started with the launch of the joint OECD-Eurostat Expert Group on Disparities in a National Accounts Framework (EG DNA) in 2011. Its main aim was compilation of distributional measures of income, consumption, and savings across household groups that are consistent with NA definitions and totals (Fesseau and Mattonetti 2013; Fesseau et al. 2013; Eurostat 2013; Zwijnenburg et al. 2021; Coli et al. 2022).<sup>4</sup>

The World Inequality Database (WID.world) is another, perhaps more widely known, project that has developed a methodology for deriving the Distributional National Accounts (DINA), with a focus on income and wealth. Zwijnenburg (2019) discusses in detail the main differences between the EG DNA and DINA as regards their target population, unit of analysis, income concepts and methodological approaches.<sup>5</sup>

Compiling Distributional Financial Accounts in the EU starts with the work of the Expert Group on Linking Macro and Micro Data for the household sector (EG-LMM), set up in December 2015, on comparing and linking the Financial Accounts/NA and the Household

<sup>&</sup>lt;sup>1</sup> See Council Recommendation of 16 June 2022 on <u>ensuring a fair transition towards climate neutrality</u> or the multiple references to a just transition in the European Commission's proposal for a 2040 climate target, including in the title: "Securing our future - Europe's 2040 climate target and path to climate neutrality by 2050 building a sustainable, just and prosperous society" (European Commission, 2024).

<sup>&</sup>lt;sup>2</sup> Comparability is further improved among EU countries due to the European System of National and Regional Accounts (ESA 2010) – an intentionally compatible EU accounting framework that is consistent with the SNA.

<sup>&</sup>lt;sup>3</sup> Other important sources of differences between the macro and micro datasets originate from differences in data collection, classification, timing, coverage, and data quality (due to e.g. sampling and measurement errors). Some of these differences are further discussed in the text.

<sup>&</sup>lt;sup>4</sup> The resulting (experimental) data of this work can be accessed through <u>https://stats.oecd.org/Index.aspx?DataSetCode=EGDNA\_PUBLIC</u> and <u>https://ec.europa.eu/eurostat/web/experimental-statistics/ic-social-surveys-and-national-accounts</u>.

<sup>&</sup>lt;sup>5</sup> For example, instead of households, DINA focuses on adult individuals aged 20 years and older, and instead of focusing on the household sector only, DINA distributes income and wealth of other sectors in the domestic economy to adult individuals to match the corresponding economy-wide measures.

Finance and Consumption Survey (ECB 2020). This work of reconciling macro and micro information on financial and non-financial wealth is now being carried out by the ECB Expert Group on Distributional Financial Accounts (EG DFA). For further details, see e.g. Engel et al. (2022).

Yet, another related initiative, launched in 2017, is the Eurostat-OECD Expert Group on joint distributions of income, consumption and wealth at micro level (EG ICW). Compared to the EG DNA that applies a top-down approach, the EG ICW is a bottom-up approach and aims at obtaining the distributions income, consumption and wealth in the population by joining individual records of different household surveys (Balestra and Oehler, 2023). In particular, the joint distributions allow estimation of saving rates, affordability of essential services, multidimensional poverty and inequality, and of impact of taxes on different household groups.<sup>6</sup>

While the results of the above-mentioned initiatives are valuable, they are generally not adequate for a comprehensive integrated macro-micro modelling purpose. In such cases, it is preferable to directly utilize the underlying micro-datasets that provide detailed information at individual household level. Cazcarro et al. (2022) present a procedure for adjusting household consumption microdata to be directly incorporated into macroeconomic models. Van Ruijven et al. (2015) review and assess literature on methods to include household heterogeneity in global long-term Computable General Equilibrium (CGE) models.

There are basically three ways to incorporate income distribution and other aspects of household heterogeneity into macro/CGE models (Savard 2003; Colombo 2010; Bourguignon and Bussolo 2013; Van Ruijven et al. 2015).<sup>7</sup> First, a single representative household is extended to multiple representative household types, or even to all individual households from a survey, while maintaining the overall structure of the macro model. In a second approach, a relative income distribution, either assumed or estimated from household-level income data, is applied ex-post to a macro-model results. This direct income modelling has no feedback impact on the macro model and does not consider other aspects of household heterogeneity. Finally, the third approach involves integrating macro models with microsimulation models in a sequential (top-down) or iterative (top-down/bottom-up) manner. Here, one might utilize non-behavioral/accounting/arithmetic microsimulation model, or opt for a more sophisticated microsimulation model with behavioral responses of households, such as demand systems and occupational choices.

On the use of household-level data whether for macro-micro modelling or other purposes, two broad groups of empirical work can be distinguished. One group of studies concentrates on diverse topics via econometric estimation or ex-post (distributional) analysis using the (series of the) most recent survey data. Here, concerns often arise regarding the outdatedness of such data. Obviously, the first-best solution is to carry out such surveys at regular basis. However, there is a time delay due to data collection, processing, analysis and/or harmonizing the data across countries before the dataset is made public. Conducting regular surveys also requires solid funding and available human resources. Depending on the purpose of a study, an alternative viable solution, which fully aligns with the objective of this paper and is much less resource- and time-consuming, is to update the existing microdata using the most recent available information on the microrelevant aggregate variables.

The second group of studies focuses on the impact analysis of future (climate, environmental, economic, demographic and other) projections, such as those envisaged in the EU climate target plan for 2030 (Weitzel et al., 2023) or in the impact assessment

<sup>&</sup>lt;sup>6</sup> The corresponding experimental statistics are available at: <u>https://ec.europa.eu/eurostat/web/experimental-statistics/income-consumption-and-wealth</u>

<sup>&</sup>lt;sup>7</sup> The International Journal of Microsimulation published two special issues, one in Spring 2010 on "Macro-micro analytics: Background, motivation, advantages and remaining challenges" and another in Spring 2016 on "Macro-micro analytics: A guide to combining computable general equilibrium and microsimulation modelling frameworks", with many interesting technical papers and applications. For a recent macro-micro modelling application, see e.g. Connolly et al. (2024).

underlying the European Commission's proposal for a 2040 climate target (European Commission, 2024). To be able to do household-level distributional analysis, particularly within the macro-micro modelling framework, we propose projecting the existing consumer expenditure survey into the future in alignment with a particular "macro" outlook of interest. If certain drivers of the macroeconomic development (e.g. income groups) affect the distributional outcomes of the micro-data of interest (such as expenditure shares for energy goods), then using a static micro dataset might introduce a bias into the results. For example, as income increases, expenditure shares of food and energy are expected to decline. Higher energy costs due to the introduction of a carbon price may then be felt less by households and effects might be overstated by using a static dataset to represent household expenditure patterns. This holds true in particular for assessing policies in the medium to long term, where such changes can be expected to be more relevant.

Obviously, projecting changes of household attributes (such as e.g. age, employment, education) over time due to economic development or policy shocks presents a considerable challenge. However, it is not always necessary to project changes in all household characteristics as captured in micro datasets. For the purposes of our work, we incorporate changes in consumption expenditures (shares) and population growth into our microdata projections. As later discussed in Section 3, our approach allows for more elaborate projections at the household level if the relevant information, such as projections on household age composition and/or urban-nonurban divide by regions, is available.



Figure 1. A sketch of our micro-data projection approach

*Note*: Base year may also be referred to as the reference or benchmark year, for which both macro- and microlevel data are available.

To facilitate our upcoming discussion, we present in **Figure 1** the bird's-eye view of our microdata projection procedure at this initial stage. We start with a specific reference (alternatively, benchmark or base) year – the most recent one, for which both the corresponding macro and micro datasets are available. In general, however, depending on the availability, quality and/or nature of both data at hand, the reference-year dataset may also represent a combined picture of the corresponding data for more than one year.

Due to inherent differences between the macro and micro data (Section 2), in practice gaps will persist in the corresponding aggregate consumption figures, even after certain feasible adjustments towards harmonization of the two reference-year datasets are made. For our purposes, these adjustments are applied to the base-year and projected macrodata, while maintaining the benchmark micro-data unchanged as recorded in the original surveys. The rationale behind this first-step adjustment choice is that the base-year household-level consumption figures and structure serve as benchmark data for our projections of the corresponding micro-data into the future.

The relative macro-micro gaps, obtained for the reference year, are then taken as constant in our estimation of future projections of household consumer expenditures. Population projections are incorporated through appropriate adjustments in household survey weights. To ensure that the projected household consumption expenditures (shares) for each consumption category are estimated to be as close as possible to their corresponding figures in the reference-year micro-data, we employ the biproportional adjustment technique in our household-level expenditure projections (see e.g. Kruithof 1937; Stone et al. 1942; Bacharach 1965; Bregman 1967; Ireland and Kullback 1968; McDougal 1999; Miller and Blair 2009).<sup>8</sup> Formally, this closeness aim is captured by the relative entropybased objective function of the underlying optimisation problem. Obviously, the extent of proximity between the benchmark and projected figures is driven and limited by the macrooutlook constraints imposed during the projections.

The remainder of the paper is structured as follows. Section 2 delves into the macro-micro gaps in consumption data, from both theoretical and empirical perspectives. Our micro-data projection method is explained in Section 3. In Section 4, we explore the relevance of micro-data projections for empirical distributional analysis within the macro-micro modelling framework. Finally, Section 5 gives concluding remarks.

<sup>&</sup>lt;sup>8</sup> This method is also known as 'iterative proportional fitting procedure' in statistics or economics, 'RAS method' in economics, 'raking' in survey statistics, and 'matrix scaling' in computer science. Bregman (1967) refers to the method as 'Sheleikhovskii's method', noting that it "was proposed in the 1930's by the Leningrad architect G.V. Sheleikhovskii for calculating passenger flow" (p. 192). Krupp (1979) refers to it as 'Kruithof's projection method' due to Kruithof (1937), who applied the method to estimate telephone communications traffic. For an historical review, see e.g. Lahr and de Mesnard (2004), while for an excellent comprehensive technical and historical analysis of the method, see Idel (2016).

#### 2 Macro-micro gaps in aggregate consumption expenditures

To be able to showcase the quantitative results of our micro-data projection approach, at this point we specify the data employed in this work. However, it must be noted that the methodology is general and can be used for other macro projections and the corresponding micro-data for other countries and/or years.

As a macro-data set, we utilize the projections of household consumption expenditures from the Global Energy and Climate Outlook (GECO, Keramidas et al. 2021) 2021 baseline scenario. For the EU, this time series baseline is fully compatible with the economic, energy and emission trends of the EU Reference scenario (European Commission, 2021a) that was used to assess e.g. the "Fit for 55" policy package. Projected input-output tables<sup>9</sup>, consistent with the GECO report, underly the JRC-GEM-E3 macro model (Capros et al. 2013) which is used for our macro-level evaluation purposes.<sup>10</sup>

As a micro-data set, we use the Household Budget Survey (HBS) data of the EU households for the reference year of 2015, which is documented in Eurostat (2020b). Due to the voluntary nature of the HBS, not all EU Member States participated historically or even currently participate in its compilation. Specifically, the HBS 2015 wave does not include the survey data of Austrian households. As such, the Austrian microdata of consumption survey for 2014-2015 was obtained from the national statistical office of Austria (Statistics Austria 2018) and incorporated into the EU HBS 2015 wave. For the sake of brevity, in the current work this combined dataset is referred to as the EU-HBS-2015.

#### 2.1 Understanding macro-micro data discrepancies

To link the macro and micro models in a more consistent manner, a better understanding of the differences of the corresponding consumption expenditure and income data is essential. In this subsection, we discuss the inherent gaps in the macro and micro consumption expenditure datasets at comparable aggregate levels.<sup>11</sup> The subsequent sections present the quantitative extent of such gaps in our data and the adjustments made to harmonize the two.

National Accounts (NA) and the EU Household Budget Survey (HBS) are the main sources of, respectively, macro and micro consumption expenditure data. Thus, the inherent conceptual and data collection differences of these data sources lead to misalignments of the macro and micro consumption aggregates. In particular, the following differences between the two consumption datasets are worth highlighting (see also e.g. Eurostat, 2018a, 2018b, 2020; Deaton 2001; Deaton and Kozel, 2005):

- *Reference population*. In comparison to the NA figures, the HBS excludes a portion of the population that is not covered in social surveys. This includes individuals residing in institutional (or collective) households or without a registered place of residence. Examples of non-private dwelling include retirement homes, hospitals, nursing homes, prisons, religious institutions, hotels, and boarding schools. In addition, certain households, such as those living in overseas territories or in sparsely populated areas, may be missing from the HBS data.
- Domestic vs national concept of consumption. The NA consumption data utilizes the domestic concept of consumption, which excludes the resident consumption abroad but includes the non-resident consumption in the national territory. In contrast, consumption expenditures reported in the HBS are based on the national concept of consumption. This means that they cover expenditures of residents (private

<sup>&</sup>lt;sup>9</sup> The input-output tables are publicly available at <u>https://data.jrc.ec.europa.eu/dataset/721dcbda-7302-40cc-afe4-4adc3654fe1c</u>.

<sup>&</sup>lt;sup>10</sup> See also Weitzel et al. (2023) for a more recent application to the assessment of the 2030 climate target.

<sup>&</sup>lt;sup>11</sup> In the current report we do not go into the details of misalignments and consequent necessary adjustments of the macro- and micro-level income variables. Preliminary work on the comparative analysis and adjustments of income variables in the EU-SILC and EU Household Budget Survey (HBS) for the reference year of 2010 is documented in Temursho (2021). This study also serves as a partial basis of the current paper, incorporating further refinements to the initial methodology and applying it to a more recent HBS data.

households) both nationally and abroad, while excluding non-resident consumption in the national territory.

- *Measurement and coverage issues*. It is widely recognized, for example, that the HBS consumption data on demerit goods (e.g. alcoholic beverages, tobacco, narcotics) could be biased due to the estimation and measurement errors. Further, most micro-data sources, including the HBS, often largely undercover, hence do not represent well, the wealthiest population (e.g. the top 1% of households). In addition, the necessary balancing procedures used by NA statisticians might introduce biases in the resulting NA consumption figures.
- *Category-specific differences.* NA impute and include Financial Intermediation Services Indirectly Measured (FISIM) into the consumption category "Miscellaneous goods and services", which is not included in the HBS. Similarly, insurance services and wages in kind are included in the NA consumption data but excluded from the corresponding HBS figures. Some specific NA sub-items have no counterpart in the micro-data sources, such as employers' imputed social contributions (D122 and D612), FISIM, investment income attributed to insurance policyholders (D441), investment income payable on pension entitlements (D442), and social transfers in kind (D63). In turn, HBS includes second-hand goods (e.g. clothes, cars) traded domestically between households, which cancel out in the NA consumption aggregates. HBS includes expenditures on repairs of owner-occupied dwellings that are, however, considered as intermediate consumption in the NA.
- Classification inconsistencies. It is possible that certain transactions are classified differently in the two datasets. For example, wages and salaries paid while on sick or maternity leave may be recorded as wages and salaries in micro sources, which however are classified as social benefits in the NA data. Similarly, the income received by a sleeping or silent partner participating in an unincorporated enterprise is typically considered as property income by micro sources but as mixed income in NA (OECD, 2020).

To achieve a complete match between the macro and micro consumption expenditure data, some of the aforementioned differences can be explicitly addressed (such as reference population differences, as outlined in Eurostat, 2020a), while others are considerably complex and require a significant amount of detailed data for proper treatment (e.g. distinguishing between domestic vs. national concepts of consumption).

In summary, there are many reasons, often interconnected in complex ways, for the inconsistencies between the micro and macro data sources, which naturally lead to potentially significant discrepancies in the corresponding aggregate variables. Due to the lack of detailed information, it is practically impossible to fully reconcile the two datasets. Nonetheless, certain feasible adjustments must be made to the two data sources to enable meaningful integration of macro and micro models. This integration leads to more realistic and reliable assessments of the distributional impacts of policies of interest.

#### 2.2 Quantitative evaluation of the macro-micro gaps

Before projecting the micro-data (Section 4), certain adjustments need to be made to maximally align the micro and macro expenditure data for the reference year of 2015. We note that the consumption expenditure aggregates obtained from the projected inputoutput tables, underlying the JRC-GEM-E3 model, are consistent with the NA accounting concepts and principles.

The first adjustment step aligns with the "population scope adjustments" outlined in Eurostat (2020a) and OECD (2020). Specifically, it involves excluding (part of) consumption of non-private households (related to the reference population issue touched upon in Section 2.1) from the corresponding NA totals. This exclusion is based on the premise that "the composition and behaviour of people living in non-private dwellings may be completely different from private households" (OECD, 2020, p. 6). To implement this adjustment, we multiply the original NA expenditure aggregates by country-specific

population adjustment coefficients, which are derived as the ratio of the EU-HBS-2015 total population figures to those of the GECO 2021 that are used in the JRC-GEM-E3 model. The EU-HBS-2015 population figures are calculated as the sum of household sample weights (HA10) multiplied by household size (HB05). The population figures used for computing the population-scope adjustment coefficients, both from the EU-HBS-2015 and GECO 2021 (the latter originating from the projections of the EU Ageing report), pertain to the reference year of 2015.

For transparency, **Table 1** presents the resulting population adjustment coefficients and the population growth factors of GECO 2021, derived for the five-year projection years spanning from 2020 to 2050, all compared to the reference year of 2015. These factors are used in the later steps of our micro-macro data alignment procedure. Note that population-scope adjustment does *not* affect the original NA macro shares of consumption expenditures for individual countries, as all national data are multiplied by the same scaling factor. However, it does influence any derived indicators pertaining to groups of countries, such as the expenditure shares at the EU level.

Country	Population		Population grow	wth factors (wi	th respect to t	he reference ye	ear of 2015)	
Country	adjustment coef.	2020	2025	2030	2035	2040	2045	2050
AT	0.9800	1.031	1.046	1.060	1.069	1.076	1.080	1.081
BE	0.9888	1.022	1.035	1.044	1.050	1.055	1.058	1.058
BG	0.9740	0.964	0.929	0.895	0.864	0.835	0.810	0.786
CY	0.9953	1.052	1.099	1.140	1.172	1.197	1.218	1.236
CZ	0.9230	1.016	1.023	1.020	1.013	1.007	1.002	0.998
DE	0.9365	1.018	1.022	1.021	1.020	1.018	1.016	1.012
DK	0.9291	1.024	1.037	1.050	1.060	1.066	1.070	1.073
EE	0.9483	1.011	1.004	0.994	0.983	0.973	0.964	0.954
EL	0.9782	0.987	0.969	0.950	0.932	0.914	0.896	0.876
ES	0.9799	1.022	1.041	1.050	1.058	1.064	1.065	1.062
FI	0.9880	1.009	1.010	1.007	0.999	0.989	0.977	0.964
FR	0.9782	1.011	1.024	1.034	1.043	1.049	1.052	1.052
HR	1.0086	0.961	0.933	0.907	0.882	0.856	0.830	0.804
HU	0.9788	0.992	0.984	0.976	0.968	0.958	0.949	0.941
IE	0.9861	1.064	1.127	1.175	1.220	1.260	1.295	1.324
IT	0.9948	0.992	0.989	0.987	0.983	0.977	0.968	0.956
LT	0.9929	0.961	0.928	0.882	0.840	0.802	0.766	0.733
LU	0.9458	1.105	1.169	1.221	1.265	1.301	1.330	1.352
LV	0.9898	0.961	0.913	0.861	0.814	0.773	0.736	0.702
MT	0.9481	1.153	1.260	1.329	1.385	1.431	1.470	1.505
NL	0.9340	1.030	1.049	1.062	1.070	1.074	1.073	1.071
PL	0.9741	0.998	0.988	0.973	0.956	0.937	0.917	0.896
PT	1.0016	0.993	0.985	0.973	0.959	0.943	0.924	0.903
RO	0.9998	0.969	0.930	0.895	0.863	0.834	0.806	0.780
SE	0.8224	1.058	1.101	1.136	1.167	1.196	1.225	1.253
SI	0.9812	1.018	1.024	1.020	1.014	1.008	1.000	0.989
SK	1.0003	1.007	1.008	1.002	0.992	0.978	0.963	0.947

**Table 1.** Population-scope adjustment coefficients and projected population growth factors

*Note*: Population adjustment coefficient is the ratio of the EU-HBS-2015 to the GECO 2021 (or JRC-GEM-E3) total population figures. In our application, we set the population-scope adjustment coefficients to unity (instead of the estimated values of being marginally larger than one) for HR, PT and SK. *Source*: own elaboration based on data from EU-HBS-2015 and The 2021 Ageing Report (European Commission, 2021b)

Given the nature of the JRC-GEM-E3 input-output tables (IOTs), we do not carry out other adjustments of the 2015 macro consumption expenditures to further align them with the corresponding micro-data. Unlike other datasets, the consumption demands in the JRC-GEM-E3 IOTs are already distinguished by the main COICOP categories, using a consumption matrix to bridge production sectors with consumption categories (Cai and Vandyck, 2020). Therefore, we can skip the usual product and commodity classifications matching. Additionally, reconciling differences between basic and purchasers' price

expenditures is not needed, as the JRC-GEM-E3 IOT consumption expenditure totals are already provided in users' prices, ensuring comparability with the micro-level expenditures.

It is crucial to emphasize that we regard the EU-HBS-2015 as "sacred" micro-data, thus we refrain from making any adjustments of it in the 2015 macro-micro data alignment process. The rationale behind this decision is our aim to maintain the household-level consumption figures and structure exactly as they were recorded in the original survey data. As detailed later, these country-specific consumption expenditure figures and structures from the reference year will serve as a benchmark for our projections of the micro consumption expenditures.

Let us first look in some detail into the differences between the macro and micro consumption expenditure data, both in terms of shares and values. The macro (population-scope adjusted) and micro consumption expenditure shares are shown in **Table 2**, while the macro-micro percentage differences of consumption shares and levels are reported in **Table 3**. The results are reported for 14 JRC-GEM-E3 consumption categories, defined in **Table A.1** in the Appendix, which also shows their mapping to the European classification of individual consumption according to purpose (ECOICOP) commodity categories.

It follows from these tables that the differences between the macro and micro consumption shares and levels may be considerable. On average, across all the 14 considered products and all 27 EU countries, the microdata-based aggregate consumption expenditure shares are found to be *larger* than their macro equivalents by 21%, ranging from about -6% for Bulgaria (BG) to 50% for Slovenia (SI). If, instead, we look into the weighted average differences, with the weights being the averages of the corresponding macro and micro consumption shares of the considered 14 products as reported in **Table 2**, the overall micro-to-macro expenditure share discrepancy reduces from 21% to 13%. Hence, larger relative macro-micro gaps of aggregate consumption shares, on average, are found for consumption categories with smaller expenditure shares.

It should be noted that the category 'Housing and water charges' (c3), obtained from the micro-data and used for our simulation purposes, excludes imputed rentals for housing (EUR\_HE042). This explains why we find large (negative) discrepancies for category c3 for almost all EU countries **Table 3**. We prefer to use micro-data without imputed rentals for housing as our focus is mainly on households' actual expenditures, imputed rentals data are not available for the Czech Republic and Malta, and "the fact that countries used different estimation methods to calculate the imputed rent for the HBS 2015 wave is likely to have seriously reduced comparability across the countries" (Eurostat, 2020, p. 36).

However, to be more consistent with the macro or NA data, we report in Table A.2 in the Appendix similar results of the micro-to-macro gaps when the EU-HBS-2015 includes imputed rents. As follows from this later table, now we observe that the microdata-based consumption shares for Housing are mostly larger than their macro equivalents. Similar qualitative results were found in Eurostat (2015) when comparing the consumption expenditure structure of the HBS and NA for the reference year of 2010 (Table 16), concluding that the HBS "seems to overestimate the imputed rent for owner-occupier dwellings in comparison to the National Accounts" (p. 45). On the same issue, Eurostat (2020b) concludes that "underreporting of these categories [housing, water, electricity, gas and other fuels, CP04] is not common in the HBS survey because they generally occur only once a month" (p. 43). Note that our results quantitatively are generally not comparable to those reported in Eurostat (2015, 2020b) because of the different product classifications used.

	JRC-GEM-E3 aggregate consumption expenditure shares, 2015 (%)												EU-HBS-2015 aggregate consumption expenditure shares, 2015 (%)															
	c1	c2	c3	c4	c5	c6	c7	c8	c9	c10	c11	c12	c13	c14	c1	c2	c3	c4	c5	c6	c7	c8	c9	c10	c11	c12	c13	c14
AT	13.3	5.9	17.5	4.6	7.4	1.0	3.8	2.4	7.8	2.3	1.9	20.0	11.5	0.7	15.6	5.5	13.6	5.2	8.2	1.3	4.2	6.5	7.6	0.8	1.6	17.5	11.1	1.2
BE	18.9	5.4	18.5	3.2	7.1	0.9	6.7	2.2	7.5	1.0	2.2	11.9	14.1	0.3	17.6	5.3	9.8	6.2	7.2	1.2	5.4	6.3	8.0	1.1	3.5	14.2	13.7	0.6
BG	23.5	2.7	13.7	5.5	5.9	1.2	6.5	1.5	11.5	5.3	4.7	11.3	6.0	0.7	38.3	4.3	4.8	12.3	4.1	1.0	6.3	0.5	6.4	1.5	5.2	9.3	5.4	0.6
CY	18.9	5.2	12.6	3.1	4.9	0.9	5.4	2.3	8.7	1.9	2.7	20.7	10.1	2.7	19.8	6.9	7.6	4.5	6.0	0.9	6.2	3.6	9.4	1.3	4.8	14.0	9.8	5.4
CZ	23.3	3.1	18.9	4.0	6.6	1.0	2.6	2.6	6.7	1.8	3.2	15.7	10.1	0.5	24.3	5.3	10.5	11.8	6.1	1.4	2.8	2.4	7.1	1.6	4.4	13.5	8.3	0.6
DE	14.6	4.7	20.1	3.2	8.4	1.0	5.3	3.1	8.0	2.4	2.2	11.7	14.4	0.8	16.0	5.6	13.3	7.4	6.4	1.0	4.9	6.0	6.5	1.9	3.1	15.0	12.0	1.0
DK	16.1	4.2	22.6	6.0	8.3	0.9	2.8	3.5	7.1	1.4	1.7	12.7	12.1	0.6	16.4	4.7	14.5	8.5	7.4	0.7	2.7	6.7	6.8	1.8	2.9	13.9	12.4	0.5
EE	28.0	6.0	13.2	7.0	4.9	0.9	2.9	1.8	8.4	3.0	2.4	12.3	8.7	0.4	27.4	5.3	7.1	8.9	7.1	1.2	4.5	6.3	6.0	1.5	4.6	12.3	6.5	1.3
EL	21.2	3.5	17.5	4.0	3.6	0.4	4.1	1.6	4.3	7.2	4.3	17.8	8.7	1.9	26.8	5.9	6.7	7.1	5.3	0.6	7.7	2.8	7.2	1.7	4.2	12.6	8.0	3.4
ES	16.5	4.2	20.0	3.8	4.8	0.8	3.9	1.8	7.9	2.2	2.5	20.2	10.0	1.5	21.6	6.5	8.6	5.2	5.3	1.0	4.5	3.9	9.1	1.7	3.7	16.8	10.4	1.8
FI	16.2	3.8	23.1	5.5	6.2	0.7	4.2	2.7	8.6	2.3	2.3	13.3	10.9	0.3	16.8	3.5	15.3	4.2	6.3	0.8	4.1	7.2	8.6	2.6	3.1	12.4	14.9	0.2
FR	16.0	3.7	22.4	4.5	6.1	0.9	4.2	2.2	8.7	2.6	2.6	12.0	13.9	0.4	19.8	4.7	11.3	5.1	6.2	0.7	1.9	7.2	6.3	2.1	2.8	12.9	18.5	0.7
HR	28.2	4.4	12.2	4.8	5.1	0.7	3.6	1.3	5.7	3.2	3.6	17.4	8.9	0.9	32.9	6.8	5.7	10.6	4.4	0.7	2.9	1.8	9.5	1.7	5.5	6.5	9.9	1.0
HU	26.1	3.5	14.6	2.7	4.9	1.0	4.8	2.2	8.9	2.3	4.0	13.2	10.3	1.7	28.1	4.2	8.7	13.0	4.0	0.7	5.1	1.8	7.9	1.5	7.2	8.8	8.2	0.9
IE	14.1	3.9	19.0	2.8	5.4	0.5	5.0	2.4	6.9	4.6	2.8	20.5	9.5	2.7	17.0	5.4	9.9	6.0	4.9	0.6	2.9	7.3	7.4	1.3	4.8	15.4	14.2	2.8
IT	16.9	6.0	20.9	1.8	6.7	0.7	3.4	1.7	10.3	1.8	2.5	14.9	11.4	0.9	25.8	6.2	9.2	6.1	5.3	0.8	6.0	3.0	9.9	1.2	3.3	11.3	11.1	0.8
LT	29.8	5.9	10.7	3.2	7.4	1.4	5.1	2.6	11.1	2.0	2.6	8.3	9.5	0.4	35.5	7.0	3.5	10.7	6.0	0.7	6.7	1.9	7.3	1.2	4.3	7.5	6.9	0.8
LU	16.9	5.8	22.1	1.4	5.9	0.8	2.7	3.3	11.3	0.8	1.6	12.2	14.4	0.9	12.8	6.8	12.3	4.8	8.3	1.1	3.1	10.0	6.7	1.3	3.2	16.8	11.8	1.0
LV	27.5	5.8	15.4	5.3	4.9	0.9	4.4	1.5	8.2	2.4	2.5	12.6	7.3	1.3	29.9	6.1	5.9	9.7	4.9	0.8	6.4	2.5	8.7	2.0	4.4	10.8	6.7	1.3
MT	17.3	4.4	9.0	2.5	8.1	1.5	4.4	2.6	8.1	2.1	3.5	23.2	12.0	1.2	22.1	7.9	5.6	2.8	7.9	1.3	5.6	5.3	6.6	2.3	4.3	13.3	12.1	2.8
NL	15.7	5.6	21.1	2.5	7.3	0.6	3.4	2.4	7.7	2.3	3.1	13.7	14.2	0.6	15.7	5.3	13.5	5.3	7.1	0.8	1.5	5.5	7.7	1.8	3.8	12.8	17.6	1.5
PL	18.1	5.5	18.5	3.1	8.6	1.0	3.2	4.5	6.4	3.7	2.0	12.1	12.9	0.3	28.3	5.8	9.3	12.2	5.3	0.8	5.6	1.3	6.6	1.4	5.4	9.8	7.0	1.1
PT	22.2	4.9	13.6	4.5	5.9	1.1	5.8	2.3	10.8	1.9	2.5	8.3	15.2	1.0	19.9	4.3	7.0	7.9	4.9	0.7	6.9	4.7	11.5	1.5	4.1	14.2	9.6	2.8
RO	20.2	6.6	14.1	5.3	5.1	0.9	5.0	3.6	6.9	1.9	2.2	15.2	11.7	1.3	46.1	5.7	4.9	13.1	3.9	0.6	4.9	0.4	4.2	1.6	5.0	4.3	4.8	0.4
SE	20.7	4.5	16.6	6.6	4.9	1.1	4.1	1.7	11.1	3.0	6.2	7.9	10.2	1.3	16.0	5.0	16.6	4.1	9.9	1.0	2.5	6.9	8.3	1.7	3.7	15.4	8.8	0.2
SI	17.3	5.0	19.0	5.2	7.4	0.7	3.0	2.6	10.0	2.4	2.7	13.0	11.6	0.2	18.8	6.5	5.8	9.4	5.0	0.9	2.5	6.9	12.9	0.4	5.6	11.3	12.9	1.0
SK	22.0	5.4	11.5	4.1	5.4	1.3	4.2	3.1	12.1	1.3	3.0	14.0	11.5	1.2	25.6	5.4	8.0	13.2	5.5	1.1	3.2	4.8	5.9	1.7	5.6	10.2	8.9	0.8
EU27	16.8	4.7	20.0	3.6	6.8	0.9	4.3	2.5	8.5	2.4	2.6	13.6	12.6	0.8	20.1	5.5	11.2	6.5	6.2	0.9	4.1	5.3	7.6	1.7	3.4	13.6	12.8	1.1

Table 2. Macro and micro country-level consumption expenditure shares, 2015 (%)

*Note*: Household survey weights are appropriately accounted for when obtaining the EU-HBS-2015 aggregate expenditure shares. Note that population-scope adjustment of the NA consumption figures does not affect the original macro consumption expenditure shares. The 14 household consumption categories (c1 to c14) in JRC-GEM-E3 and their mapping to the ECOICOP classification is given in Table A.1 in the Appendix. *Source*: own elaboration based on the EU-HBS-2015 and GECO 2021 (JRC-GEM-E3) consumption data.

	c1	c2	c3	c4	c5	c6	c7	c8	c9	c10	c11	c12	c13	c14	Mean	Wmean
					Differe	ences betv	veen the r	nicro and	macro con	nsumption	expendit	ure shares	(%)			
AT	17.7	-7.6	-22.3	13.1	10.2	23.2	12.8	171.4	-2.5	-64.6	-14.2	-12.2	-3.0	69.5	13.7	5.1
BE	-6.8	-1.1	-47.4	92.3	0.9	25.8	-19.2	182.2	7.4	7.2	59.6	19.4	-2.8	77.5	28.2	8.1
BG	63.1	58.6	-64.7	122.3	-30.8	-19.5	-3.7	-65.2	-44.1	-70.7	10.9	-17.6	-10.5	-17.6	-6.4	15.5
CY	5.0	32.1	-39.9	43.3	24.0	-2.0	14.4	55.0	8.1	-28.8	80.2	-32.6	-3.3	98.4	18.1	5.5
CZ	4.1	70.8	-44.5	196.8	-8.0	40.9	7.1	-7.0	4.8	-12.9	40.2	-14.0	-17.6	27.5	20.6	11.1
DE	9.1	18.1	-33.6	130.3	-23.4	4.9	-8.4	91.8	-18.6	-23.1	41.0	27.9	-17.2	30.7	16.4	6.6
DK	1.3	11.9	-35.6	43.2	-10.2	-15.9	-2.0	92.0	-4.6	27.0	66.4	9.5	1.9	-14.9	12.1	4.1
EE	-2.1	-11.7	-46.3	27.8	44.7	39.2	51.1	249.0	-29.1	-50.8	90.0	0.2	-24.9	240.7	41.3	11.3
EL	26.5	65.9	-61.6	75.6	45.3	51.7	87.3	77.7	68.8	-76.8	-0.3	-29.0	-7.1	81.2	28.9	13.0
ES	30.6	55.1	-57.0	34.7	10.9	27.9	16.9	117.6	14.4	-22.8	50.1	-16.7	4.3	16.8	20.2	7.0
FI	3.5	-5.9	-33.7	-24.6	2.1	15.0	-4.0	167.4	0.6	14.7	34.5	-6.5	36.8	-31.0	12.1	6.2
FK	23.8	26.7	-49.4	12.4	1.3	-15.7	-55.0	221.2	-27.9	-17.0	8.0	()./	33.4	72.8	17.3	10.8
нк	10.8	54.3	-53.1	122.2	-12.5	-7.8	-19.7	41.0	10.2	-48.8	52.1	-02.5	10.6	21.8	13.0	12.1
HU	20.9	20.4	-40.4	3/9.3	-19.0	-52.0	42.1	-16.7	-10.2	-32.3	62.5	-55.4	-20.5	-44.9	24.1	23.0
15	20.0	2.4	-47.0	222.6	=0.0	10.9	-42.1	70.2	1.2	-/1./	22.1	-24.0	49.7	4.5	24.1	14.0
11	10.1	18.5	-50.1	232.0	-21.1	-50.3	31.2	-26.4	-34.2	-32.3	62.7	-24.2	-3.1	-10.8	13.7	14.4
	-24.2	18.3	-07.2	234.0	42.6	28.3	14.1	204 5	-34.2	-30.1	106.3	37.6	-20.1	97.5	15.7	14.4
IV	-24.2	49	-44.3	83.3	42.0	-19.7	45.6	66.4	6.2	-16.2	73.2	-14.9	-10.1	3.7	12.3	66
MT	27.7	79.7	-37.2	11.0	-2.8	-11.4	26.9	102.7	-18.4	73	23.6	-42.6	0.6	128.6	21.1	7.6
NL	0.4	-5.1	-36.1	116.3	-2.0	35.6	-55.3	135.1	-0.8	-20.2	22.0	-6.1	24.0	140.5	24.9	6.9
PL	56.4	5.0	-49.8	290.9	-38.3	-18.9	77.5	-71.0	4.3	-61.7	165.3	-18.8	-45.7	287.6	41.6	27.3
PT	-10.3	-11.2	-48.2	74.2	-18.1	-39.3	19.0	102.3	6.6	-21.6	65.5	71.0	-36.8	196.9	25.0	10.0
RO	128.4	-13.2	-65.4	145.9	-22.7	-29.2	-3.1	-87.8	-39.1	-14.3	124.5	-71.9	-58.8	-67.1	-5.3	35.4
SE	-22.3	10.3	-0.1	-38.0	102.4	-9.5	-38.9	315.5	-25.6	-43.6	-40.5	93.6	-14.2	-85.1	14.6	17.3
SI	8.9	31.1	-69.7	82.2	-32.9	33.9	-18.9	162.5	28.9	-80.9	108.4	-12.6	11.1	448.7	50.1	15.4
SK	16.2	0.6	-29.8	218.1	2.9	-10.8	-23.8	53.5	-51.4	38.7	84.4	-26.7	-22.4	-33.4	15.4	14.9
Average	17.9	21.0	-46.0	113.5	0.7	2.9	7.1	97.1	-4.7	-25.4	55.4	-7.8	-6.3	64.6	20.7	12.6
					Differ	ences bet	ween the	micro and	macro co	nsumptior	n expendit	ure levels	(%)			
AT	-30.9	-45.8	-54.4	-33.6	-35.3	-27.7	-33.8	59.2	-42.8	-79.2	-49.7	-48.5	-43.1	-0.6	-33.3	-38.3
BE	-47.1	-44.0	-70.2	9.0	-42.8	-28.7	-54.2	60.0	-39.1	-39.2	-9.6	-32.3	-44.9	0.6	-27.3	-38.7
BG	-32.4	-34.3	-85.4	-7.9	-71.3	-66.6	-60.1	-85.6	-76.8	-87.9	-54.0	-65.8	-62.9	-65.8	-61.2	-52.1
CY	-41.4	-26.3	-66.5	-20.0	-30.8	-45.3	-36.1	-13.5	-39.7	-60.3	0.6	-62.4	-46.0	10.7	-34.1	-41.1
CZ	-43.5	-7.3	-69.8	61.1	-50.0	-23.5	-41.9	-49.5	-43.1	-52.7	-23.9	-53.3	-55.3	-30.8	-34.5	-39.7
DE	-39.3	-34.3	-63.0	28.2	-57.4	-41.6	-49.0	6.7	-54.7	-57.2	-21.5	-28.8	-53.9	-27.2	-35.2	-40.6
DK	-43.3	-37.5	-64.0	-19.9	-49.8	-53.0	-45.2	7.3	-46.7	-29.0	-6.9	-38.8	-43.0	-52.4	-37.3	-41.8
EE	-58.5	-62.6	-77.2	-45.8	-38.7	-41.0	-35.9	47.9	-70.0	-79.1	-19.5	-57.5	-68.2	44.4	-40.1	-52.8
EL	-39.3	-20.4	-81.6	-15.7	-30.3	-27.2	-10.1	-14.8	-19.0	-88.9	-52.2	-65.9	-55.4	-13.1	-38.1	-45.8
ES	-25.2	-11.1	-75.3	-22.8	-36.5	-26.7	-33.0	24.7	-34.4	-55.8	-14.0	-52.2	-40.2	-33.1	-31.1	-38.7
FI	-34.1	-40.1	-57.8	-52.0	-35.0	-26.7	-38.8	70.3	-35.9	-27.0	-14.3	-40.4	-12.9	-56.0	-28.6	-32.3
FK	-31.6	-29.9	-72.0	-37.8	-44.0	-53.4	-/5.5	77.6	-60.1	-54.1	-40.3	-40.5	-26.2	-4.4	-35.2	-38.7
	-35.2	-19.7	70.5	127.4	-54.5	-32.0	-30.2	-20.3	-13.2	-73.5	-20.8	-60.5	-42.5	-30.0	-41.2	-41.0
IF	-40.8	-40.3	-70.5	34.5	-00.2	-00.5	-47.3	92.0	-33.6	-82.5	3.9	-53.3	-00.0	-72.7	-41.0	-30.0
IT	-20.5	-46.2	-77.2	72.9	-59.0	-38.5	-8.5	-7.3	-50.2	-64.8	-30.8	-60.6	-49.6	-56.7	-35.5	-41 3
LT	-59.2	-59.4	-88.8	14.7	-71.9	-83.0	-55.0	-74.8	-77.5	-78.8	-44.2	-69.0	-75.4	-32.4	-61.0	-60.8
LU	-74.0	-59.5	-80.9	12.7	-51.1	-56.0	-60.9	4.4	-79.6	-42.2	-29.2	-52.8	-71.9	-62.4	-50.2	-59.8
LV	-59.4	-60.8	-85.7	-31.6	-62.6	-70.0	-45.6	-37.9	-60.3	-68.7	-35.3	-68.2	-65.5	-61.3	-58.1	-60.2
MT	-38.6	-13.5	-69.8	-46.6	-53.2	-57.4	-38.9	-2.5	-60.7	-48.4	-40.5	-72.4	-51.6	10.0	-41.7	-48.2
NL	-32.3	-36.0	-56.8	46.0	-33.8	-8.5	-69.8	58.7	-33.0	-46.1	-17.6	-36.6	-16.3	62.3	-15.7	-27.8
PL	-40.5	-60.1	-80.9	48.6	-76.6	-69.2	-32.5	-89.0	-60.3	-85.5	0.9	-69.1	-79.3	47.4	-46.2	-51.6
PT	-57.4	-57.8	-75.4	-17.2	-61.1	-71.2	-43.5	-3.9	-49.3	-62.8	-21.4	-18.8	-70.0	41.1	-40.6	-47.7
RO	-31.1	-73.8	-89.6	-25.9	-76.7	-78.7	-70.8	-96.3	-81.6	-74.1	-32.3	-91.5	-87.6	-90.1	-71.4	-59.2
SE	-58.3	-40.8	-46.4	-66.8	8.6	-51.5	-67.2	122.9	-60.1	-69.7	-68.1	3.8	-54.0	-92.0	-38.6	-37.1
SI	-40.8	-28.7	-83.5	-0.9	-63.5	-27.2	-55.9	42.7	-29.9	-89.6	13.3	-52.5	-39.6	198.2	-18.4	-37.3
SK	-53.1	-59.4	-71.7	28.4	-58.5	-64.0	-69.2	-38.0	-80.4	-44.0	-25.5	-70.4	-68.7	-73.1	-53.4	-53.6
Average	-42.3	-30 /	-72 5	2.4	-49.6	-47 5	-48.2	28	-51/	-63.2	-24.6	-53.5	-51.6	-17.8	-30.7	-44.3

Table 3. Differences between the EU-HBS-2015 and JRC-GEM-E3 aggregate consumption expenditure shares and levels, 2015 (%)

*Note*: The reported differences of shares/levels are defined as 100\*[(EU-HBS-2015 consumption share/level)/(JRC-GEM-E3 expenditure share/level) -1]. "Mean" represents a simple arithmetic average of the presented 14 differences along each row, while "Wmean" is the corresponding weighted average, with weights being equal to the average macro and micro expenditure shares reported in **Table 2**. *Source*: own elaboration based on EU-HBS-2015 and JRC-GEM-E3 data.

One could also speculate on possible explanations of the qualitative differences of other aggregate expenditure categories reported in **Table 3**. For instance, as reported in Eurostat (2015, 2020b), in most countries HBS reports more expenditures on 'Food and non-alcoholic beverages' (CP01) than in the NA. On the other hand, micro sources often underestimate household expenditures on "sensitive products" such as 'Alcoholic beverages, tobacco and narcotics' (CP02). These macro-micro counteracting effects should

be part of the explanations of the differences found for 'Food, beverages and tobacco' (c1) in **Table 3**.

In terms of consumption levels, the differences may also be quite considerable. As follows from the bottom part of **Table 3**, across all products and all countries, the micro aggregate consumption expenditures are, on average, *smaller* than their macro counterparts by about 40%. In other words, the micro aggregated consumption expenditures, on average, "cover" about 60% of the corresponding NA data. Following Eurostat (2018), we define a coverage rate for each consumption category as a ratio between the EU-HBS-2015 aggregated data and the equivalent NA consumption figures.<sup>12</sup> TableA.3 in the Appendix shows the coverage rates (in a heatmap) corresponding to the macro-micro level gaps reported in **Table 3**. The country average coverage rates range from 29% for Romania to 84 for the Netherlands. In terms of consumption categories, the lowest average-acrossall-27EU-countries coverage rate is found for 'Housing and water charges' (c3), which is largely due to the exclusion of imputed rents.<sup>13</sup> The highest average coverage rates of 103% and 102% are detected for, respectively, 'Purchase of vehicles' (c8) and 'Fuels and power' (c4). In general, Education (c14) and 'Purchase of vehicles' (c8) show the highest standard deviations of the coverage rates of, respectively, 61% and 59%, compared to the mean standard deviation of 26%. The least variability of coverage rates across countries are found for 'Housing and water charges' (c3) and 'Food, beverages and tobacco' (c1), with the corresponding standard deviations of 11% and 13%, respectively.

In terms of product-specific coverage rates, these vary widely, from as low as 4% in Romania for 'Purchase of vehicles' (c8) to an extreme outlier of 298% in Slovenia for Education (c14). This latter figure is due to the small value of Education expenditure in Slovenia as reported in GECO 2021. Overall, however, all the reported coverage rates of household consumption are in line with the findings in Eurostat (2018) when comparing the HBS and NA data for the year of 2010. In that study, the coverage rates were also found to differ considerably across different COICOP categories and the EU countries, ranging from 6% for Education in Sweden to 128% for 'Housing, water, electricity, gas and other fuels' in Cyprus, with an overall average coverage rate of 69% (see Figure 2 in the report).<sup>14</sup> Obviously, quantitatively our results generally will not match those reported in Eurostat (2018) because of the use of different datasets and commodity classifications.

The coverage rates for the reference year of 2015 in Table A.3 are taken as given in all of our future projections of micro consumption expenditures. Specifically, these relative gaps are applied to translate the projected (population-adjusted) macro consumption expenditures into the corresponding households' aggregate expenditures, as illustrated in **Figure 1**. These projected aggregate expenditures are considered consistent with the micro-data aggregate consumption values and overall structure, and will serve as constraints in the projections of household-level expenditures by consumption categories.

<sup>&</sup>lt;sup>12</sup> While Eurostat (2018) defines coverage rates in "percentage ratio" terms, we prefer to keep them in proportional (or simple relative) form, which are used later in our projections. But in the discussions, we might use percentages when referring to specific coverage rates (meaning the latter being implicitly multiplied by 100).

<sup>&</sup>lt;sup>13</sup> The corresponding average coverage rate when imputed rents are accounted for is 81% (see also Table A.2).

<sup>&</sup>lt;sup>14</sup> Similarly, in the last exercises of the EG DNA for fifteen EU and OECD countries, very different coverage rates (with wider range) for twelve main consumption items and across countries are obtained, in both national and Eurostat centralised exercises (see Coli et al., 2022, Figures 3.4.2 and 3.4.4, pp. 22, 24).

# **3** Projection of household-level consumption expenditures in line with macro consumption trends

In the preceding section, we detailed the necessary adjustments made to align the projected macro consumption expenditures with the corresponding aggregate household expenditures. In order to generate the underlying household-level consumption expenditure projections, it is essential to consider the following data-consistency conditions and/or circumstances.

- In each EU country, the projected household-level consumption expenditures for specific commodities should add up to the corresponding aggregate figures that are derived from the macro-to-micro alignment process. Adhering to these constraints ensures that our micro-data projections adequately account for all the major changes at play, such as substitution effects, as captured by the macro model and the corresponding macro projections (here, the JRC-GEM-E3 model and the GECO 2021 baseline, respectively).
- Without any explicit modelling of household behaviour, the structure and values of the original household-level consumption data (here, the EU-HBS-2015) should be *minimally* changed to keep its extensive informational value and reliability in the projections. Our use of a bi-proportional approach, also called RAS method (see also footnote 8), guarantees that the estimated household consumption expenditure values and/or shares are as close as possible cell-wise to their corresponding figures in the EU-HBS-2015 data.<sup>15</sup>
- It is essential to factor in population dynamics in the micro-data projections. If more granular information is available, accounting for demographic changes becomes feasible. This is particularly vital for long-term projections, where factors such as age distribution and migration patterns have a more substantial impact.

In what follows, we present our method for projecting household-level consumption expenditure data.<sup>16</sup> First, let us introduce some notation. Let  $e_{hp,ref} (\geq 0)$  be household h's expenditure spent on consumption category p as reported in the original EU-HBS-2015 survey (or the reference micro-data, hence the superscript ref), and  $E_{h,ref} = \sum_p e_{hp,ref}$  be h's total consumption expenditure in the reference year ref, which here is 2015. The sample weight of household h in the EU-HBS-2015 is denoted by  $w_{h,ref}$ . These variables pertain to individual countries. For simplicity and clarity in presentation purposes, we omit country identifiers since the proposed microdata projection procedure is implemented separately for each country.

Our microdata projection method consists of the following steps.

Step 1: Estimate microdata-relevant aggregate (*ag*) consumption expenditures for the JRC-GEM-E3 consumption categories j=c1,c2, ..., c14 and for all projection years, *year* = [2025, 2030, ..., 2050], as follows:

$$C_{j,year}^{ag} = \frac{\sum_{h} e_{hj,ref} w_{h,ref}}{c_{j,ref}^{ag,adj}} \times C_{j,year}^{ag,adj} = CoverageRate_{j,ref} \times C_{j,year}^{ag,adj},$$
(1)

where  $C_{j,year}^{ag,adj}$  is the macro-level (here, population-scope) adjusted (*adj*) aggregate private consumption of category *j*. Notice from equation (1) that the unexplained differences between macro and micro aggregate consumption expenditures from the reference year are held constant for all future projection years. For our empirical case,

<sup>&</sup>lt;sup>15</sup> Dietzenbacher and Miller (2009) formally showed that updating a transactions matrix or the corresponding input or output coefficients matrices gives exactly the same outcome. For a discussion of the key properties of the RAS method and its extended versions, see Temursho et al. (2021).

<sup>&</sup>lt;sup>16</sup> This approach can be used straightforwardly for projecting income sources data, or for projecting micro-data that includes both consumption expenditures and income sources.

the precise values of these gaps in relative terms, also referred to as coverage rates in Section 3, are given in Table A.3.

Step 2: Further disaggregate the projected aggregate consumption expenditures. The aggregate private consumption expenditures for the 14 consumption categories in JRC-GEM-E3 from step 1, which have been corrected for population-scope and other unexplained macro-micro differences, are allocated to 52 commodities. These commodities represent the most detailed disaggregation level utilized in our microsimulations. For this disaggregation step, we use the JRC-GEM-E3 and ECOICOP mapping (see Table A.1 in the Appendix) and the sub-shares of the corresponding aggregate consumption categories. These sub-shares represent the respective expenditure (sub)structure in the EU-HBS-2015 data and are used due to the lack of projections at this finer level of commodity disaggregation. We note that it is essential to account for the household sample weights in the calculation of the required consumption expenditure sub-shares.

This step results in detailed aggregate consumption expenditure figures  $C_{p,year}^{ag}$  for our ECOICOP consumption categories p=1,2,...,52.<sup>17</sup> Since the utilized sub-shares sum to one, this allocation step ensures that  $\sum_{p \in j} C_{p,year}^{ag} = C_{j,year}^{ag}$  for all products  $p \in j$  and all 14 JRC-GEM-E3 consumption categories j.

Step 3: Project household-level total consumption expenditures. For a specific projection year, *year* = [2025, 2030, ..., 2050], we allocate the difference of the economy-wide consumption expenditure of that year and the reference year, denoted as  $\Delta_{year} \equiv \sum_{p} C_{p,year}^{ag} - \sum_{h} E_{h,ref} w_{h,ref}$ , among all households. To include all households as implicitly captured by the survey, it is essential to consider households' sample weights explicitly. The gap  $\Delta_{year}$  is then distributed proportionally based on households' new consumption expenditure shares in total expenditures:

$$E_{h,year}w_{h,year} = E_{h,ref}w_{h,ref} + \left(\frac{E_{h,year}w_{h,year}}{\sum_{h}E_{h,year}w_{h,year}}\right)\Delta_{year},$$
(2)

where  $E_{h,year}$  and  $w_{h,year}$  refer, respectively, to the total consumption expenditure and sample weight of household *h* in the projection year of interest.

To account for population growth over the considered period (from the reference to the projection year), we define the projected household sample weight as:

$$w_{h,year} = f_{pop,year} \times w_{h,ref}, \qquad (3)$$

where  $f_{pop,year}$  denotes population growth factor, which are reported in **Table 1**. Note that the implicit assumption behind equation (3) is the *constant composition* of households as in the reference year of 2015, both in terms of household types' representativeness across the country and household size. Thus, the population outlook of the macro model (GECO 2021 baseline) is explicitly accounted for in our micro-data projections by appropriately modifying the representativeness, or sample weights, of households. This sole adjustment also implies that we have assumed a fixed size and composition of households in the projections, mirroring those in the reference period.

However, we note that more elaborate projections of household sample weights that capture the prevalence of changing household size and composition is feasible in the presence of the corresponding information. For example, one could incorporate anticipated shifts in household type representativeness (e.g. increasing urban population

 $<sup>^{17}</sup>$  To avoid additional notation, we adopt subscript *j* to denote the broader JRC-GEM-E3 consumption categories, and subscript *p* to represent the finer 52 commodity disaggregation in our EU-HBS-2015 dataset.

vis-à-vis rural population) and/or changes in household size and composition. Instead of a simple proportional adjustment of the reference year's household weights as in (3), then one would allow for a more nuanced adjustments of the household sample weights, accounting for the projected change in other dimensions of household characteristics.

Since we want the economy-wide consumption expenditure consistency condition  $\sum_{h} E_{h,year} w_{h,year} = \sum_{p} C_{p,year}^{ag}$  to hold valid for each projection year, equation (3) can be shown to boil down to the following simple expression:

$$E_{h,year}w_{h,year} = \frac{E_{h,ref}w_{h,ref}}{\sum_{h}E_{h,ref}w_{h,ref}} \times \sum_{p} C_{p,year}^{ag}.$$
(4)

Hence, the share of total consumption expenditure for all households of type h in a country total consumption remains exactly identical for both the reference and projection years. This outcome is entirely reasonable in the absence of further information regarding the distribution of economy-wide consumption expenditures across households.

If further information is available, such as total consumption or income growth of households with certain characteristics, one can easily modify the rule for (extra) expenditure allocation in equation (2). For example, if households in urban areas and/or specific geographic locations (as captured by the available NUTS classification in consumer surveys) experience higher gains/growth based on certain quantitative indicators, these could (should) be used to project the household-level expenditures.

Equations (3) and (4) together imply that the total expenditure of an individual household h for the projected year of interest is simply a constant factor  $\mu$  (> 0) of its reference year's total consumption expenditure, i.e.:

$$E_{h,year} = \mu \times E_{h,ref}$$
, where (5a)

$$\mu = \frac{\sum_{p} c_{p,year}^{ag}}{\sum_{h} E_{h,ref} w_{h,ref}} \times \frac{w_{h,ref}}{w_{h,year}} = \left(\frac{\sum_{j} c_{j,year}^{ag}}{\sum_{h} E_{h,ref} w_{h,ref}}\right) \left(\frac{1}{f_{pop,year}}\right).$$
(5b)

Note from (5a)-(5b) that the total expenditure adjustment factor  $\mu$  accounts for both the projected *change in economy-wide consumption expenditure* and *population growth*. These are captured, respectively, by the first and second terms in (5b). As expected, country consumption growth increases individual household *h*'s total expenditure. On the contrary, a rise in population leads to a reduction in *h*'s total expenditure, as a given economy-wide consumption needs to be allocated among a larger number of households (or people).

As a sidenote, observe from (5a) that since the (positive) multiplier  $\mu$  is identical for all households in each country and the household sample weights are also multiple of the reference year's weights as given in (3), the Member State (MS)-specific (equivalized) total expenditure-based deciles remain unchanged as in the reference micro-data (here, EU-HBS-2015). However, since  $\mu$  differs across countries and  $w_{h,year}$  changes across countries due to the distinct population factors, any MS group-specific and EU-wide deciles would be affected by such projections of household total consumption expenditures.

Step 4: Estimate the expenditures of all household types for all (detailed) consumption categories. Using the bi-proportional adjustment (RAS) method, we derive a "weighted consumption expenditures matrix" for all projection years, whose typical *hp*-element is defined as  $T_{hp,year} \equiv e_{hp,year} w_{h,year}$ . For each projection year, we impose the following row and column sums constraints on  $T_{hp,year}$  in order to incorporate the results of the previous steps:

$$\sum_{p} T_{hp,year} = E_{h,year} w_{h,year} \text{ for all } h, \text{ and}$$
(6a)

$$\sum_{h} T_{hp,year} = C_{p,year}^{ag} \text{ for all products } p.$$
(6b)

To be able to implement the RAS procedure, one needs to have a benchmark (or a reference) matrix, which for our purposes is obtained from the EU-HBS-2015 and has a typical element equal to  $T_{hp,ref} = e_{hp,ref} w_{h,ref}$ . Although  $T_{hp,ref}$  will not satisfy the above two constraints (otherwise there were no need for micro-data projections), it is the property of the RAS method that the obtained elements in  $T_{hp,year}$  are as close as possible cell-wise to their corresponding entries in the reference-year weighted expenditure matrix  $\{T_{hp,ref}\}$ . This adjustment ensures that the above-mentioned row- and column-sum constraints hold in the projected consumption expenditures.<sup>18</sup>

It is often more preferable to have household-group-specific projections of the economywide consumption expenditures. For instance, it would be more reasonable to have the projected decrease of a country food consumption such that its decline is largest in the low-income category. Such income-group-specific constraints need to be imposed explicitly, in which case the constraints in (6b) are defined separately for each household group. In a setting, where there are several constraints imposed on various types of households, one will have to use a multidimensional extensions of the RAS approach in implementing step 4 (see e.g. Krupp 1978; Holý and Šafr 2023).<sup>19</sup>

Step 5: Derive the implied individual household consumption expenditures for each consumption category. Given that the new household sample weight is given by (3), the expenditures for individual households are readily obtained from:

$$e_{hp,year} = T_{hp,year}/w_{h,year}$$
 for all households *h* and all products *p*. (7)

As a final note, we emphasize that the variations in consumption expenditure shares and levels, compared to those in the reference year or, equivalently, year-to-year changes, are largely dictated by the imposed macro consumption expenditure and population dynamics. Although the given micro-macro consumption discrepancies from the reference year (as captured by the resulting coverage rates) do also play a role, it is the imposed macro-level constraints that are the dominant factors shaping the evolution or changes in micro-data throughout the projection years.

<sup>&</sup>lt;sup>18</sup> See e.g. Junius and Oosterhaven (2003) and Temurshoev et al. (2013) for mathematical details of the optimization problem behind RAS or its generalized version, the latter allowing for updating negative elements that could exist when a reference micro-data also includes (net) income sources.

<sup>&</sup>lt;sup>19</sup> However, in some special cases, it is possible to use the "simpler" two-dimensional RAS in imposing more than two types of constraints. For example, in estimating OECD intercountry input-output tables, diagonalizing inter-country trade flows allows using the standard RAS to incorporate sectoral imports constraints, in addition to constraints on sectoral exports and total imports (OECD, 2018). Similar "diagonalization" trick could also be used in a micro-data projection setting to impose expenditure constraints that are specific to a particular household type (e.g. according to income groups). However, in general, we recommend using the multidimensional RAS in cases with more than two types of constraints due to the theoretical considerations and implied practical consequences, whose discussion falls beyond the scope of this paper.

#### 4 Empirical assessments

#### 4.1 Micro-level projections for GECO 2021 baseline

Following our methodology detailed in the previous sections, we projected household-level consumption expenditures aligned with the GECO 2021 baseline projections for 2025, 2030, 2035, 2040, 2045 and 2050. As discussed in Section 2, we have observed differences of a wide range of magnitudes between the (comparable) micro- and macro-level consumption expenditure shares and absolute values. For our purposes, however, it is crucial to have the overall consistency in the evolution of these values over time in both datasets. Particularly important is capturing the evolution of macro expenditure shares within our micro projections.

For readability purposes, we discuss the results in terms of the 14 consumption categories in JRC-GEM-E3 rather than the more detailed 52 categories, for which micro-projections have been carried out. The averages of country- and category-specific changes, compared to 2015, in both macro and micro expenditure shares across all 27 EU countries are presented in **Figure 2**. In the original macro GECO 2021 projections (the first subgraph), we observe mostly smooth-over-time average decrease in consumption shares of 'Purchase of vehicles' (by 33.8% in 2050 compared to 2015), 'Fuels and power' (-27.6%), 'Food, beverages and tobacco' (-20.3%), 'Operation of personal transport equipment' (-12.4%), and 'Cloth and footwear' (-6.1%). The EU consumption shares of the remaining nine categories are projected to increase over time, with the largest average changes projected for public transport including aviation, 'Transport services' (increasing by 37.4% in 2050 compared to 2015), 'Household equipment and operation' (24.1%), 'Medical care and health' (19.6%), and 'Recreational services' (10.5%).

The middle plot in **Figure 2** shows the corresponding average changes in the imposed macro consumption shares, which have been adjusted for population scope and other differences between the macro and micro datasets (Section 2.2). It is evident that these changes generally align well with the evolution of the GECO 2021 macro consumption shares. Obviously, the two will not match exactly due to the necessary adjustments made to the original macro consumption data to align them with the corresponding micro-level aggregate consumption expenditures. The differences in the original and imposed macro consumption figures are primarily attributed to the presence of the coverage rates applied to each consumption category during the macro-micro harmonization process.

The final graph illustrates the EU-wide average of country-specific percentage changes in the (weighted) mean household budget shares for each projection year compared to those in 2015. As expected, these changes closely follow those that are imposed during the household expenditure estimation process.

Similarly, we obtained satisfactory results in terms of consistency in the dynamics of the macro and micro aggregate consumption shares at the individual EU country levels. When computing the correlation coefficients between the changes over time (relative to 2015) of the original (non-adjusted) macro consumption shares and of the mean household expenditure shares for all 378 data points (=14 consumption categories x 27 EU countries), we found nearly perfect correlations ranging between 0.99 and 1 for all projection years. This implies that the effect of macro-data adjustments before implementing the micro-data projections barely affect the evolution over time of the original data at the country level as well.



#### Figure 2. Average EU-wide changes of the consumption expenditure shares of the macro and micro projections relative to 2015 (%)

Note: Sample weights are accounted for in computing the household mean budget shares. Source: own elaboration.



Figure 3. Boxplots of differences of household budget shares for 2030 vs. 2015 by decile (%)

*Note:* Deciles are based on equivalized total expenditure. D1 refers to the poorest decile, D10 to the richest decile. *Source*: own elaboration.

To dig deeper into the household-specific budget shares differences, in **Figure 3** we show the distributions (standard boxplots) of the percentage differences of household budget shares in 2030 relative to 2015 by country and expenditure decile for four selected consumption categories. Obviously, the overall differences across EU countries are dictated by the constraints on consumption and population dynamics, imposed during the projections. The differences across and along household deciles are the outcome of the RAS updating technique without decile-specific constraints and, besides the imposed restrictions, reflect the relative size and variability of the respective household

expenditures in the reference year. However, as indicated earlier, if necessary, householdgroup-specific constraints can also be easily imposed. For example, higher electricity, gas, and other residential fuel prices would disproportionately affect poorer households not only because low-income households typically allocate a higher proportion of their budget to these consumption categories, but also because richer households have more room for fuel substitution, such as e.g. being able to install solar panels. Therefore, one may want to project the overall decline in residential energy expenditure shares ('Fuels and power' in **Figure 3**) in a manner that predominantly comes from households in the upper income distribution.

As mentioned in Section 3, any MS-group or EU-wide household income classification would change in the projections due to changes in economy-wide consumption expenditures and population growth, as these would affect households' affluence levels differently across the EU countries. As an illustration, **Figure 4** shows the differences in expenditure-based EU deciles in 2050 compared to those in 2015. Note that when computing EU-wide deciles, household total expenditures are taken per adult equivalent, and the price differences across countries are accounted for using the 2015 Purchasing power standards (PPS) factors.



Figure 4. Changes of households across EU-wide household expenditure deciles: 2050 vs. 2015

From **Figure 4** it follows that most households in thirteen EU countries maintain their positions in the EU-wide expenditure decile classification. The most significant relative positive changes occur in Hungary and Ireland, where many households move up by two levels in their EU-wide affluence deciles, as indicated by the corresponding medians in the boxplots. In contrast, many households in Luxembourg experience a decline by two levels in this EU ranking. These shifts in household classifications of households within the EU context simply reflect the underlying projected changes in countries' consumption values and population growth, also aligning with the evolution of total consumption (and GDP) per capita projections.

#### 4.2 Variations in distributional impacts due to using different micro-data

In this section, we examine the distributional impacts of the macro price changes resulting from one of the scenarios analysed in Weitzel et al. (2023) for reaching a 55% reduction in EU greenhouse gas emissions by 2030 compared to 1990 levels. Specifically, for illustrative purposes, we select the MIX scenario that incorporates the effects of both regulatory measures and price-based policies and come closest to the policy package now

*Note:* For each household, the difference is calculated as its EU decile in 2050 minus that in 2015. Median values are highlighted as black dots inside white circles, while mean values are represented by red stars. *Source*: own elaboration.

in place. In particular, this scenario includes an intensification in transport and energy policies through e.g. (partial) implementation of standards for vehicles and building codes, as well as extending carbon pricing for the buildings sector and transport under a second EU ETS. For further details, the reader is referred to Weitzel et al. (2023). The corresponding average EU price changes, obtained from the JRC-GEM-E3 model, are presented in **Table 4**, along with the mean budget shares by expenditure decile for all EU households as derived from the EU-HBS-2015.<sup>20</sup>

	FOODBYERDC	Clotherur	HousingWr.		elspomer	thequipOpr	Hearcookdon,	MedCittealth	PrchVehicles	Opros lins bego	1521005uej	Communication	Recreation	Mscheoou	Faucation
	EU households mean budget shares by expenditure decile (%)														
D1	41.8	3.2	8.	6	15.2	3.1	0.4	5.2	0.1	3.4	1.3	6.0	4.7	<u></u> ε	.7 0.3
D2	33.1	4.1	10.	9 📃	13.2	3.7	0.6	4.9	0.3	5.5	1.4	5.7	6.8	9	.2 0.6
D3	29.1	4.4	13.	3 🔲	11.1	3.9	0.7	4.2	0.4	6.5	1.4	5.2	8.3	10	.7 0.6
D4	26.2	4.7	14.	5 📃	9.7	4.3	0.8	3.9	0.6	6.8	1.4	4.7	9.7	11	.7 0.7
D5	24.2	5.0	14.	6 📃	8.7	4.6	0.9	3.8	1.0	7.2	1.4	4.3	11.1	12	.4 0.9
D6	22.5	5.2	14.	7 🔲	7.7 📘	5.0	0.9	3.8	1.4	7.5	1.5	4.0	12.1	13	.0 0.9
D7	21.0	5.4	14.	0 📃	7.0	5.5	0.9	3.8	1.9	7.6	1.6	3.7	13.3	13	.3 1.0
D8	19.4	5.7	13.	5 📘	6.2	5.9	0.9	3.8	2.8	7.8	1.7	3.3	14.7	13	.3 1.0
D9	17.3	5.9	12.	1	5.4	6.4	1.0	4.3	4.6	8.0	1.9	3.0	16.0	13	.3 1.0
D10	13.6	5.6	9.	5	4.0	8.3	1.0	5.2	10.7	7.4	2.1	2.2	16.5	13	.0 1.0
							E	U average p	rice change	s (%)					
Simple average	0.10	0.07	1.6	2	7.43	0.10	0.11	0.10	0.83	1.95	1.17	0.01	0.19	0.	0.00
Weighted average	0.12	0.07	1.7	5	8.80	0.08	0.09	0.06	0.63	1.51	1.11	0.02	0.20	0.	0.00

**Table 4.** EU-wide household mean expenditure shares (%, 2015) and average price shocks (%)

*Note:* D1 refers to the poorest decile, D10 to the richest decile. Price changes are given relative to the baseline. In computing weighted average price changes, projected consumption figures for 2030 are used as weights. *Source*: own elaboration based on EU-HBS-2015 and JRC-GEM-E3 results.

The distributional impacts of a climate policy depend on the magnitude of the corresponding price changes in different consumption categories and households' exposure to these changes, as captured by their budget shares. The price changes include general equilibrium effects, which for example in case of energy related categories, include the combined effect of price changes of the different fuels in the respective consumption bundle (incorporating the carbon price component that depends on the emission intensity of different fuels), changes in the fuel mix, and efficiency improvements.

To assess the impact of using different micro-data on the distributional outcomes of the MIX scenario's price changes, we compute the corresponding welfare effects both before and after transfers. The tax revenues generated from the MIX scenario policies in each EU countries serve as the source of these transfers, which are allocated to all households in each Member State on equivalized household size basis. For each individual household, the welfare measure before transfers is defined as the compensatory monetary income that keeps the household's purchasing power fixed. In other words, this additional money ensures that the household's original consumption bundle (before price changes) remains exactly affordable at the new prices. This Slutsky compensating variation is equivalent to the actual cost differences of the initial (pre-price shock) consumption bundle, caused solely due to the price changes.<sup>21</sup> When households receive lump-sum transfers, the

<sup>&</sup>lt;sup>20</sup> We note that the average price changes reported in Weitzel et al. (2023, Fig. 8, p. 12) do not exactly match those presented in Table 4 for two reasons. First, the price shocks reported in Weitzel et al. (2023) represent the median values of country-specific price changes, as also given in Temursho et al. (2020, Table 5, p. 47). Second, the country coverage of the two studies differs due to using distinct (2010 or 2015) waves of the HBS survey: while Weitzel et al. (2023) cover 25 countries, excluding Austria and Netherlands, this paper covers all the current 27 EU countries.

<sup>&</sup>lt;sup>21</sup> From micro-economic theory perspective, this amount of income compensation is more than enough to maintain the initial utility level. Consequently, some authors describe consumers' reaction to a price change, with the adjusted income that keeps the initially chosen consumption bundle just affordable, as the "law of overcompensated demand" (Cornes, 1992). The advantage, however, is that "everything is observable" and "we do not need any information about tastes in order to perform the experiment" (Cornes, 1992, p. 99).

Slutsky compensating income is reduced by the transfer amount. For formal details, see Temursho et al. (2020) and Fulvimari et al. (2023).

**Figure 5** presents the EU-wide mean welfare impacts, expressed as percentage of household total expenditures. Subplot (a) shows the EU relative welfare impacts before transfers by EU-wide expenditure deciles for cases when the underlying micro-data come from the EU-HBS-2015 or its projections for 2025, 2030, 2040, and 2050. The corresponding results after transfers are shown in subplot (b).



Figure 5. EU-wide mean welfare impacts by EU decile (% of total expenditure)

*Note*: Deciles are based on total expenditure expressed in purchasing power standards (PPS) for 2015 and computed for all EU households. D1 refers to the poorest decile, D10 to the richest decile. The shorthand of e.g. "micro2030" indicates that the underlying data is the projected micro-data for 2030. *Source*: own elaboration.

In view of the obtained results, several points are worth highlighting. First, subplot (a) in **Figure 5** reveals that using outdated micro-data, which do not capture the current or most relevant consumption patterns of households and population dynamics, results in an overestimation of the considered climate policy costs for all household groups. Obviously, this is not a surprising result, since as households change their consumption behaviour in line with the overarching aims of climate policies, the distributional impacts of such policies should also diminish.

Second, the use of projected micro-data consistent with macroeconomic projections also reduces the regressivity of direct costs. This occurs because the relatively uniform (or even slightly increasing, in absolute value) reductions in energy expenditure shares across EU households' income groups lead to a lesser burden of costs (relative to total expenditure) for poorer households as they allocate a (much) higher proportion of their budget to energy goods (Table 4).

Third, similar to the impacts on costs, the use of macro-consistent micro-data projections reduces the benefits from transfers as well, as shown by the after-transfer relative welfare impacts in subplot (b) in **Figure 5**. When running integrated macro-micro assessments, we rescale the household-level results so that the overall country-level welfare impacts match those obtained from the JRC-GEM-E3 model. This macro-micro consistency requirement is implemented for the after-transfer case, whose resulting rescaling factors are also applied to the corresponding before-transfer micro impacts in each country and each scenario considered. This final step in our micro-assessments implicitly accounts for all other impact mechanisms (e.g. changes in factor income) that are considered in the macro model but are not represented explicitly on the micro level. As such the rescaling procedure brings consistency in aggregate outcome (in terms of compensating variation relative to income), while maintaining the distributional patterns obtained directly from the micro-data. This explains why the average impacts of all the after-transfer outcomes are identical, and thus the illustrated welfare impact lines necessarily intersect.

Irrespective of the uniform overall average welfare outcomes, we find different welfare impacts across household groups when using different micro-data. In line with our earlier results, the use of outdated micro-data leads to overestimation of either the positive or negative effects of a climate policy. In this case, households in the lower (resp. upper) part of the expenditure distribution are assessed to gain (resp. lose) more when using the outdated EU-HBS-2015, in contrast to the outcomes implied by using the macro-consistent micro-data projections. As before, these differences are due to the projected changes in household consumption patterns, population dynamics, and income (total expenditure) changes. In countries, where population is projected to decline (resp. rise; see Table 1), the mean absolute value of transfers per adult equivalent is increasing (resp. decreasing) over time, given the fixed size of the country-specific tax revenue to be allocated across all households. However, for welfare assessments it is the relative size of transfers compared to total expenditure (income) that holds more relevance. In this regard, we find a consistent decreasing trend in the share of transfers in income over the projected years. Consequently, transfers become less relevant as households become richer. This explains the flatter pattern observed over time in the after-tax welfare impacts lines depicted in Figure 5.

Finally, some contemplation reveals that employing different micro-data projections may be quite useful in capturing uncertainties related to the speed at which consumers adapt to the needs and dynamics of the green economy. Suppose we are evaluating the impact of a price change scenario for the projection year of 2040. The primary or "central" estimates of the distributional impacts would be based on the outcomes that use the projected micro-data for 2040. However, it would be valuable to run the same price shocks using the projected micro-data for, say, 2035 and 2045 to capture the possibility that consumers may in reality delay or accelerate the pace of change in their green-economyfriendly consumption behaviour (e.g. adoption of energy-efficient installations and/or solar panels in private homes). In this way, one would be able to account for the different rates at which households may adjust their consumption habits.<sup>22</sup> The corresponding distributional impact lines would then show the associated uncertainty range or the "lower and upper bounds" of the welfare impact estimates.

<sup>&</sup>lt;sup>22</sup> For instance, in the latest draft update (as of June 2023) of the <u>National Integrated Energy and Climate Plan</u> <u>2023-2030</u> (PNIEC) of Spain to the European Commission, the initial target of 23% reduction in greenhouse gas emissions in 2030 compared to 1990 is increased to a 32% reduction target. It also increases the share of renewables from originally planned 42% to 48% of final energy consumption in 2030. In the electricity sector, the renewable mix is now set at 81% in 2030 compared to 74% target in the 2020 PNIEC. One of the factors behind these more ambitious targets is the observed significant growth in self-consumption, which indicates a (much) faster speed of adoption of renewable energy by consumers than previously anticipated.

#### 5 Concluding remarks

In this paper we propose a new approach to project/estimate/update household-level consumer expenditures that are in line with the pre-specified values of aggregate consumption expenditures and population dynamics. The projected consumer expenditures are particularly relevant for conducting distributional analysis in conjunction with future climate, environmental, economic and demographic macro-projections, such as those envisaged in the EU climate target plan for 2040. However, the approach can also be readily used for the purposes of other micro-data applications, where an update of consumer expenditures is deemed to be necessary.

To conduct integrated macro-micro assessments, the two underlying sets of data need to be first reconciled. We have elaborated on the inherent discrepancies between macro- and micro-level consumption data. In our empirical examination of this issue, we compared aggregate consumption expenditures derived from the Household Budget Survey (HBS) data of the 27 EU countries for the reference year of 2015 with the corresponding figures used in the JRC-GEM-E3 model. Considerable macro-micro expenditure differences were found across various consumption categories and EU countries. Significant differences were observed not only in terms of consumption levels but also in consumption shares. The most important explanations for these discrepancies are provided in the text.

As an illustration of the usefulness of consumer expenditure projections, we carried out an integrated macro-micro assessment of selected near-term policies in achieving the European Green Deal objective of reaching climate neutrality by 2050 (European Commission, 2019). Specifically, we focused on a scenario that combines some policy elements of both regulations and carbon pricing towards achieving the EU greenhouse gas emission reduction target of 55% below 1990 levels by 2030. The following key conclusions were drawn from these assessments.

First, utilizing outdated household consumption expenditure micro-data could lead to an overestimation of direct climate policy costs as well as benefits from compensatory measures of (tax) revenue recycling.

Second, the use of outdated microdata may result in a more pronounced regressivity of direct climate costs as well as more progressivity in household welfare outcomes after revenue recycle. Both of these main results are driven by the changes in household consumption structure, population dynamics, and total expenditure or income (GDP) growth as foreseen in a macro-outlook of interest that are properly captured in the corresponding projections of household-level consumer expenditures.

Third, one may well use different consumer expenditure projections within a macro-micro modelling framework to account for uncertainty related to the speed at which consumers adapt to the needs and dynamics of the (foreseen) green economy (or any other scenario under modelling consideration). The corresponding lower and upper bounds of welfare estimates can be valuable for better capturing the uncertainty surrounding the distinct and largely unpredictable pace at which consumers alter their consumption behaviour over time, such as e.g. adoption of solar panels at private homes. In addition, the welfare results of various micro-data projections would simply capture the relative uncertainty or robustness of results of implementing distinct set of policy tools underlying (each of) the considered scenarios/projections.

The possibility of using consumer expenditure projections allows for other applications of the projected micro-data. For example, along with different macro scenarios, one can present projections of the corresponding distributional and inequality measures, as well as that of other useful indicators such as energy poverty and transport poverty. This becomes particularly relevant when comparing different projected micro-scenarios. Given that the macro-constraints imposed on the estimation of household consumption expenditures could reflect only price changes and/or only quantity changes, various useful indicators could be derived when comparing the resulting micro-data projections. One limitation in the illustrative empirical study of this paper is that our projections of individual household expenditures were based solely on (average) macro changes, without explicitly considering or modelling the corresponding constraints across different household types. For example, if the macro-level expenditure share of oil/gas for heating is projected to decline by 50%, it is unlikely that in reality all households would reduce their corresponding expenditure shares by the same percentage. Instead, some households may entirely switch technologies, reducing the corresponding budget share by 100%, while others may only see marginal reductions (if at all), perhaps due to energy efficiency measures. However, as discussed in the theoretical part of the paper, the household type-specific constraints can also be explicitly imposed during the micro-data projections.

It would be of interest to empirically assess the performance of the proposed micro-data projection approach. The ideal micro-data for such analysis would consist of surveys that track the same households over time. Suppose one has access to such consumer expenditure surveys for the reference years of 2015 and 2020. Then, by using the 2010 survey as the benchmark micro-data and diverse aggregates (which may also be categorized by distinct household types) derived from the 2020 survey as macro-projections, one could update the 2010 consumer expenditure data to the year 2020. However, since the actual 2020 survey is available, it is readily possible to evaluate the performance of the projection approach directly. We expect an improved projection performance when more macro-constraints obtained from the 2020 survey are imposed. Such exercises could also prove valuable in identifying better ways of imposing certain macro-level changes, as it may not always be straightforward to incorporate them directly into the micro-projections. Changes in the age composition of households, shifts between urban and rural population, and/or shifts in consumption patterns resulting from migration flows could serve as such examples.

#### References

- Bacharach M. (1965), Estimating nonnegative matrices from marginal data, *International Economic Review*, 6(3), pp. 294–310.
- Ballester C. and F. Oehler (2023), Measuring the joint distribution of household income, consumption and wealth at the micro level: Methodological issues and experimental results, European Union / OECD.
- Bourguignon F. and M. Bussolo (2013), Income distribution in computable general equilibrium modeling. In: Peter B.D. and Dale,W.J. (Eds.), *Handbook of Computable General Equilibrium Modeling*, Vol. 1. Elsevier, pp. 1383–1437 (Chapter 21).
- Bregman L.M. (1967), The relaxation method of finding the common point of convex sets and its application to the solution of problems in convex programming, USSR Computational Mathematics and Mathematical Physics, 7(3), pp. 200 –217.
- Cai M. and T. Vandyck (2020), Bridging between economy-wide activity and household-level consumption data: Matrices for European countries, *Data in Brief*, 30, 105395.
- Capros P., Van Regemorter D., Perry M., Ciscar J., Paroussos L., Pycroft J., Karkatsoulis P., Abrell J. and B. Saveyn (2013), GEM-E3 model documentation, Publications Office of the European Union. https://doi.org/doi/10.2788/47872
- Cazcarro I., Amores A.F., Arto I. and K. Kratena (2022), Linking multisectoral economic models and consumption surveys for the European Union, *Economic Systems* Research, 34(1), pp. 22-40.
- Coli A., Istatkov R., Jayyousi H., Oehler F. and O. Tsigkas (2022), Distributional national account estimates for household income and consumption: Methodological issues and experimental results, European Union / OECD.
- Colombo G. (2010), Linking CGE and microsimulation models: A comparison of different approaches, *International Journal of Microsimulation*, 3(1), pp. 72-91.
- Connolly K., Eiser D., Kumar A., McGregor P.G. and R. Roy (2024), A micro-macro-economic modelling approach to major welfare system reforms: The case of a Universal Basic Income for Scotland, *Structural Change and Economic Dynamics*, 68, pp. 259-268.
- Cornes, R. (1992). Duality and Modern Economics. Cambridge University Press, Cambridge.
- Deaton A. (2001), Counting the world's poor: Problems and possible solutions. World Bank Research Observer 16(), 125–147.
- Deaton A. and V. Kozel (2005), Data and dogma: The great Indian poverty debate, World Bank Research Observer, 20(2), pp. 177–199.
- Deming W.E. and F.F. Stephan (1940), On a least squares adjustment of a sampled frequency table when the expected marginal totals are known, *Annals of Mathematical Statistics*, 11(4), pp. 427–444.
- Dietzenbacher E. and R.E. Miller (2009), RAS-ing the transactions or the coefficients: It makes no difference, *Journal of Regional Science*, 49(3), 555–566.
- ECB (2020), Understanding household wealth: Linking macro and micro data to produce distributional financial accounts, *ECB Statistics Paper Series*, No 37 / July 2020.
- Engel J. Gayá Riera P., Grilli J. and P. Sola (2022), Developing reconciled quarterly distributional national wealth insight into inequality and wealth structures, *ECB Working Paper Series*, No. 2687/ July 2022.
- European Commission (2009), GDP and beyond: Measuring progress in a changing world, COM (2009) 433, August 2009.
- European Commission (2019), The European Green Deal, COM(2019) 640 final.
- European Commission (2021a), EU reference scenario 2020 Energy, transport and GHG emissions: trends to 2050.
- European Commission (2021b), The 2021 ageing report: Economic & budgetary projections for the EU member states (2019-2070), Institutional Paper 148.

European Commission. (2023), Strategic foresight report 2023. COM(2023) 376.

- European Commission. (2024), Securing our future Europe's 2040 climate target and path to climate neutrality by 2050 building a sustainable, just and prosperous society. COM(2024) 63
- Eurostat (2015), Household budget survey 2010 wave, EU quality report, Eurostat Directorate-General of the European Commission, 2015.
- Eurostat (2018a), Concepts for household consumption comparison between micro and macro approach, Archive, <u>https://ec.europa.eu/eurostat/statistics-</u> <u>explained/index.php?title=Concepts for household consumption -</u> <u>comparison between micro and macro approach&oldid=507513#Relevance and coverage r</u> <u>ates for household consumption</u>
- Eurostat (2018b), Comparison of household income: European Union Statistics on Income and Living Conditions and National Accounts – Methodological note, <u>https://ec.europa.eu/eurostat/documents/7894008/9077550/Methodological note.pdf</u>
- Eurostat (2013), European household income by groups of households, *Statistical working papers* 201, Luxembourg, 2013.
- Eurostat (2020), Distribution of income and consumption for the household sector: Eurostat centralised exercise Methodological note, <u>https://ec.europa.eu/eurostat/web/experimental-statistics/ic-social-surveys-and-national-accounts</u>
- Eurostat (2020b), Household budget survey 2015 wave, EU quality report (version 1), Eurostat Directorate-General of the European Commission, 2020.
- Fesseau, M. and M. Mattonetti (2013), Distributional measures across household groups in a National Accounts Framework: Results from an experimental cross-country exercise on household income, consumption and saving, OECD Statistics Working Papers, No. 2013/04, OECD Publishing, Paris.
- Fesseau, M., F. Wolff and M. Mattonetti (2013), A cross-country comparison of household income, consumption and wealth between micro sources and National Accounts aggregates, OECD Statistics Working Papers, No. 2013/03, OECD Publishing, Paris.
- Fulvimari A., Temursho U., Vaitkeviciute A. and M. Weitzel (2023), Economic and distributional effects of higher energy prices on households in the EU, Publications Office of the European Union, Luxembourg, 2023, doi:10.2760/919027, JRC133708.
- Holý V. and K. Šafr (2023) Disaggregating input–output tables by the multidimensional RAS method: A case study of the Czech Republic, *Economic Systems Research*, 35:1, 95-117.
- Idel M. (2016), A review of matrix scaling and Sinkhorn's normal form for matrices and positive maps, *arXiv:1609.06349* [math.RA].
- Ireland C.T. and S. Kullback (1968), Contingency tables with given marginals, *Biometrika*, 55(1), pp. 179–188.
- Junius T. and J. Oosterhaven (2003), The solution of updating or regionalizing a matrix with both positive and negative elements, *Economic Systems Research*, 15, 87–96.
- Keramidas, K., Fosse, F., Diaz Vazquez, A., Dowling, P., Garaffa, R., Després, J., Russ, H.P., Schade, B., Schmitz, A., Soria Ramirez, A., Vandyck, T., Weitzel, M., Tchung-Ming, S., Diaz Rincon, A., Rey Los Santos, L. and Wojtowicz, K., Global Energy and Climate Outlook 2021: Advancing towards climate neutrality, EUR 30861 EN, Publications Office of the European Union, Luxembourg, 2021, ISBN 978-92-76-42314-0, doi:10.2760/410610, JRC126767.
- Kruithof R. (1937), Telefoonverkeersrekening, De Ingenieur 52, pp. E15–E25.
- Krupp R.S. (1979), Properties of Kruithof's projection method, *Bell System Technical Journal*, 58(2), pp. 517–538.
- Lahr M. and L. de Mesnard (2004), Biproportional techniques in input-output Analysis: Table updating and structural analysis, *Economic Systems Research*, 16(2), pp. 115-134.
- Lequiller F. and D. Blades (2014), *Understanding National Accounts*, second edition, OECD Publishing, <u>http://dx.doi.org/10.1787/9789264214637-en</u>
- McDougall R. (1999), Entropy theory and RAS are friends, GTAP Working Paper No. 6, May.
- Miller R. E. and P.D. Blair (2009), *Input–output analysis: Foundations and extensions* (2nd ed.). Cambridge University Press.

- OECD (2018), Development of the OECD inter-country input-output database 2018 edition, OECD Directorate for Science, Technology and Innovation.
- OECD (2020), Guidelines: Distributional information on household income, consumption and saving in line with national accounts, Statistics and Data Directorate.
- Savard L. (2003), Poverty and income distribution in a CGE-Household microsimulation model: Topdown/bottom up approach, CIRPEE Working Paper 03-43, Laval University, Quebec.
- Statistics Austria (2018), Standard documentation: Household budget survey 2014/15, Directorate Social Statistics, Organizational unit Living Conditions, Social Protection.
- Stiglitz J., Sen A. and J. Fitoussi (2009), Report by the Commission on the Measurement of Economic Performance and Social Progress September 2009.
- Stone R., Champernowne D.G. and J.E. Meade (1942), The precision of national income estimates, *Review of Economic Studies*, 9, pp. 111–125.
- Temursho U. (2021), Linking the macro and micro models in the JRC top-down modelling approach, JRC internal document (August 31, 2021), registered as Ares(2021)5376307.
- Temursho U. and M. Weitzel (2024), Consumer demand in EU member states: Estimating a linear expenditure system for the 27 EU countries, JRC Technical Report, Publications Office of the European Union, Luxembourg (forthcoming).
- Temursho U., Oosterhaven J. and M.A. Cardenete (2021), A multi-regional generalized RAS updating technique, *Spatial Economic Analysis*, 16 (3), pp. 271-286.
- Temursho U., Weitzel, M. and T. Vandyck (2020), *Distributional impacts of reaching ambitious nearterm climate targets across households with heterogeneous consumption patterns*, Luxembourg: ISBN 978-92-76-21604-9, doi:10.2760/89463, JRC121765.
- Temurshoev U., Miller R.E. and M.C. Bouwmeester (2013), A note on the GRAS method, *Economic Systems Research*, 25, 361-367.
- UNECE (2011), *Canberra Group Handbook on Household Income Statistics*. Second edition, Geneva, United Nations.
- Van Ruijven B.J., O'Neill B.C. and J. Chateau (2015), Methods for including income distributions in global CGE models for long-term climate change research, *Energy Economics*, 51, pp. 530-543.
- Weitzel M., Vandyck T., Rey Los Santos L., Tamba M., Temursho U. And K. Wojtowicz (2023), A comprehensive socio-economic assessment of EU climate policy pathways, *Ecological Economics*, 107660.
- Zwijnenburg J. (2019), Unequal distributions: EG DNA versus DINA approach, AEA Papers and Proceedings, 109, pp. 296-301.
- Zwijnenburg J., Bournot S., Grahn D. and E. Guidetti (2021), Distribution of household income, consumption and saving in line with national accounts: Methodology and results from the 2020 collection round, OECD Statistics Working Papers, No. 2021/01, OECD Publishing, Paris, <u>https://dx.doi.org/10.1787/615c9eec-en</u>

### Appendix

Code	JRC-GEM-E3 consumption	Code	ECOICOP broad commodities	Mapping
	categories			
c1	Food beverages and tobacco	cp011	Food	c1
c2	Clothing and footwear	cp012	Non-alcoholic beverages	c1
c3	Housing and water charges	cp021	Alcoholic beverages	c1
c4	Fuels and power	cp022	Tobacco	c1
c5	excluding heating and cooking	cp031	Clothing	c2
	appliances	cp032	Footwear including repair	c2
c6	Heating and cooking appliances	cp041	Actual rentals for housing	c3
c7	Medical care and health	cp043	Maintenance and repair of the dwelling	c3
			Water supply and miscellaneous services relating to the	2
c8	Purchase of vehicles	cp044	dwelling	c3
c9	equipment	cp0451	Electricity	c4
c10	Transport services	cp0452	Gas	c4
c11	Communication	cp0453	Liquid fuels	c4
c12	Recreational services	cp0454	Solid fuels	c4
c13	Miscellaneous goods and services	cp0455	Heat energy	c4
c14	Education	cp051	Furniture and furnishings, carpets and other floor coverings	c5
	Eddedion	cn052	Household textiles	c5
		cp052	Household appliances	c5
		cp055	Glasswara, tableware and beusehold utensils	c5
		cp054	Tools and equipment for house and garden	c5
		cp055	Goods and convises for routine bousehold maintenance	c5
		cp050	Medical products configures and equipment	c5 e7
		cp061	Out patient convises	c7
		cp002	Hospital convices	c7
		cp003	Rusehaaa of vehicles	۲ د
		cp071	Spare parts and accessories	60
		cp0721		C9
		cp0722	Puels and iupricants	C9
		cp0723	Other convices in respect of personal transport equipment	69
		cp0724	Deservices in respect of personal transport equipment	C9
		cp0731	Passenger transport by railway	-10
		cp0732	Passenger transport by road	c10
		cp0733	Passenger transport by air	c10
		cp0734	Passenger transport by sea and mand waterway	-10
		cp0735	Combined passenger transport	c10
		cp0736		c10
		cp081	Tolenhone and telefox equipment	c11
		cp082	Telephone and telefax equipment	c11
		chog2	Audio-visual, photographic and information processing	C11
		cp091	equipment	c5
		cp092	Other major durables for recreation and culture	c5
		cp093	Other recreational items and equipment, gardens and pets	c12
		cp094	Recreational and cultural services	c12
		cp095	Newspapers, books and stationery	c13
		cp096	Package holidays	c12
		cp10	Education	c14
		cp111	Catering services	c12
		cp112	Accommodation services	c12
		cp121	Personal care	c13
		cp123	Personal effects n.e.c.	c13
		cp124	Social protection	c13
		cp125	Insurance	c13
		cp126	Financial services n.e.c.	c13
		cp127	Other services n.e.c.	c13

#### Table A.1. The JRC-GEM-E3 and ECOICOP classifications and mapping

	c1	c2	c3	c4	c5	c6	c7	c8	c9	c10	c11	c12	c13	c14	Mean	Wmean
					Differer	nces betwe	en the mic	ro and ma	cro consur	nption exp	enditure s	hares (%)				
AT	6.8	-16.2	23.6	2.6	0.0	11.8	2.4	146.2	-11.5	-67.8	-22.2	-20.3	-12.0	53.8	6.9	4.4
BE	-21.0	-16.2	27.0	62.9	-14.6	6.5	-31.6	139.1	-9.0	-9.2	35.2	1.1	-17.7	50.3	14.5	4.8
BG	31.4	27.8	70.6	79.1	-44.2	-35.2	-22.5	-72.0	-55.0	-76.4	-10.7	-33.6	-27.9	-33.6	-14.4	11.8
CY	-11.3	11.6	73.8	21.1	4.8	-17.2	-3.3	31.0	-8.7	-39.9	52.2	-43.1	-18.3	67.6	8.6	7.0
CZ	4.1	70.8	-44.5	196.8	-8.0	40.9	7.1	-7.0	4.8	-12.9	40.2	-14.0	-17.6	27.5	20.6	11.1
DE	-6.3	1.4	27.3	97.8	-34.2	-9.9	-21.3	64.7	-30.1	-33.9	21.1	9.9	-28.9	12.3	5.0	4.8
DK	-11.0	-1.8	10.6	25.8	-21.1	-26.1	-14.0	68.6	-16.3	11.5	46.1	-3.9	-10.5	-25.3	2.3	1.9
EE	-2.1	-11.7	-46.2	27.7	44.7	39.2	51.1	248.9	-29.2	-50.8	90.0	0.1	-24.9	240.6	41.2	11.3
EL	5.5	38.3	27.2	46.4	21.1	26.5	56.1	48.1	40.8	-80.6	-16.9	-40.8	-22.6	51.1	14.3	7.0
ES	3.1	22.4	39.3	6.3	-12.4	1.0	-7.7	71.8	-9.6	-39.1	18.5	-34.2	-17.7	-7.8	2.4	3.8
FI	-12.3	-20.2	22.0	-36.1	-13.5	-2.4	-18.6	126.8	-14.6	-2.7	14.0	-20.7	16.0	-41.5	-0.3	4.0
FR	5.2	7.7	9.8	-4.4	-13.9	-28.3	-62.3	173.0	-38.7	-29.5	-8.2	-8.5	13.4	46.9	4.5	5.4
HR	-4.9	25.7	90.9	80.9	-28.7	-24.9	-34.6	15.4	35.8	-58.3	23.9	-69.4	-10.0	-0.8	2.9	12.5
HU	-13.6	-3.2	82.2	285.3	-35.4	-45.4	-14.5	-34.6	-27.8	-45.6	46.5	-46.5	-36.1	-55.7	4.0	20.1
IE IT	-2.0	12.5	41.7	76.2	-26.0	-5.1	-53.0	151.6	-13.0	-//.0	36.1	-38.8	21.4	-15.2	7.8	9.5
11	16.4	-21.3	47.4	153.3	-39.9	-9.9	34.0	35.8	-27.0	-48.4	1.3	-42.3	-26.2	-36.6	2.6	8.1
	-7.6	-8.1	135.3	159.6	-30.5	-61.5	1.8	-42.9	-49.0	-52.0	26.2	-29.9	-44.2	53.1	3.2	18.0
	-40.5	-7.5	41.0	157.9	11.9	0.0	-10.5	136.9	-55.5	32.5	61.9	7.9	-55.7	-14.0	20.8	11.2
LV	-1.3	-4.8	-5.1	11.0	-9.2	-27.1	32.1	51.0	-3.0	-24.0	57.2	-22.8	-16.2	-5.9	0.2	2.6
	27.7	19.7	-37.2	95.2	-2.0	-11.4	20.9	102.7	-16.4	7.5	23.0	-42.0	0.0	128.0	21.1	7.0
DI	-14.0	-12.4	22.5	226.0	-48.6	-32.3	-01.7	-75.8	-13.0	-68.1	4.5	-19.0	-54.7	222.3	24.5	18.2
PL DT	-28.3	-12.4	S1.5	30.2	-40.0	-52.5	-40.1	-73.6	-14.8	-00.1	32.2	-32.3	-34.7	137.2	10.5	10.2
RÓ	79.9	-23.1	77 7	93.6	-34.5	-44.3	-4.5	-90.4	-14.0	-37.4	76.8	-77.9	-45.5	-74.1	-14.7	24.8
SE	-33.8	-6.0	74.2	-47.2	72.5	-22.9	-47 9	254.1	-36.6	-51.9	-49 3	65.0	-26.9	-87.3	4.0	18.1
SL	-5.5	13.7	-3.9	58.1	-41.8	16.2	-29.6	127.8	11.9	-83.4	80.8	-74.2	-3.6	376.0	35.2	7 3
SK	0.7	-12.8	76.7	175.9	-10.8	-22.6	-33.9	33.1	-57.8	20.3	60.0	-36.4	-32.7	-42.3	8.4	14.5
Average	-0.2	3.3	37.2	79.5	-13.9	-11.8	-8.7	69.2	-18.9	-36.4	31.9	-21.5	-20.1	42.0	9.4	9.8
					Differe	nces betwe	een the mi	cro and ma	cro consu	mption exp	enditure l	evels (%)	-			
AT	-30.9	-45.8	-20.1	-33.6	-35.3	-27.7	-33.8	59.2	-42.8	-79.2	-49.7	-48.5	-43.1	-0.6	-30.9	-32.5
BE	-47.1	-44.0	-15.0	9.0	-42.8	-28.7	-54.2	60.0	-39.1	-39.2	-9.6	-32.3	-44.9	0.6	-23.4	-29.9
BG	-32.4	-34.3	-12.2	-7.9	-71.3	-66.6	-60.1	-85.6	-76.8	-87.9	-54.0	-65.8	-62.9	-65.8	-56.0	-42.5
CY	-41.4	-26.3	14.8	-20.0	-30.8	-45.3	-36.1	-13.5	-39.7	-60.3	0.6	-62.4	-46.0	10.7	-28.3	-29.3
CZ	-43.5	-7.3	-69.8	61.1	-50.0	-23.5	-41.9	-49.5	-43.1	-52.7	-23.9	-53.3	-55.3	-30.8	-34.5	-39.7
DE	-39.3	-34.3	-17.5	28.2	-57.4	-41.6	-49.0	6.7	-54.7	-57.2	-21.5	-28.8	-53.9	-27.2	-32.0	-32.1
DK	-43.3	-37.5	-29.6	-19.9	-49.8	-53.0	-45.2	7.3	-46.7	-29.0	-6.9	-38.8	-43.0	-52.4	-34.8	-35.1
EE	-58.5	-62.6	-77.2	-45.8	-38.7	-41.0	-35.9	47.9	-70.0	-79.1	-19.5	-57.5	-68.2	44.4	-40.1	-52.8
EL	-39.3	-20.4	-26.8	-15.7	-30.3	-27.2	-10.1	-14.8	-19.0	-88.9	-52.2	-65.9	-55.4	-13.1	-34.2	-38.4
ES	-25.2	-11.1	1.1	-22.8	-36.5	-26.7	-33.0	24.7	-34.4	-55.8	-14.0	-52.2	-40.2	-33.1	-25.7	-24.7
FI	-34.1	-40.1	-8.3	-52.0	-35.0	-26.7	-38.8	70.3	-35.9	-27.0	-14.3	-40.4	-12.9	-56.0	-25.1	-21.9
FR	-31.6	-29.9	-28.6	-37.8	-44.0	-53.4	-75.5	77.6	-60.1	-54.1	-40.3	-40.5	-26.2	-4.4	-32.1	-31.5
HR	-39.2	-19.7	22.0	15.6	-54.5	-52.0	-58.2	-26.3	-13.2	-73.3	-20.8	-80.5	-42.5	-36.6	-34.2	-28.1
HU	-46.8	-40.3	12.3	137.4	-60.2	-66.3	-47.3	-59.7	-55.5	-66.5	-9.7	-67.0	-60.6	-72.7	-35.9	-26.0
IE	-25.2	-14.1	8.1	34.5	-43.5	-27.6	-64.2	92.0	-33.6	-82.5	3.9	-53.3	-7.3	-35.3	-17.7	-16.4
IT	-20.5	-46.2	0.6	72.9	-59.0	-38.5	-8.5	-7.3	-50.2	-64.8	-30.8	-60.6	-49.6	-56.7	-30.0	-26.2
LT	-59.2	-59.4	4.0	14.7	-71.9	-83.0	-55.0	-74.8	-77.5	-78.8	-44.2	-69.0	-75.4	-32.4	-54.4	-47.9
LU	-74.0	-59.5	-38.4	12.7	-51.1	-56.0	-60.9	4.4	-79.6	-42.2	-29.2	-52.8	-71.9	-62.4	-47.2	-51.4
LV	-59.4	-60.8	-61.0	-31.6	-62.6	-70.0	-45.6	-37.9	-60.3	-68.7	-35.3	-68.2	-65.5	-61.3	-56.3	-57.8
IVI I	-38.6	-13.5	-69.8	-46.6	-53.2	-57.4	-38.9	-2.5	-60.7	-48.4	-40.5	-72.4	-51.6	10.0	-41.7	-48.2
NL	-32.3	-36.0	-3.5	46.0	-33.8	-8.5	-69.8	58.7	-33.0	-46.1	-17.6	-36.6	-16.3	62.3	-11.9	-1/.7
PL	-40.5	-60.1	-40.1	48.6	-76.6	-69.2	-32.5	-89.0	-60.3	-85.5	0.9	-69.1	-79.3	47.4	-43.2	-46.1
PI PO	-57.4	-57.8	12.7	-17.2	-01.1	-/1.2	-43.5	-3.9	-49.3	-02.8	-21.4	-18.8	-70.0	41.1	-54.5	-33.7
SE	-51.1	-73.8	-52.0	-25.9	-70.7	-70.7	-70.8	122.0	-61.0	-74.1	-52.5	-51.5	-67.0	-90.1	-07.5	-32.2
SI	-30.3	-40.8	-30.8	-00.8	-63.5	-27.2	-07.2	42.9	-20 0	-89.6	12.2	-52.5	-34.0	108.2	-34.3	-23.7
SK	-40.0	-20.7	-35.0	28.4	-58.5	-27.2	-69.2	-38.0	-29.9	-44.0	-25.5	-70.4	-68.7	-73.1	-13.5	-32.7
	33.1	20.4	10.2	2.4	40.0	47.5	40.2	20.0	54.4	(2.2	24.6	F2 F	E1.C	17.0	26.0	25.0

**Table A.2.** Differences between the EU-HBS-2015 and JRC-GEM-E3 aggregate consumption expenditure shares and levels, including imputed rentals for housing, 2015 (%)

*Note*: The reported differences of shares/levels are defined as 100\*[(EU-HBS-2015 consumption share/level)/(JRC-GEM-E3 expenditure share/level) -1]. "Mean" represents a simple arithmetic average of the presented 14 differences along each row, while "Wmean" is the corresponding weighted average, with weights equal to the average macro and micro (including imputed rentals for housing) expenditure shares. *Source*: own elaboration based on the EU-HBS-2015 and JRC-GEM-E3 consumption data.

## **Table A.3.** Coverage rates of the EU-HBS-2015 as compared with the JRC-GEM-E3 consumption expenditures, 2015

AT	0.691	0.542	0.456	0.664	0.647	0.723	0.662	1.592	0.572	0.208	0.503	0.515	0.569	0.994		
BE	0.529	0.560	0.298	1.090	0.572	0.713	0.458	1.600	0.609	0.608	0.904	0.677	0.551	1.006		
BG	0.676	0.657	0.146	0.921	0.287	0.334	0.399	0.144	0.232	0.121	0.460	0.342	0.371	0.342		
CY	0.586	0.737	0.335	0.800	0.692	0.547	0.639	0.865	0.603	0.397	1.006	0.376	0.540	1.107		
CZ	0.565	0.927	0.302	1.611	0.500	0.765	0.581	0.505	0.569	0.473	0.761	0.467	0.447	0.692	-	2.5
DE	0.607	0.657	0.370	1.282	0.426	0.584	0.510	1.067	0.453	0.428	0.785	0.712	0.461	0.728		
DK	0.567	0.625	0.360	0.801	0.502	0.470	0.548	1.073	0.533	0.710	0.931	0.612	0.570	0.476		
EE	0.415	0.374	0.228	0.542	0.613	0.590	0.641	1.479	0.300	0.209	0.805	0.425	0.318	1.444		
EL	0.607	0.796	0.184	0.843	0.697	0.728	0.899	0.852	0.810	0.111	0.478	0.341	0.446	0.869		~
ES	0.748	0.889	0.247	0.772	0.635	0.733	0.670	1.247	0.656	0.442	0.860	0.478	0.598	0.669		2
FI	0.659	0.599	0.422	0.480	0.650	0.733	0.612	1.703	0.641	0.730	0.857	0.596	0.871	0.440		
FR	0.684	0.701	0.280	0.622	0.560	0.466	0.245	1.776	0.399	0.459	0.597	0.595	0.738	0.956		
HR	0.608	0.803	0.244	1.156	0.455	0.480	0.418	0.737	0.868	0.267	0.792	0.195	0.575	0.634		
HU	0.532	0.597	0.295	2.374	0.398	0.337	0.527	0.403	0.445	0.335	0.903	0.330	0.394	0.273	_	1.5
IE	0.748	0.859	0.323	1.345	0.565	0.724	0.358	1.920	0.664	0.175	1.039	0.467	0.927	0.647		
т	0.795	0.538	0.228	1.729	0.410	0.615	0.915	0.927	0.498	0.352	0.692	0.394	0.504	0.433		
LT	0.408	0.406	0.112	1.147	0.281	0.170	0.450	0.252	0.225	0.212	0.558	0.310	0.246	0.676		
LU	0.260	0.405	0.191	1.127	0.489	0.440	0.391	1.044	0.204	0.578	0.708	0.472	0.281	0.376		
LV	0.406	0.392	0.143	0.684	0.374	0.300	0.544	0.621	0.397	0.313	0.647	0.318	0.345	0.387	-	1
ΜТ	0.614	0.865	0.302	0.534	0.468	0.426	0.611	0.975	0.393	0.516	0.595	0.276	0.484	1.100		
NL	0.677	0.640	0.432	1.460	0.662	0.915	0.302	1.587	0.670	0.539	0.824	0.634	0.837	1.623		
PL	0.595	0.399	0.191	1.486	0.234	0.308	0.675	0.110	0.397	0.145	1.009	0.309	0.207	1.474		
ΡT	0.426	0.422	0.246	0.828	0.389	0.288	0.565	0.961	0.507	0.372	0.786	0.812	0.300	1.411	_	0.5
RO	0.689	0.262	0.104	0.741	0.233	0.213	0.292	0.037	0.184	0.259	0.677	0.085	0.124	0.099		
SE	0.417	0.592	0.536	0.332	1.086	0.485	0.328	2.229	0.399	0.303	0.319	1.038	0.460	0.080		
SI	0.592	0.713	0.165	0.991	0.365	0.728	0.441	1.427	0.701	0.104	1.133	0.475	0.604	2.982		
SK	0.469	0.406	0.283	1.284	0.415	0.360	0.308	0.620	0.196	0.560	0.745	0.296	0.313	0.269		
	c1	c2	c3	c4	c5	c6	c7	c8	c9	c10	c11	c12	c13	c14		
				(	Consump	tion cate	gories (J	IRC-GEN	1-E3 clas	sification	1)					

*Note*: The presented coverage rates give the same information as the micro-macro level percentage differences reported in the bottom part of Table 2, but in ratio terms. JRC-GEM-E3 household consumption categories (c1 to c14) are defined in Table A.1. *Source*: own elaboration based on the EU-HBS-2015 and JRC-GEM-E3 consumption data.

### IOpedia Research Paper Series

is an online publication series available at: www.iopedia.eu

All rights reserved. This work may be reproduced or otherwise disseminated in whole or in part if the appropriate citation is made.

Temursho U., Weitzel M. and R. Garaffa (2024), Projection of householdlevel consumption expenditures in a macro-micro consistent framework, *IOpedia Research Paper No.05*, April 2024, wwww.IOpedia.eu.