Modelling well-being and non-economic drivers in the Eurogreen model

WP 6, Task 6.1, Deliverable 6.1

September 2025

WISER: Well-being in a Sustainable Economy Revisited

WISER – 101094546

This project has received funding from the European Union's Horizon 2022 research and innovation program under grant agreement No 101094546.

Project Information

Project acronym:	WISER
Full title of project:	Well-being in a Sustainable Economy Revisited
Call identifier:	101094546
Type of action:	RIA
Start date:	1 October 2023
End date:	30 September 2026
Grant agreement no:	101094546

Deliverable 6.1 – Report of the empirical analysis, synthesis of modelling and preliminary results

WP :	6 Social viability of the transition to sustainability: Scenario analysis
Due Date:	
Submission Date:	
Responsible Partner:	
Version:	01
Status:	
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Deliverable Type:	Working paper
Dissemination Level:	Scientific audience

Statement of originality

This report contains original unpublished work except were indicated otherwise. The work of others and published material has been indicated through citation, quotation or both.

Version History

Version	Date	Author	Partner	Description
01	24/07/2025	Simone D'Alessandro, David Cano, Angela Parenti, Pietro Guarnieri	Stefano Bartolini, Francesco Sarracino, Giulia Slater	Brainstorming, Table of Contents, Slideshow
02	19/09/2025	David Cano Ortiz, Simone D'Alessandro		First draft
03	21/09/2025	David Cano Ortiz, Simone D'Alessandro, Pietro Guarnieri, Angela Parenti	Stefano Bartolini, Francesco Sarracino, Giulia Slater	Final version

Abbreviations and Acronyms

Abbreviation	Fully written
IAM	Integrated Assessment Model
GDP	Gross Domestic Product
ISTAT	*Istituto Nazionale di Statistica* (National Statistics Institute of Italy)
AVQ	*Aspetti della vita quotidiana* (Aspects of Daily Life survey)
HBS	Household Budget Survey
SHIW	Survey of Household Income and Wealth
CV	Compensating Variation
QUAIDS	Quadratic Almost Ideal Demand System

Table of Contents

List of Figures

List of Tables

Modelling well-being and non-economic drivers in the EUROGREEN model

1 Introduction

Wellbeing is increasingly regarded as key dimension for public policy. It is advocated both as a way of measuring societal progress, offering an alternative to the standard unidimensional GDP, and as a policy objective itself, aimed at improving people's wellbeing rather than merely promoting unlimited growth in output and consumption (Kubiszewski et al., 2025; O'Mahony, 2022). Focusing on the second aspect, it is however necessary to assess the impact of policies aimed at enhancing wellbeing. Apart from evaluating their effectiveness in improving wellbeing itself, it is especially crucial to understand their consequences for society and the economy at large, in dimensions such as household consumption, polluting emissions, income inequality, and public finances. This is important because it determines whether such policies can promote a just and sustainable society – one in which people's wellbeing improves, inequalities and environmental impacts are reduced, and societal transformations are effectively supported in the political arena to make them sustainable over time.

For such a study we use EUROGREEN, a macrosimulation model devised to explore just transition scenarios and the interplay between environmental and social goals (Cieplinski et al., 2021; D'Alessandro et al., 2020). This is an analytic tool that encompasses all the mentioned dimensions in a theoretically coherent and data-driven framework to simulate the effects of a wide range of policies (Campigotto et al., 2024). Our main purpose herein is the introduction of wellbeing drivers into a dynamic macroeconomic framework. To this purpose, we must identify the main drivers of wellbeing that are suitable to include in EUROGREEN, investigate the impact of changes in wellbeing in households' decisions, and model and analyze these effects through simulations. These are the main components of Task 6.1 to which this Deliverable is devoted.

The identification of indicators builds on the conceptual foundations outlined in Work Package 1, by which we choose to focus on several dimensions of wellbeing rather than utilizing a single univocal indicator. Namely, we consider subjective wellbeing from a life satisfaction scale; measures of social capital and of barriers to access to public services; the perception and satisfaction with the broader environmental context in which households live, including both natural and built surroundings; and different measures of income inequality, which is still an important element of wellbeing capturing both material resources and social comparisons among households. Following the defensive consumption hypothesis (Bartolini et al., 2023; Bartolini & Sarracino, 2014), all these dimensions are crucial for people's happiness not to be channeled towards higher private consumption and material footprint. Along these lines, we aim to test two hypotheses. First, that people consume to compensate for the emotional distress and collective disempowerment caused by poor social capital, and second, that policies able to promote social capital would expand wellbeing, reduce consumption and increase sustainability.

For the first hypothesis we conduct an extensive work to, first, construct several indicators drawing from the *Multipurpose Survey on Households: Aspects of Daily Life* for Italy, and second, to integrate such indicators with information for income and consumption from other dataset through statistical matching techniques. We then concentrate on analyzing empirically the relationship between wellbeing—across all its said dimensions—and consumption, since any assessment of wellbeing effects must be grounded on observed relations in data. Moreover, here we focus not only on the relation between wellbeing and the total level of consumption, but especially on the effects of wellbeing alongside price and income effects on consumption composition. Consumption composition is crucial since consumption is still the main form to satisfy material needs in capitalist market economies, so an exclusive focus on total expenditure risks being reductionist when there are still people who do not have their material needs granted. It also allows us to analyze the differential impact across consumption categories which are important from a wellbeing perspective, such as necessary goods versus luxury or positional ones. Furthermore, this framework of multiple wellbeing indicators affecting multiple consumption categories together with price and income effects allows us to capture social barriers, which are related, on the one hand, to consumption patterns and reaction to prices (e.g. carbon pricing policies), but also, on the other hand, to the state of public infrastructure and services—for which the consideration of barriers to access indicators and several consumption categories plays a pivotal role.

For the second hypothesis, in turn, we introduce an important novelty in the Eurogreen model: a households' module that increases heterogeneity, integrates the income generation process at the individual level with consumption at the household level, and allows for a better depiction of the consumption process, which is more easily linked to available data. Given the extension of the empirical work to explore the relation between wellbeing and consumption, and of the modeling work related to the households' module, the exploration of wellbeing policies in Eurogreen is still preliminary: we include the estimated effects of wellbeing, add variables for wellbeing indicators, and simulate exogenous changes in social capital, as a way of approximating the final effect of such policies.

This deliverable is thus organized as follows. After this introduction, the second section reports in detail the technical aspects of linking data on wellbeing, income and consumption through statistical matching of different datasets. In the third section we describe the empirical strategy to assess the relationship between wellbeing and consumption, through regressions of total household expenditure, the estimation of an integrated demand system to measure the effect of prices, income and wellbeing on consumption composition, and an analysis of how price shocks affect households' standard of living across different levels of wellbeing. In the fourth section we explain the main modifications to the Eurogreen model—with an extensive explanation of the households' module in the Appendix—and conduct preliminary simulations of wellbeing-enhancing policies. Finally, the fifth section concludes.

2 Integration of datasets on wellbeing, income and consumption

2.1 Introduction on data processing

In this section we construct a dataset that is the result of matching three different sources. These are the *Survey of Household Income and Wealth* (SHIW) conducted by the Bank of Italy on a biannual basis, with information on income and savings of Italian households; the *Household Budget Survey* (HBS) from ISTAT, which records in detail the spending behavior of households residing in Italy; and finally, the survey *Aspects of Daily Life* (AVQ, from the Italian name *Aspetti di Vita Quotidiana*) from ISTAT as well, with information on the living conditions, well-being and habits of citizens in various areas, such as leisure time, health, social participation and use of technology.

The need to combine SHIW and HBS arises to have household income and consumer spending disaggregated into categories in a single dataset. The addition of AVQ allows a series of non-economic indicators of household well-being to be included in the analysis.

The study covers a four-year period ranging from 2014 to 2017. Since SHIW was released on a biannual basis, the matching procedure has been implemented as follows:

- YEAR 2014: SHIW 2014 + HBS 2014 + AVQ 2014
- YEAR 2015: SHIW 2014 + HBS 2015 + AVQ 2015
- YEAR 2016: SHIW 2016 + HBS 2016 + AVQ 2016
- YEAR 2017: SHIW 2016 + HBS 2017 + AVQ 2017

The hypothesis behind this choice is that the Italian economic scenario has not changed significantly enough in the periods 2014-2015 and 2016-2017, to determine relevant alterations of the income structure.

2.2 Matching between SHIW and HBS

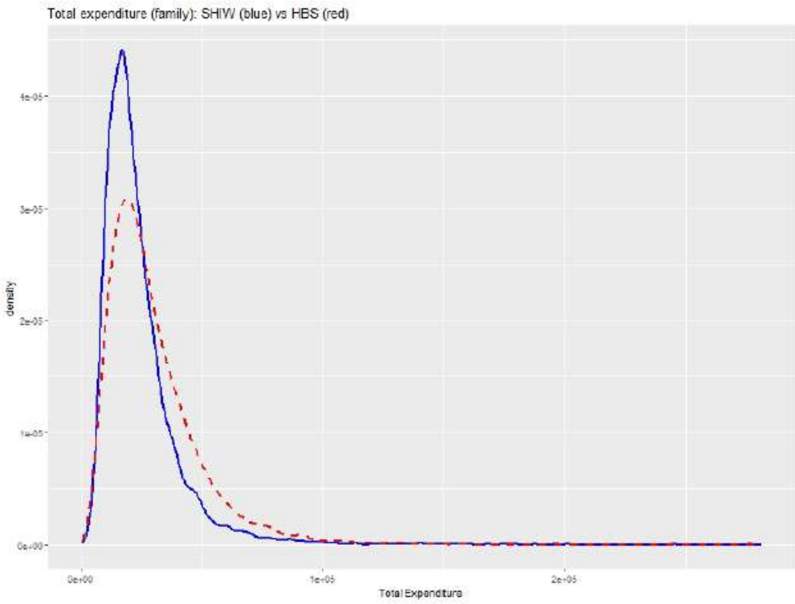
For the matching between SHIW and HBS, the procedure described by Akoğuz et al. (2020, p. 29) was followed, but a preliminary stage of harmonization of the common variables and the necessary pre-match checks were carried out.

The data pre-processing phase started with a general detection of outliers, meaning extreme values in the distributions of continuous variables such as income and expenditure measures, as well as data entry errors. Afterward, we proceeded by encoding variable outcomes uniformly between datasets to set the ground for the creation of family-level variables. HBS's structure allowed us to row-sum for the characteristics of interest, as it is built in a way that each row corresponds to a family. Total annual expenditure of the family was present in the original version of the dataset as "*sp_tot_str_aggr_1*". Quite the opposite, in SHIW each row represents a family member, and it is possible to trace the composition of each nucleus thanks to the family-identification number "*nquest*". Family-level variables were derived by grouping by "*nquest*" and counting. For the creation of family income and total expenditure we followed the approach described in the SHIW documentation (Banca D'Italia, 2012), taking care to account for all those measures defined at group level but displayed for each member only once.

Concerning head of household and their characteristics, we decided to define them as the family component with the highest income. This person is easily identifiable in HBS thanks to the dummy variable "*max_percettore*", whereas in SHIW we searched, for each family, who the member with highest earnings was.

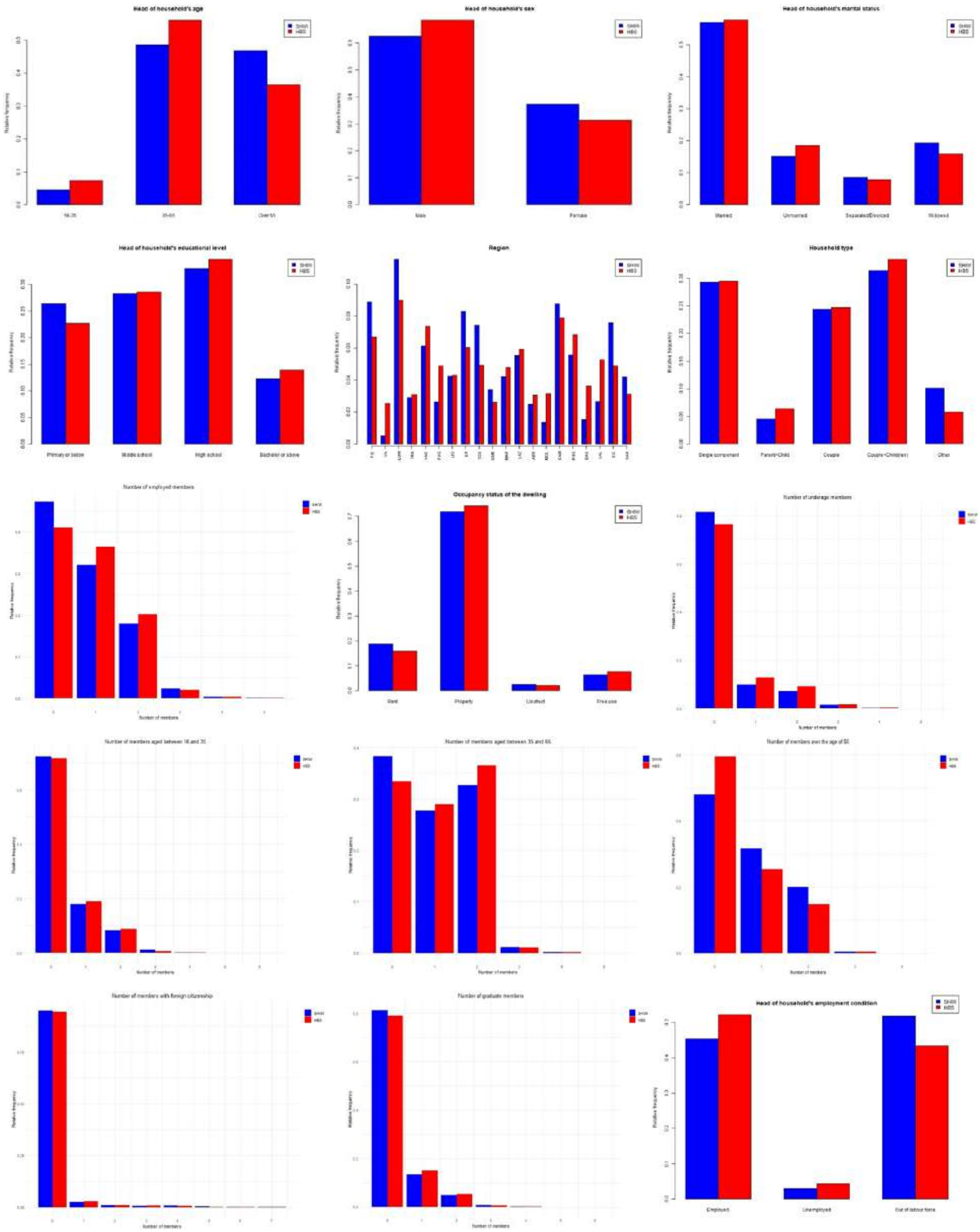
We then eliminated from HBS and SHIW all the superfluous variables, only leaving family attributes, head of household features and total annual expenditure and income of the family. The list of variables in common in the two sources is the following: sex of head of household, age of head of household, educational level of head of household, marital status of head of household, employment condition of head of household, household type, total annual expenditure of the family, occupancy status of the dwelling, region, number of underage members, number of members aged between 18 and 35, number of members aged between 35 and 65, number of members over the age of 65, number of graduate members, number of members with foreign citizenship and number of employed members. Distributions of these variables were plotted both for SHIW and HBS to determine to what extent they overlap, and the resulting graphs are displayed here.

Figure 1: Total expenditure in HBS and SHIW



The overlap between the sample distributions of the annual total household expenditure variable is not as good as the remaining common variables as can be observed in Figure 1. The mean value is 24153 euros in SHW and 30004 euros in HBS. This discrepancy is consistently observed across the literature (Akoğuz et al., 2020; Coli & Tartamella, 2008). There may be several reasons behind this inconsistency. Firstly, the definitions of variables might not be the same for the two datasets, so that incongruities emerge when aggregated measures are computed. A further explanation can be the different methods that the two surveys use to calculate total expenditure. For instance, the expenditure variables in the HBS dataset are reported as monthly figures. However, the dataset does not specify whether these amounts refer to household spending in a specific month or to their average monthly expenditure. If they represent spending in a single month, multiplying them by 12, as we did to estimate annual household expenditures, may produce inaccurate results because of seasonality. However, Figure 2 shows that the matching variables between the two datasets follow similar distributions, which validates their chose for the procedure.

Figure 2: Distribution of matching variables in SHIW and HBS



We then proceeded with the implementation of the matching strategy after having observed a globally satisfactory level of overlap in distributions. Therefore, we conduct the following steps:

- Income in SHIW was regressed using the variables common to both datasets as independent variables;
- Using the estimated coefficient values, the fitted values of household income were calculated in both SHIW and HBS;
- For each household in SHIW, the closest corresponding household in HBS was sought on the basis of the proximity of these fitted values;
- The observed income value in SHIW was added to the closest corresponding row in HBS. Due to the smaller number of rows in SHIW compared to HBS, the matching was not 1:1.

2.3 Matching with AVQ and definition of wellbeing indicators

Afterwards, we went on with the creation of family variables in AVQ. As the dataset configuration corresponds to the SHIW's one, we grouped by "*profam*", the family identification number, and we counted the number of members with the characteristics of interest. A large number of missing values were observed for the marital status and occupation variables, but a more detailed analysis has shown that in both cases all the units were also family members of less than 18 years. We just considered them unmarried in the first case and out of labour forces in the second.

A caveat must be made in the identification of the head of household in this context. The AVQ dataset does not allow for an exact identification of the member of the family with highest income, since there is neither a dummy variable to recognize them, nor income data available to derive this information. Hence, we chose to assume that the family member earning more matches the reference person of the survey. To understand whether this hypothesis is reasonable, we checked the number of cases to which it holds true in HBS and SHIW. The results show that this correspondence works in 89% of cases in HBS and in 82% of cases in SHIW.

Non-economic indicators of wellbeing are then constructed at individual level as linear combination of existing variables in the dataset, with the goal of providing measures of a broad range of life aspects defining individual's wellness which are not proxied or necessarily correlated with income. The areas these indicators focus on are subjective wellbeing, social capital, ease of access to private and public services, and quality of the living area and environmental conditions.

Life satisfaction is measured using by *lifesatisf*, that replicates a variable that specifically asks this question to individuals. Social capital defines the degree of inclusion of the individual in communities or groups and their closeness to other people in wider terms. Specifically, the variable *relationship_f* describes the presence of people the person can count on in case of need, considering relatives, friends and neighbors. It can be seen as a degree of social integration. Conversely, *trust_f* proxies to what extent the individual believes that other people would not take advantage of them in a situation of vulnerability. It is computed as the mean of three variables, each of which gives the scale of how likely the person finds that their wallet, if lost, would be returned by, respectively, a neighbor, a policeman or a stranger. Higher values correspond to higher levels of trust. Although not strictly connected to social proximity, the indicator *transport_f* summarizes the frequency of use of public transport (bus, train and tram), providing an idea both on the person's use of time, and their closeness to their centers of interest such as the workplace.

A series of indicators then capture the presence of barriers to services, either private or public. In particular, the variable *barhealth_f* synthetizes the presence of obstacles in accessing health hubs like pharmacies and first aid centers. *Barpuboff_f* gives account of difficulties in reaching other type of public services, such as postal offices, police stations and local municipality offices, whereas *barpubserv_f* describes how hard it is to find waste disposal hubs as well as public energy providers' offices on the territory. Concerning private services, the indicator *barstores_f* focuses on the presence of grocery stores and supermarkets in the area where the individual lives. For all the previous indexes, higher values indicate greater difficulty in accessing services, and it is plain to see how a high score obtained in many of these measures depicts a scenario of serious isolation, negatively impacting people's lives.

Two final indicators proxy the quality of the area where the family lives, both in terms of how well preserved the neighborhood is and of its environmental conditions. *Neighbquality_f* is a summary measure describing how dirty, noisy and polluted the district is, as well as to what extent the risk of criminality is present there. Lastly, *environment_f* is an indicator of satisfaction with the environmental conditions of the area in which the individual lives. For both the indexes, higher scores indicate better living conditions. The family-level measure of each indicator is obtained as mean of the values of single members. The number of NA was negligible in this case, and we only dropped families whose vector of indicators was not full (i.e. free of NA values). The composition of the indicators is shown in the following table.

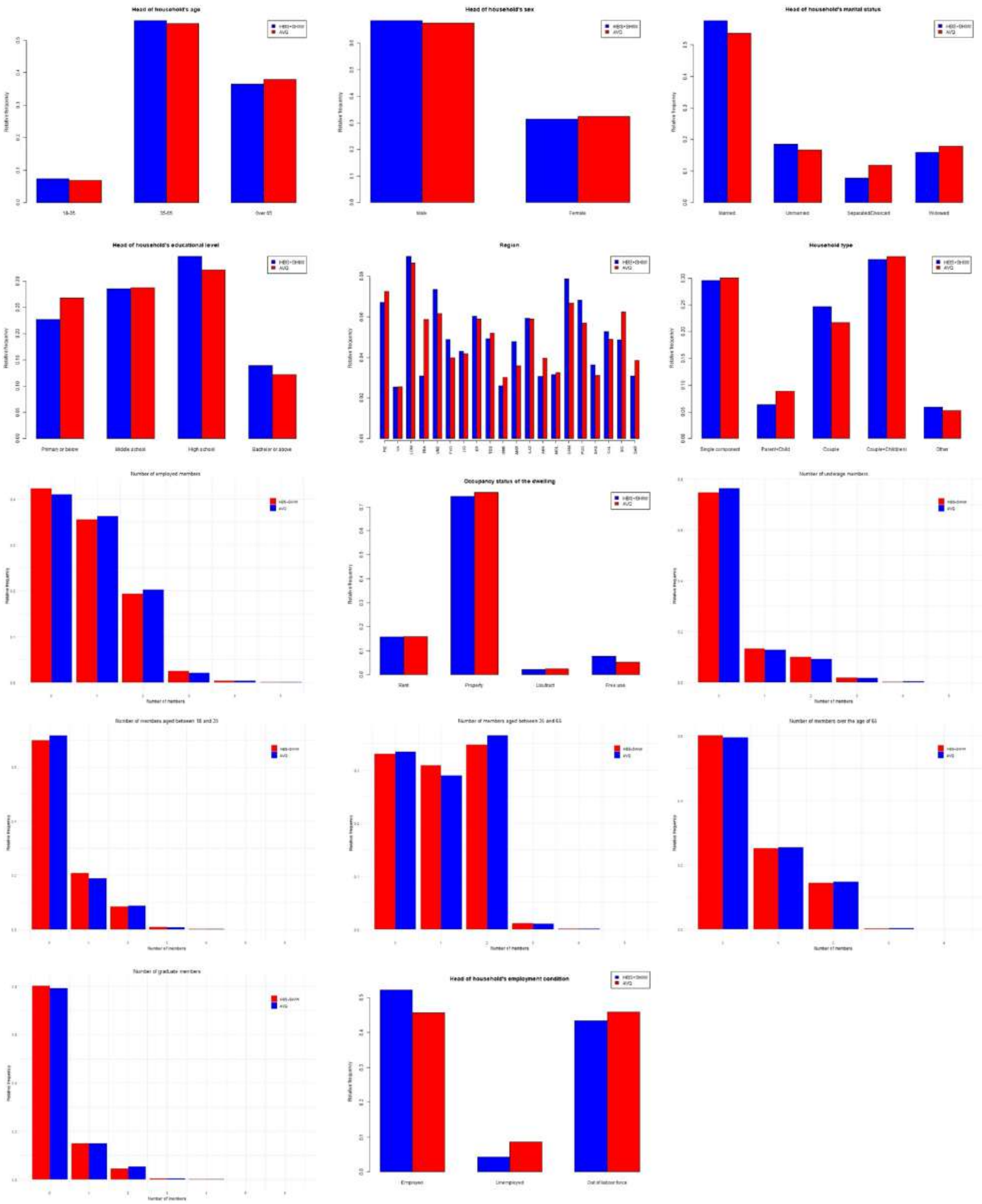
Table 1: Indicators of non-monetary drivers of wellbeing

Variable	Description	Support
Lifesatisf	Indicator of overall life satisfaction (variable *VOTOVI*).	
Relationship	Indicator of the presence of people on whom the individual can rely in case of need. For each individual, it is the average between *PARENT*, *AMICI2*, and *VICINI*. 1 indicates absence and 2 indicates presence of support.	[1 ; 2]

Trust	Indicator of the level of trust in others. For each individual, it is the average of *FIDU1*, *FIDU2*, and *FIDU3*. Higher values correspond to higher levels of trust.	[1 ; 4]
Transport	Indicator of public transport usage frequency. For each individual, it is the average between *USOTRAM*, *USTRE*, and *USOPUL*. Higher values indicate more frequent use of public transport.	[1 ; 5]
Barhealth	Indicator of barriers to accessing healthcare services. For each individual, it is the average between *FARMA* and *PRSOC*. Higher values indicate greater difficulty in accessing services.	[1 ; 3]
Barpuboff	Indicator of the presence of barriers to accessing public offices. For each individual, it is the average between *UFFPO*, *POLICE*, and *UFFCOM*. Higher values indicate greater difficulty in accessing services.	[1 ; 3]
Barstores	Indicator of the presence of barriers to accessing stores selling essential goods. For each individual, it is the average between *MERCAT* and *SMERC*. Higher values indicate greater difficulty in accessing services.	[1 ; 3]
Barpubserv	Indicator of the presence of barriers toaccessing public services (e.g., waste disposal). For each individual, it is the average of *CASS, SEGAS*, and *SLUCE*. Higher values indicate greater difficulty in accessing services.	[1 ; 3]
Neighbquality	Indicator of the quality level (understood as absence of degradation) of the neighborhood of residence, which takes into account aspects such as noise, pollution, crime, etc. For each individual, it is the average between *TRAF, INQAR, RUMORE, CRIM, ODSGR, ILLSTR, CONPAV,* and *SPORCO*. Higher values indicate greater "quality."	[1 ; 4]
Environment	Indicator of satisfaction with the environmental conditions of the area in which the individual lives. Higher values indicate greater satisfaction.	[1 ; 4]

Once the indicators were created, as was done in the previous case, we proceeded by comparing the distributions of common variables between the two sources to be merged, meaning AVQ and what we previously obtained as a result of the first matching, namely HBS + SHIW. The list of common variables is the following: sex of head of household, age of head of household, educational level of head of household, marital status of head of household, employment condition of head of household, household type, occupancy status of the dwelling, region, number of underage members, number of members aged between 18 and 35, number of members aged between 35 and 65, number of members over the age of 65, number of graduate members and number of employed members.

Figure 3: Distribution of matching variables in AVQ and HBS+SHIW



Since the overlap of distributions for each common variable was satisfactory as shown in Figure 3, we carried out the matching strategy as follows: for each row of AVQ, we searched for the closest row among those of HBS+SHIW using Mahalanobis distance as the distance metric. Once the closest row pairs were obtained, for each pair, the vector of non-economic indicators was transferred from AVQ to HBS+SHIW.

The final result is a dataset of 16,804 rows (for the year 2014). For each household, there is information on the household itself and on the characteristics of the head of household, identified as the family member with the highest income, as well as income, disaggregated annual consumption expenditure and non-economic indicators of wellbeing. The whole procedure has been replicated to construct datasets for years 2015, 2016 and 2017 too.

3 Empirical analysis

3.1 Wellbeing indicators

In this section we explore empirically the effect of non-monetary drivers off wellbeing on both total consumption expenditure of households, and on their consumption composition. Given that these indicators are observed at the individual level while consumption is observed for households, we compute household wellbeing for each indicator as the average of all its members. To reduce the number of indicators and focus on the more relevant ones, we exclude *transport* and *barstores* from the analysis—these are strongly correlated with transport usage and other barriers of access, respectively, so the new information they convey is limited. On the other hand, we create a composite indicator of barriers to access as the average of public servies and offices (*barriers*) as the average of *barhealth*, *barpuboff*, and *barpubserv*.

In addition to the wellbeing indicators already described, we also include different measures of income inequality. Although its role as a determinant of wellbeing is disputed and relatively small (Ngamaba et al., 2018), it remains an important factor to consider in relation to consumption and interhousehold comparisons.

Inequality is defined for the variable *household's disposable income excluding imputed rents* from SHIW[1] and measured within groups of households defined by year, region, and

[1] Imputed rents are a fictional flow of income imputed to house owners, aiming to capture the use and provision of housing services made by themselves. If added as income, households living in their own houses are treated as if they were renting it and their income would thus be artificially inflated. For inequality measurement it is therefore better to exclude imputed rents as a source of income. In SHIW's nomenclature, the resulting variable is y – yca2.

type of household.[2] We employ both objective and subjective indicators of income inequality. The objective measure is the Gini index within each group (*gini*), and the subjective measure is the percentage difference of each household's income with respect to the median of the group (*relativeposition*). This measures the position of a household within its group's distribution through which we aim to capture the subjective perception of inequality; negative values indicate incomes below the median, and positive values indicate incomes above the median.

We exclude from the dataset the observations with zero or negative expenditure, which results in 64.160 observations for the four waves of HBS pooled. Table 2Table *2* presents the descriptive statistics for total household expenditure (in current prices, annualized) and our wellbeing indicators.

Table 2: Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
expenditure	64,160	23276.78	16850.99	99.96	307558.2
lifesatisf	64,160	6.942116	1.563465	0	10
relationship	64,160	1.723856	0.4292192	1	3
trust	64,160	2.646586	0.5886145	1	4
barriers	64,160	1.661567	0.5234843	1	4
neighbqual	64,160	2.910766	0.6218078	1	5
environment	64,160	2.826993	0.671442	1	4
relativeposition	63,297	0.148155	0.7234168	-0.999993	15.37163
gini	64,160	0.3040604	0.0297821	0.1528243	0.4544076

Table 3 presents the correlation coefficients among the indicators of non-economic drivers of wellbeing in the sample. There is a positive correlation among indicators that tend to increase wellbeing—life satisfaction, relationships, trust, satisfaction with environment, and neighborhood quality; there is a positive correlation between the indicators that tend to decrease wellbeing—barriers to public services and Gini; and there is a negative correlation between indicators of the two groups. Correlations are generally small in magnitude, suggesting that the indicators are not redundant and capture distinct dimensions of wellbeing. The highest correlation occurs between neighborhood quality and environmental satisfaction, as expected for such indicators, but it is nevertheless not that high (0,42). The second highest correlations occur between life satisfaction and

[2] Controlling for the variable *type of household* to define the groups allows us to use absolute income rather than equivalized income to make the comparisons, since we are already accounting for differences in households' age and size composition.

environmental satisfaction (indicating that this is an important element of overall life satisfaction)

Table 3: Correlation coefficients among wellbeing indicators

	lifesatisf	relations.	trust	barriers	neighbq.	environ.	relpos.	gini
lifesatisf	1.0000							
relationship	0.1574*	1.0000						
trust	0.2326*	0.1907*	1.0000					
barriers	-0.1518*	-0.0756*	-0.1281*	1.0000				
neighbqual	0.1044*	0.0523*	0.1074*	-0.0733*	1.0000			
environment	0.2094*	0.0688*	0.1754*	-0.0685*	0.4244*	1.0000		
relativeposition	0.0499*	0.0540*	0.0557*	-0.0332*	-0.0308*	-0.0076	1.0000	
gini	-0.0732*	0.0104*	-0.0639*	0.1050*	-0.0335*	-0.0701*	0.0476*	1.0000

Correlations are more striking for inequality indicators. The Gini index correlates positively with relationships, which is somewhat counterintuitive: it means that households have stronger relationships when they belong to a group with higher inequality. However, the correlation is quite small. On the other hand, subjective inequality having a positive correlation with indicators that increase wellbeing suggests that this variable may be capturing an income effect by which higher incomes are associated with higher wellbeing. We further investigate this issue by splitting such variable in two: *ineq_pos*, equal to ineq if positive and zero otherwise; and *ineq_neg*, the absolute value of ineq if negative and zero otherwise. Their correlations with the other wellbeing indicators are shown in Table 4. According to these correlations, having an income above the median appears to be associated with higher wellbeing in other dimensions, with an opposite and stronger relation for incomes below the median. This suggests that higher inequality across similar households does not have a symmetric effect on wellbeing, with a negative and higher impact for poorer households, which is also expected.

Table 4: Positive and negative subjective inequality correlations

	ineq_pos	ineq_neg
lifesatisf	0.0341	-0.0676
relationship	0.0464	-0.0478
trust	0.0421	-0.0648
barriers	-0.0249	0.0388
neighbqual	-0.032	0.0126
environment	-0.0157	-0.0176
relativeposition	0.9561	-0.6291
gini	0.0697	0.0342

3.2 Total expenditure effect

To explore the relationship between wellbeing indicators and consumption we first run regressions of the logarithm of total household consumption expenditure excluding imputed rents on the indicators of wellbeing. Indicators are included first separately, grouped into categories of different dimensions of wellbeing, and then all together.

We thus run eight regressions. In the first one we only include demographic controls, regional dummies, and the logarithm of household income, which are all included across all regression. The second regression considers only the indicator for life satisfaction, capturing subjective wellbeing. The third includes relationships and trust, capturing the social capital dimension. The fourth includes barriers to public services, neighborhood quality, and environmental satisfaction, capturing the public and environmental dimensions of wellbeing. The fifth includes the Gini index, to capture objective inequality. The sixth and seventh regressions focus on subjective income inequality: the sixth includes the overall indicator, while in the seventh it is split into positive and negative components. Finally, the eighth regression includes all the indicators of wellbeing (with subjective inequality split).

As demographic controls, we include a set of dummy variables for household-head and household characteristics, and regional dummies as well with Sardinia as reference. For the household head, we include *male* (female as reference), *age3564* and *age65* (age ranges 35–64 and 65+, with younger adults as reference), *emp* and *unemp* (employed and unemployed, with inactive as reference), and *midskill* and *highskill* (education level, with low skill as reference). For household characteristics, we include the number of *children* and *elders*, number of income earners (*n_perc*), and a dummy for renting (*tenant*).

Results are reported in Table 5. Demographic controls are generally significant and stable cross regressions, although some important changes are observed in the last three regressions (6, 7 and 8), which are the ones including subjective inequality. Specifically, including these variables makes *age35-64* non-significant, makes *emp* and *elders* significant, increases the effect of *male*, *age65*, *children*, *n_perc* and *tenant*, and reduces the effect of *midskill* and *highskill*. This confirms the importance of subjective income inequality in determining household expenditure, and of the income level in general. However, note that the income (*lny*) also reduces its coefficient in the last three regressions, but it remains significant, nevertheless. This suggests that subjective inequality captures more than an income effect, even if it is closely related to income.

Table 5: Regression of total household expenditure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
male	0.0636***	0.0629***	0.0636***	0.0628***	0.0621***	0.0791***	0.0867***	0.0807***
	(0.00587)	(0.00582)	(0.00588)	(0.00591)	(0.00585)	(0.00623)	(0.00628)	(0.00624)
age3564	0.0355***	0.0363***	0.0351***	0.0348***	0.0356***	0.00779	-0.00212	-0.00316
	(0.00879)	(0.00879)	(0.00872)	(0.00881)	(0.00880)	(0.00845)	(0.00845)	(0.00853)
age65	-0.0818***	-0.0816***	-0.0824***	-0.0814***	-0.0801***	-0.162***	-0.186***	-0.183***
	(0.0174)	(0.0175)	(0.0174)	(0.0176)	(0.0175)	(0.0179)	(0.0182)	(0.0185)
emp	-0.0136	-0.0142	-0.0137	-0.0138	-0.0135	-0.0369***	-0.0448***	-0.0461***
	(0.00946)	(0.00946)	(0.00947)	(0.00942)	(0.00943)	(0.00921)	(0.00928)	(0.00911)
unemp	-0.184***	-0.181***	-0.183***	-0.184***	-0.183***	-0.198***	-0.177***	-0.174***
	(0.0158)	(0.0157)	(0.0158)	(0.0158)	(0.0157)	(0.0151)	(0.0152)	(0.0150)
midskill	0.206***	0.205***	0.206***	0.202***	0.206***	0.173***	0.159***	0.151***
	(0.0123)	(0.0122)	(0.0123)	(0.0123)	(0.0122)	(0.0115)	(0.0112)	(0.0110)
highskill	0.353***	0.352***	0.352***	0.349***	0.353***	0.227***	0.213***	0.203***
	(0.0191)	(0.0192)	(0.0193)	(0.0191)	(0.0191)	(0.0164)	(0.0159)	(0.0160)
children	0.0884***	0.0878***	0.0882***	0.0886***	0.0889***	0.122***	0.134***	0.136***
	(0.00386)	(0.00384)	(0.00387)	(0.00385)	(0.00379)	(0.00438)	(0.00433)	(0.00427)
elders	0.00884	0.00898	0.00889	0.00872	0.00689	0.0329***	0.0380***	0.0324***
	(0.00695)	(0.00698)	(0.00690)	(0.00701)	(0.00714)	(0.00684)	(0.00687)	(0.00707)
n_perc	0.148***	0.148***	0.148***	0.148***	0.148***	0.177***	0.191***	0.191***
	(0.00364)	(0.00363)	(0.00363)	(0.00364)	(0.00359)	(0.00423)	(0.00416)	(0.00405)
tenant	0.157***	0.158***	0.158***	0.156***	0.157***	0.177***	0.195***	0.196***
	(0.0100)	(0.0101)	(0.0100)	(0.00996)	(0.0100)	(0.00942)	(0.00919)	(0.00907)

Table 5: Regression of total household expenditure (continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
lny	0.310***	0.310***	0.310***	0.309***	0.309***	0.159***	0.0957***	0.0901***
	(0.0116)	(0.0116)	(0.0116)	(0.0116)	(0.0116)	(0.00973)	(0.00929)	(0.00933)
lifesatisf		0.00385*						0.00434**
		(0.00157)						(0.00160)
relationship			0.000615					-0.00279
			(0.00595)					(0.00645)
trust			0.00778					0.00414
			(0.00407)					(0.00418)
barriers				-0.0232***				-0.0235***
				(0.00553)				(0.00572)
neighbquality				-0.00809*				-0.00744
				(0.00384)				(0.00411)
environment				0.000255				-0.00335
				(0.00397)				(0.00416)
gini					-0.286			-0.916***
					(0.176)			(0.228)
relativeposition						0.277***		
						(0.0116)		
ineq_pos							0.259***	0.264***
							(0.0106)	(0.0110)
ineq_neg							-0.622***	-0.632***
							(0.0244)	(0.0243)
_cons	6.074***	6.050***	6.054***	6.143***	6.173***	7.477***	8.148***	8.546***
	(0.112)	(0.113)	(0.114)	(0.115)	(0.127)	(0.0980)	(0.0990)	(0.141)
N	63297	63297	63297	63297	63297	63297	63297	63297
R^2	0.445	0.445	0.445	0.445	0.445	0.486	0.491	0.492

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Coefficients for regional dummies omitted

Regarding the wellbeing indicators, their significance does not change much whether they are included separately or jointly, except for neighborhood quality and the Gini index.

Life satisfaction, barriers to public services, and the measures of inequality are significant in the final regression including all indicators, while neighborhood quality turns non-significant. The defensive consumption hypothesis is observed for relationships, neighborhood quality, and environmental satisfaction, as higher wellbeing in these dimensions is associated with lower expenditure. However, such effects are non-significant. On the other hand, life satisfaction and trust have a negative coefficient, with contradicts the hypothesis, with only the former effect being significant.

Inequality indicators, in turn, are the most significant, with the Gini index having a strong negative effect on consumption. It means that higher objective inequality within a group of similar households is associated with lower expenditure. The subjective inequality variables seem to move more in line with income, as being further above the median income has a positive effect on consumption, while being further below has a negative effect.

In general, non-monetary wellbeing indicators do not have a strong effect on overall consumption, except for life satisfaction which tends to increase consumption. On the contrary, barriers to public services and inequality tend to decrease consumption, reflecting the impact of material constraints in terms of barriers to access and low income. However, note that the effect of the income variable changes across regressions: it falls from 0,310 when no wellbeing indicator is included, to 0,090 when they all are. This responds to inequality indicators capturing part of the income effect, but such an effect alone cannot explain all the observed reduction in the income coefficient. This suggests that non-monetary wellbeing, when accounted for in several dimensions, affects overall consumption and reduces the importance of income.

3.3 Consumption composition effect and demand system

To further explore the impact of wellbeing on consumption it is thus better to look at its composition. A standard method of analysis in this case is the econometric estimation of *Demand Systems*, which allow modeling the households' decision to allocate consumption across different goods and services as a joint and interdependent process, and to estimate the effect of its main determinants. Being anchored in neoclassical consumption theory, demand systems are widely used in the estimation of demand elasticities, poverty measurement and analysis, equivalence scales among other topics.[3]

[3] See Slottje (2009) for a complete account of demand systems and their use.

Herein we will employ the Quadratic Almost Ideal Demand System (QUAIDS) model by Banks et al. (1997), who extended the original linear AIDS model of Deaton & Muellbauer (1980) by allowing non-linear quadratic Engel curves. The (QU)AIDS-type of models is the most used given its consistency with utility maximization consumer theory, the possibility to impose and test restrictions derived from such a theory, its flexibility to accommodate "almost" any demand system, the interpretability of its results, and the empirical tractability, given that its parameter-linearity and the possibility to address endogeneity issues, which make it robust and easy to handle by standard econometric packages and techniques. Moreover, the QUAIDS model can be easily extended to account for household heterogeneity through the inclusion of demographic variables, a feature that we exploit here to explore the effect of the non-economic drivers of wellbeing besides the conventional income and price effects.

It must be noted, nevertheless, that the QUAIDS model has not been exempt from criticism. Namely, some of its theory-driven assumptions limit its ability to capture important phenomena, like the interaction between income and price effects (Almon, 1996), while the quadratic function remains limited to capture the varied non-linear shapes of Engel curves (Lewbel & Pendakur, 2009).[4] However, for the purpose of exploring the effect of wellbeing on consumption, these limitations remain acceptable, especially considering the practical challenges associated with the estimation of alternative and more complex demand systems. The QUAIDS model, by contrast, remains a solid framework and offers a well-established and straightforward implementation, so we stick to it for the present analysis.

The QUAIDS model involves the estimation of a system $i = 1, \ldots, n$ equations (each representing a different consumption category) of the form:

$$w_{i_h} = \sum_{r=1}^{k} \alpha_{ir} z_{r_h} + \sum_{j=1}^{n} \gamma_{ij} \ln p_{j_h} + \beta_i \ln\left(\frac{m_h}{a(p_h)}\right) + \frac{\lambda_i}{b(p_h)} \left(\ln\left(\frac{m_h}{a(p_h)}\right)\right)^2 + \varepsilon_{i_h}$$

Here the subscript h denotes a household, each observation in the sample, omitted in the following for simplicity. w_i is the expenditure share of consumption category i in total expenditure m; p_j is the price of consumption category j; z_r is the household characteristic r in a set of k demographic shifters, among which we include the wellbeing indicators; $a(p_h)$ and $b(p_h)$ are price aggregators, ε_i is the residual term in equation i; and α_{ir}, γ_{ij}, β_i, and λ_i are the parameters to be estimated. The price aggregators $a(p_h)$ and

[4] Some alternatives to overcome this issue are the *Perhaps Adequate Demand System* (PADS) (Almon, 1979, 1996) and the *Exact Affine Stone Index* model (Lewbel & Pendakur, 2009), which have been already applied to Italy (Bardazzi & Barnabani, 2001; Di Cosmo & Tiezzi, 2025).

$b(p_h)$ are respectively the trans-log price index and a Stone-index weighted by the income coefficients, used to ensure the consistency of the expression with consumer theory. These aggregators are defined as:

$$\ln a(p) = \alpha_o + \sum_{i=1}^{n} \left(\sum_{r=1}^{k} \alpha_{ir} z_{r_h} \right) \ln p_i + \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \gamma_{ij} \ln p_i \ln p_j$$

$$b(p) = \prod_{i=1}^{n} p_i^{\beta_i}$$

Where α_o is an unidentified parameter that can be chosen freely. Herein we set $\alpha_o = 0$. Following Banks et al. (1997), it can be shown that the QUAIDS system is obtained from an indirect utility function of the form

$$\ln V = \left(\left(\frac{\ln m - \ln a(p)}{b(p)} \right)^{-1} + \lambda(p) \right)^{-1}$$

Where the additional price aggregator $\lambda(p)$ is defined as

$$\lambda(p) = \sum_{i=1}^{n} \lambda_i \ln p_i$$

This system must satisfy three conditions for internal consistency and coherence with consumer theory (Deaton & Muellbauer, 1980). First, the *additivity* condition requires that all equations sum up to zero, which means that the estimated coefficients must satisfy:

$$\sum_{i=1}^{n} \alpha_{ri} = 1 \, \forall \, r \;\; ; \;\; \sum_{i=1}^{n} \gamma_{ij} = 0 \;\; ; \;\; \sum_{i=1}^{n} \beta_i = 0 \;\; ; \;\; \sum_{i=1}^{n} \lambda_i = 0$$

This condition is easily imposed by estimating $n - 1$ equations and deriving the remaining coefficients using the above restrictions. The linearity-in-parameters of the system ensures that results are independent from the choice of the equation to drop. The second condition is *homogeneity* (of degree zero), derived from consumer theory, by which scaling all prices and income by the same factor would not change demand at all, and implies $\sum_{j=1}^{n} \gamma_{ij} = 0$. And the third condition is the *Slutsky symmetry*, by which the cross-price effects between any pair of goods should be the same, so that $\gamma_{ij} = \gamma_{ji}\ \forall\ i, j$. These last two conditions can be easily imposed and/or tested in econometric estimations (Lecocq & Robin, 2015).

Note that the QUAIDS equations are in terms of expenditure shares while prices and expenditure are in logarithm, so estimated coefficients cannot be interpreted as elasticities. However, following Green & Alston (1990) and Lecocq & Robin (2015), elasticities can be easily obtained by differentiating w_i with respect to $\ln m$ and $\ln p_j$ which yields respectively:

$$\mu_i = \beta_i + 2\lambda_i \left(\frac{\ln m - \ln a(p)}{b(p)} \right)$$

$$\mu_{ij} = \gamma_{ij} - \mu_i \left(\sum_{r=1}^{k} \alpha_{ir} z_{r_h} + \sum_{j=1}^{n} \gamma_{ij} \ln p_j \right) - \lambda_i \beta_j \left(\frac{(\ln m - \ln a(p))^2}{b(p)} \right)$$

Then, using the resulting expressions in the appropriate elasticity formulas $\partial \ln x_i / \partial \ln p_j$ and $\ln x_i / \partial \ln m$ (where x_i denotes real expenditure in category i such that $w_i = p_i x_i / m$), and denoting by δ_{ij} the Kronecker delta ($\delta_{ij} = 1$ when $i = j$ and $\delta_{ij} = 0$ when $i \neq j$), expenditure elasticities, uncompensated elasticities and compensated elasticities are computed respectively as:

$$e_i = \frac{\mu_i}{w_i} + 1$$

$$e_{ij}^{u} = \frac{\mu_{ij}}{w_i} - \delta_{ij}$$

$$e_{ij}^{c} = e_{ij}^{u} + e_i w_j$$

We split households' consumption expenditure into 9 different categories following the COICOP classification as shown in Table 6.

Table 6: Categories of consumption expenditure

N.	Name	Description and COICOP code
1	Food and tobacco	Food and non-alcoholic beverages (CP01); alcoholic beverages, tobacco and narcotics (CP02)
2	Clothing	Clothing and footwear (CP03)
3	Housing	Actual rentals for housing (CP041), maintenance and repair of the dwelling (CP043), water supply and miscellaneous services relating to the dwelling (CP044), furnishing, household equipment and routine household maintenance (CP05)
4	Electricity and gas	Electricity, gas and other fuels (CP045)
5	Health and education	Medical services (CP06) and education (CP10)
6	Transport	Purchase of vehicles, operation of personal transport equipment, transport services (CP07)
7	Communication	Communication equipment and services (CP08)
8	Culture and restaurants	Recreation and culture (CP09); restaurants and hotels (CP11)
9	Other	Personal care, personal effects, social protection, insurance, financial services, and other services (CP12)

As can be observed in Table 7, the highest share of households' consumption is devoted to food and housing, followed by transport and culture and restaurants. For some households all expenditure goes to food, housing and utilities, or health and education, and it can be seen as well that for all expenditure categories there is a percentage of households that do not consume them at all. This is higher for clothing, followed by health and education and transport, while food, housing and utilities have the lowest share of zeros (as expected). Zero expenditures are common because the HBS surveys households monthly and not all expenditure categories are bought at a sufficiently high frequency to be observed for all observations. This is a source of concern in the estimation of demand systems, and several techniques have been suggested to address it (Shonkwiler & Yen, 1999; Tauchmann, 2005). Herein we opted for grouping consumption in sufficiently broad and homogeneous categories, to minimize the share of zeros without reducing the explanatory ability of the categories. Indeed, the share of zeros is not that high for most categories, and this classification is useful as a first approximation to estimate the effect of wellbeing indicators in consumption composition.

Table 7: Descriptive statistics of expenditure shares

Variable	Obs.	Mean	Std. Dev.	Min	Max	Zero share
food & tobacco	64,160	0.2968854	0.1384617	0	1	0.0043953
clothing	64,160	0.0531865	0.0709637	0	0.6925087	0.3444046
housing	64,160	0.1560593	0.1380022	0	1	0.0047070
electricity and gas	64,160	0.0808414	0.0710808	0	1	0.0139183
health and education	64,160	0.0656673	0.0822113	0	1	0.1806266
transport	64,160	0.1160185	0.1162237	0	0.8454338	0.1832450
communication	64,160	0.0373149	0.0321169	0	0.5793902	0.1133572
culture and restaurants	64,160	0.1030334	0.100933	0	0.8454852	0.1033198
other	64,160	0.0909932	0.074895	0	0.9265145	0.0468516

Before delving into the estimation and results, please note that in the QUAIDS equations the price variable depicts the household subscript h, meaning that we employ prices differentiated by household. This is important in demand systems estimation to preserve heterogeneity and variability, and to capture the differences in quality across products and in preferences across households and is usually made by computing unit values in surveys where values and quantities of expenditure are available. Since the HBS contains only values we estimate pseudo-unit values in levels following the procedure by Menon et al. (2017), which correspond to the theoretical Stone-Lewbel prices that have been proven useful for deriving consistent results from demand systems (Moro et al., 2018). Such procedure consists of using official price indices at the regional level from Istat, the composition of consumption for each household and category across subcategories, and a set of household characteristics to estimate pseudo-unit values. These reflect the unit price paid per category, considering household-specific characteristics and consumption composition. Stone-Lewbel prices are expressed in levels rather than indices—that is, they can be read as the monetary value per unit of composite good—which is important to adequately capture complementary and substitution effects and the heterogeneity across households.

Therefore, using the expenditure shares from HBS and the estimated Stone-Lewbel prices, we estimate the QUAIDS model. We include the same demographic characteristics considered above in the regression for total expenditure, and all the wellbeing indicators, with the overall subjective inequality measure. Given that the price aggregators $a(p)$ and $b(p)$ are functions of the estimated coefficients, we follow the iterative procedure of Lecocq & Robin (2015), which departs from initial values of the aggregators and subsequently performs a series of SUR regressions, updating in each iteration the price aggregators with the relevant estimated coefficients until convergence. We impose homogeneity and symmetry as well, since it ensures the appropriate interpretability of results. Note that in the QUAIDS model the expenditure variable m is endogenous since the left-hand-side variables are shares of it. We made the estimations instrumenting expenditure with disposable income in a control function form, but the results were very similar. Therefore, we opted for not correcting such an endogeneity in the final reported results since including income as an instrument creates a collinearity when including the subjective inequality variable.

Given that the QUAIDS system involves the estimation of 9 equations and 279 parameters when wellbeing coefficients are included, we report in Table *8* only the expenditure and compensated own-price elasticities under two model specifications: with and without wellbeing indicators included among the demographic shifters.

Table 8: Estimated elasticities

	Expenditure		Compensated own-price	
	(1)	(2)	(1)	(2)
Food and tobacco	0.713***	0.720***	-0.552***	-0.554***
	(0.003)	(0.004)	(0.008)	(0.008)
Clothing	1.424***	1.423***	-1.012***	-1.006***
	(0.011)	(0.012)	(0.019)	(0.019)
Housing	1.066***	1.062***	-1.120***	-1.137***
	(0.005)	(0.006)	(0.013)	(0.013)
Electricity and gas	0.460***	0.429***	-0.855***	-0.862***
	(0.006)	(0.007)	(0.012)	(0.012)
Health and education	1.191***	1.216***	-0.995***	-0.992***
	(0.010)	(0.011)	(0.022)	(0.022)
Transport	1.368***	1.369***	-0.917***	-0.922***
	(0.006)	(0.007)	(0.012)	(0.012)
Communication	0.655***	0.663***	-1.164***	-1.170***
	(0.008)	(0.009)	(0.018)	(0.018)
Culture and restaurants	1.430***	1.407***	-0.401***	-0.424***
	(0.007)	(0.008)	(0.017)	(0.017)
Other	1.167***	1.162***	-1.118***	-1.120***
	(0.005)	(0.006)	(0.015)	(0.015)
Wellbeing indicators		Yes		Yes

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

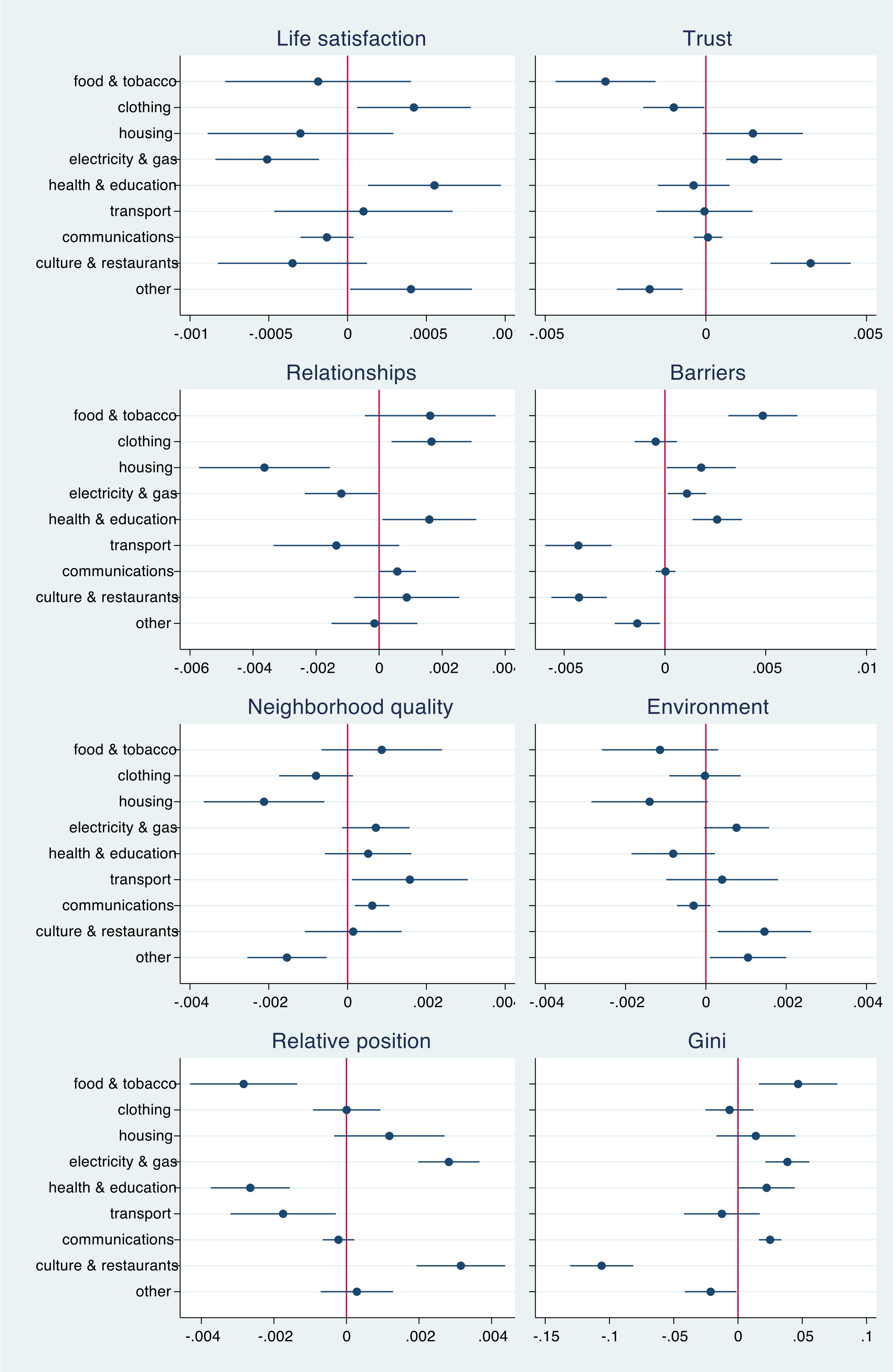
In general, we found that all categories are normal goods, since the expenditure elasticities (which can be interpreted as a proxy for income elasticities) are all positive; food, electricity and gas, and communication are necessary goods (income elasticity lower than one) while the other categories are not. This is expected, with the importance of communication explained by the importance that phone and internet connectivity has gained for ordinary life in the last decades, and the greater-than-one elasticity of housing can be explained by the inclusion in this category of furniture, maintenance, and other less frequent household expenses. The relatively high income elasticities of clothing and culture and restaurants are also expected, and somewhat striking are the high elasticities of transport and health and education, which points to the growing importance of private transport and the commodification of public goods in Italy. Regarding price elasticities, we observe that food and electricity and gas are relatively inelastic as expected, while health and education and transport are close to a unitary elasticity and other goods are inelastic. It is striking the low elasticity of culture and restaurants, which deserves further exploration.

Wellbeing indicators, in turn, seem to affect very little the income and prices elasticities, since they do not exhibit great changes between the specifications with and without such indicators. To explore further their impact, we plot in Figure 4 their coefficients across all equations. Note that several indicators are significant for different consumption categories, which means that they do have an impact on consumption composition. The interpretation of these results from the defensive consumption perspective is not so straightforward, given the broad classifications of consumption goods which prevents their classification as "goods" and "bads" or "private" and "collective". Nevertheless, interesting insights can be derived.

The expenditure share of food and tobacco increases with higher barriers to public services and Gini and decreases with higher trust and relative position. The non-significancy of other wellbeing dimensions, and the necessary character of these goods, suggest that these effects are driven by more material factors: more deprived people experience more barriers to access, and in groups with higher Gini there is a higher share of low-income people, while higher trust and relative position in the income distribution are characteristic of more well-off households, for whom the expenditure share in food tends to be lower.[5]

[5] It would be interesting to explore in further research such effects in the category *Tobacco and alcohol*, which are typical "bads" that may have a stronger association with lower wellbeing.

Figure 4:Marginal effects of wellbeing indicators



Regarding housing, its share is significantly and negatively associated with the strength of relationships and neighborhood quality, and marginally positively with barriers to access. Since this category combines necessary expenses like rents, with more discretionary ones like furniture and household equipment, it is difficult to identify which component drives the observed links with wellbeing. Households facing higher barriers to access may be more materially deprived and allocate a larger share of income to rent, while lower neighborhood quality could reduce incentives to invest in furnishings or home improvements. The negative association with the strength of relationships may indicate a reduced orientation toward housing-related "positional" or quasi-luxury expenditures, consistent with defensive consumption theory and the idea that stronger social capital diminishes the need for status-oriented spending.

For another necessary item, electricity and gas, results reflect a combination of necessity and socioeconomic positioning. While subjective wellbeing and strong social relationships are associated with lower shares—perhaps indicating that happier or more socially embedded households face fewer constraints—the positive effect of relative income position implies that households higher in the income distribution allocate a larger share to utilities, possibly due to higher consumption or investment in comfort and energy-intensive appliances. The lack of association with environmental satisfaction and neighborhood quality indicates that, for this category, expenditures are driven more by household resources and social factors than by contextual or environmental conditions. Overall, energy spending appears to capture both vulnerability among lower-income or socially isolated households and discretionary expansions among better-off households.

For clothing, in turn, the fact that only life satisfaction and the strength of relationships have a positive significant effect might imply that these goods display a symbolic or social signaling role, being consumed more for self-expression and relational purposes than for material necessity. In health and education, we also observe a dual influence of non-economic wellbeing and material constraints. The positive and significant effects of subjective wellbeing and stronger social relationships suggest that households with higher levels of wellbeing are more likely to allocate resources toward these desirable or "quality-enhancing" goods. Conversely, the positive effects of access barriers and income inequality, coupled with the negative effect of relative income position, likely reflect the disproportionate burden these services impose on more deprived households.

Expenses in transport seem more driven by material conditions, as the positive and significant coefficient of neighborhood quality suggests higher private transport expenses for these households, while the negative impact of barriers to access may just be a manifestation of such barriers. Following this argument, the negative coefficient of relative position would mean that the share of transport increases with material deprivation.

Transport expenditure share appears more driven by material conditions. The positive and significant coefficient for neighborhood quality suggests that households in better neighborhoods incur higher private transport expenses, potentially reflecting greater access to vehicles. Conversely, the negative effect of barriers to access likely reflects the limited mobility options of these households. In line with this interpretation, the negative coefficient of relative income position indicates that the transport share tends to increase among more materially deprived households, for whom transport costs represent a larger proportion of total expenditure. Communications seem related to material conditions as well, since only neighborhood quality and relative position have a positive and significant effect, reflecting higher access to such goods for better-off households.

On the other hand, culture and restaurants appear primarily as positional goods, with higher trust, relative income position, and environmental satisfaction exerting a positive and significant effect, reflecting that better-off households tend to allocate more to these discretionary and status-signaling expenditures. The non-significant effect of life satisfaction and strength of relationships suggests that subjective wellbeing and social capital do not have a strong effect in this category. Meanwhile, Gini and barriers to access have a negative effect, reflecting the constraints imposed by material deprivation on spending in these non-essential categories.

This category encompasses personal care items, social protection contributions, financial services, and various miscellaneous goods, making interpretation more complex. The positive association with wellbeing measures may indicate that households with higher subjective wellbeing are able or willing to spend more on discretionary or quality-enhancing services within this broad category, whereas the negative effects of material constraints and inequality suggest that deprived households are limited in their capacity to allocate resources to these non-essential or complementary expenditures.

Overall, the results suggest a differentiated role of wellbeing and material conditions in shaping household expenditure patterns. For necessary goods—food, housing, utilities, transport, and communications—material constraints dominate: deprivation increases expenditure shares, while higher relative income or social capital reduces them. For discretionary or positional goods, the picture is more nuanced. Spending on clothing, health, and education responds positively to subjective wellbeing and social relationships, consistent with the idea that happier or more socially embedded households can invest in quality-enhancing or expressive goods. By contrast, culture and restaurants are largely unaffected by life satisfaction or social ties, with trust and relative income position driving higher expenditures instead, highlighting the positional and status-signaling nature of these categories. These patterns partially support the theory of defensive consumption: lower wellbeing and weaker social networks may lead households to allocate more to necessary or symbolic goods to compensate for deficits, but this effect appears limited to certain categories and does not extend to explicitly aspirational or status-oriented consumption, where social trust and income play a stronger role. Overall, wellbeing measures operate through distinct mechanisms, interacting with material constraints to shape consumption in ways that are both compensatory and status-driven.

3.4 Wellbeing and the impact of price shocks

As seen in the last subsection, we can investigate the impact of non-monetary drivers of wellbeing on consumption through demand systems, which are sufficiently versatile, even if anchored in the standard neoclassical utility maximization theory of consumption. However, a more interesting question regards that non-monetary wellbeing plays in the event of economic shocks that affect households primarily through consumption. In this subsection, we exploit the whole QUAIDS structure to analyze how the energy price shocks of 2022 affected the material conditions of households, and how such effects are or not conditioned by the level of non-monetary wellbeing.[6]

This analysis is based on the concept of *compensating variation*, which measures how much households' income should rise to compensate the utility losses derived from an adverse change in relative prices (Ten Raa, 2022). Since it is based on a monetary notion of utility, the compensated variation should not be read as a welfare loss in a broad sense, but rather as the loss in the material standard of living that, from a wellbeing perspective, is nevertheless important. Here we stick to this interpretation and explore the association between such loss and the non-monetary drivers of wellbeing.

Here we study the effect of the 2022 energy price shock, given its importance in altering households' standard of living not only through higher general price levels and inflation, but also through changes in relative prices derived from the dual role of energy as a final good for consumers and intermediate input for industries, by which the shock propagates across the productive structure impacting all prices in the economy. Being it a historical event, we can exploit the observed price changes across all consumption categories to derive the total effect in both the general price level and relative prices, with no need of

[6] This analysis follows a similar empirical strategy by García (2025), who studied the impact of carbon taxes, but here we consider non-monetary drivers of wellbeing.

simulating the shock in an input-output model. Since our interest here is to explore how non-monetary wellbeing alters the standard-of-living impact of price shocks, rather than studying the effect of energy price shocks in particular, we can consider the 2022 price shock as an important study case without worrying for isolating only the effects of energy prices. Henceforth, we refer to this event as the 2022 price shock for simplicity.

To simulate the effect of the 2021–2022 price shock, we first computed the regional and monthly average prices for each product in both years. Missing values within regions were imputed using the first available observation to ensure complete coverage. The proportional change in prices between 2021 and 2022 was then calculated for each region and month. These relative price changes were subsequently applied to baseline household prices in the sample, generating a counterfactual scenario that mimics the observed price shock across regions and months.

To simulate the 2021–2022 price shock, we computed the annual change in prices for each product at the regional level, using Istat data of regional price indices per COICOP category. These regional price changes were then applied to the Stone-Lewbel prices estimated before for the sample. In this way, we create a counterfactual household-specific price vector reflecting the observed annual price increase in 2022 across regions and consumption categories.

Following García (2025), and using the formula for the indirect utility function of the QUAIDS model and the estimated coefficients, we can compute the compensated variation for each household as:

$$CV = exp\left[\ln a(p^*) + b(p^*)\left(\frac{1}{\ln V} - \lambda(p^*)\right)^{-1}\right] - m$$

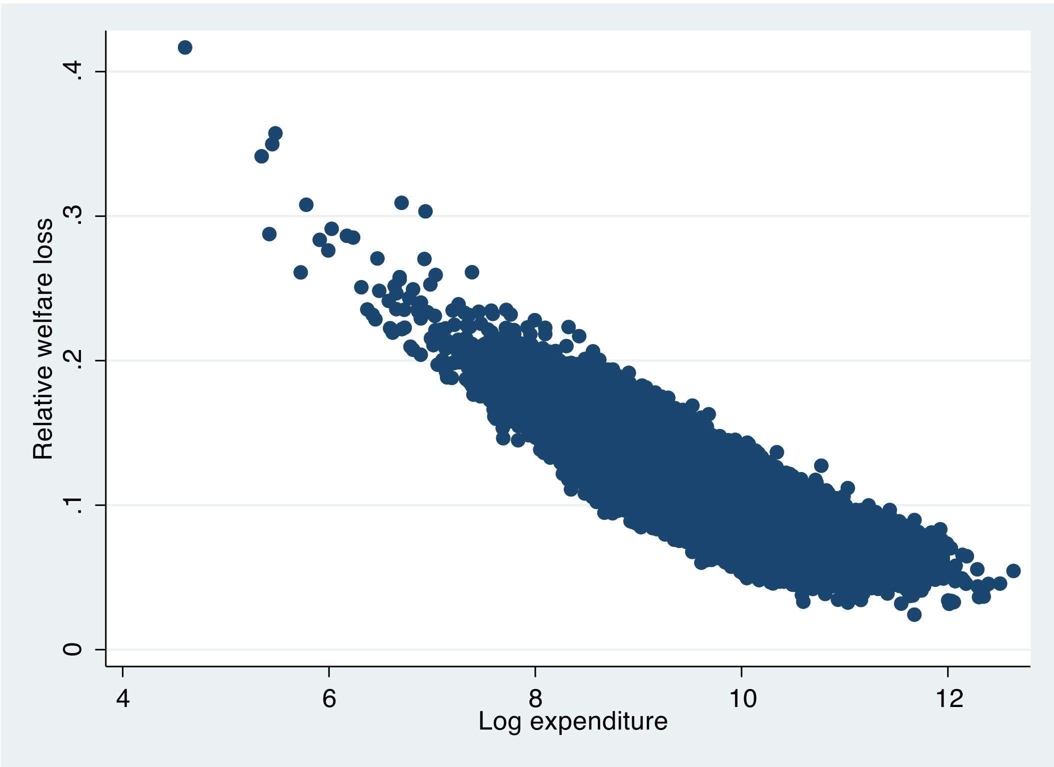
Here p^* denotes the counterfactual price vector after the simulated 2022 price shock, while V and m denotes the household indirect utility and budget before the shock. In what follows, the compensated variation is expressed in relative terms with respect to total expenditure. Recall that this variable measures the size of the standard-of-living loss with respect to expenditure, so higher values mean a higher loss.

In Table 9 it can be observed that the relative welfare loss is negatively associated with life satisfaction, strength of relationships and social capital, meaning that for households with higher wellbeing across these dimensions, the negative impact of the price shock on the standard of living was relatively lower. However, there is a positive association with barriers of access, neighborhood quality and environmental satisfaction, which is expected for the barriers of access variable, but not for the other two. This indicates that more material and environmental conditions do not help at mitigating the negative impacts of price shocks and might, in turn, increase them. The more income-related variables have the expected sign: stronger welfare losses are associated with a relatively worse position in the income distribution and a higher Gini as well. Regarding expenditure, welfare losses are higher for households with lower total expenditure, confirming that negative price shocks provoke higher losses among the more vulnerable and deprived. This can be observed in Figure 5.

Table 9: Correlation of relative CV with wellbeing indicators

	rcv
lnx	-0.8523*
lifesatisf	-0.0802*
relationship	-0.0848*
trust	-0.0365*
barriers	0.1191*
neighbqual	0.0720*
environment	0.0488*
relativeposition	-0.3516*
gini	0.0642*

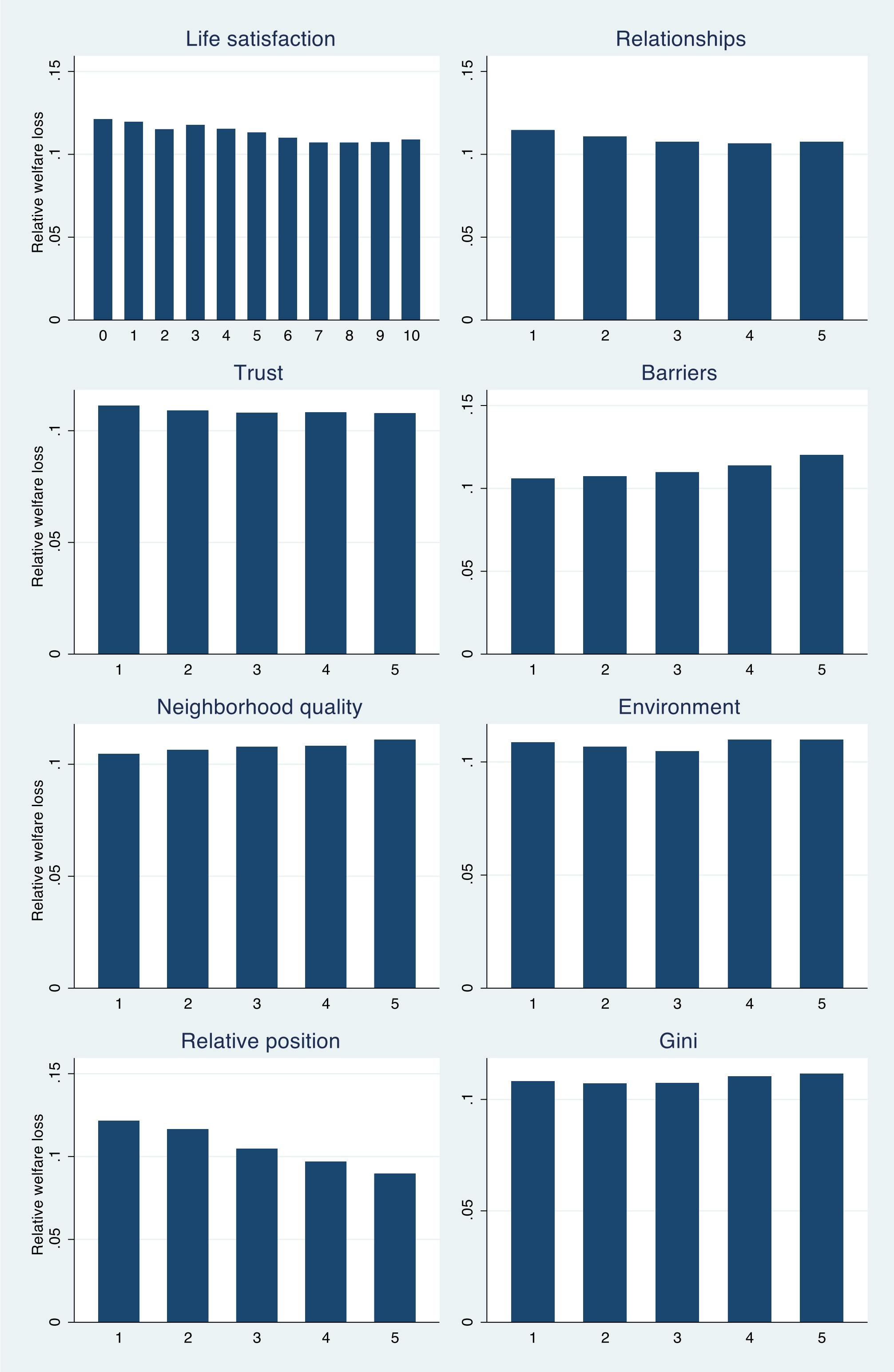
Figure 5: Welfare loss and expenditure



To study the role of wellbeing indicators in mediating the impact of the price shock we plot the size of the relative welfare loss across different levels of each wellbeing indicator. As these indicators are averages across household members, they are not properly discrete. Therefore, we discretize them taking the values closer to their modes and collapsing the extreme values so that we get five groups per indicator, measuring the intensity of each of them. Only for life satisfaction we leave the original scale, from 0 to 10, but discretized it as well to the closest integer. Results are shown in Figure 6.

It can be observed that wellbeing indicators do not have in general a strong relation with the level of the relative welfare loss, although some interesting patterns emerge. For life satisfaction and relationships, there is an inverse relation between the value of the indicator and the size of the welfare loss, meaning that higher non-monetary wellbeing in these dimensions is associated with a lower negative impact of the price shock. Neighborhood quality exhibits the opposite relation, which may respond to higher cost of living associated with higher values of this indicator. These effects are, however, very small, and for other indicators there is no discernible pattern. Only for barrier to access there is a clearer association with higher welfare loss, and for the relative position in the income distribution as well, which indicates the importance of material conditions in the effect of price shocks.

Figure 6: Relative welfare loss per levels of wellbeing indicators



4 Scenario analysis

4.1 The Eurogreen model

Eurogreen is a macrosimulation model that integrates a dynamic input-output structure into a macroeconomic demand-led model, following post-Keyensian macroeconomic theory and guaranteeing stock-flow consistency. Previous versions of the model have been applied to France (D'Alessandro et al., 2020) and Italy (Cieplinski et al., 2021) to analyze the social implications of different green transition scenarios.

Eurogreen has 21 productive industrial sectors in its input-output structure, which are associated with 16 different categories of consumption goods . On the other hand, there are 24 types of individuals differentiated by gender, skill and occupational category, plus children and capitalists, associated with 100 households differentiated by region and income quintile in the new households module. This implies a high degree of heterogeneity in production, consumption and social dimensions, which allows for a deep analysis of the intertwining between wellbeing and consumption.

At the macroeconomic level, outstanding features of the model are an endogenous stochastic process of technical change and a detailed labour market structure. Regarding technical change, the relative evolution of labour costs and intermediate inputs costs determines each period different probabilities for firms of developing either labour-saving or resource-saving innovations. The implementation of these technologies, instead, governs the dynamics of labour productivity and input-output coefficients over time. With regards to labour market, labour supply is determined by the expected incomes of entering, remaining, or exiting the labour force, depending on the occupational category of individuals, and skill composition responds to skill-specific unemployment rates, such that workers move to skills with higher job prospects.

One the other hand, labour demand is determined by expected demand and labour productivity in a Keynesian way, while skill composition of labour supply is linked to the evolution of labour productivity. Wage dynamics, on the contrary, is affected by sector-specific labour productivity, gender- and skill-specific employment rates, and overall inflation and unemployment rates, as to capture the effects of firms' labour costs, workers' bargaining power, and macroeconomic conditions affecting general cost of living and bargaining power.

Firms set basic prices as a mark-up over unit labour and capital costs (wages, social security contributions and depreciation), and the mark-up evolves over time responding to the difference between current and initial rate of capacity utilization, to capture the price effects of higher demand. Carbon costs, on the other hand, enter into purchaser prices, which also include trade and transport margins. Each sector's price reacts to prices in the other sectors following the input-output structure of the Leontief price model (Miller & Blair, 2009). On the other hand, investment plans depend on the difference between actual and normal rate of capacity utilization, following the capital stock adjustment principle. Although the model is demand led, there is the possibility of supply bottlenecks coming from capacity utilization or labour constraints. These supply constraints are accommodated by increasing the imported share of the different final demand components (consumption, government spending and investment).

The model is calibrated for 2010 (the initial year for the simulations) using data from different sources. The World Input-Output Database (WIOD) is used for the input-output structure, as well as output, value added and final demand. EU-KLEMS is used for the sectoral composition of employment, productivity, investment, and other variables differentiated by sector. EU-SILC is used for computing the wage structure. For other variables the main source is Eurostat.

4.2 The households and consumption module

The analysis of wellbeing and consumption, and its interplay with other variables like inequality, made it necessary to introduce households in the model for two main reasons. First, because consumption decisions are typically made at the household level and available data on consumption is also defined for households rather than individuals. Second, because households can represent social disparities and stratifications better than the sheer demographic divides across individuals. In this sense, as groupings of individuals, households maintain the heterogeneity at the individual level but allow to increase such heterogeneity along other important dimensions. In the case of Italy, regional disparities are an important and outstanding issue, so we decided to differentiate households across the 20 Italian regions, and further into 5 household income quintiles, so we have 100 different households, each representative of its specific region-quintile. In what follows we provide a brief description of the households module and its main novelties. A detailed explanation can be found in the Appendix.

The households module in Eurogreen integrates the income generation process at the individual level with the consumption process at the household level. The 26 types of individuals in Eurogreen derive their net income from several sources according to their individual characteristics,[7] in a process that is mainly driven by the operation of the labor market, fiscal policy and the corporate and financial sectors, which govern the dynamics of wages, taxes and transfers, and capital income respectively. The disposable income of individuals is then pooled into the 100 different household types, using the observed demographic distribution of the 26 individual types across the 100 region-quintiles in Italy. In this way, each household is representative of the demographic composition of its respective region-quintile, and its disposable income evolves endogenously with the income generation process of the model.

Consumption at the household level, in turn, is determined in two steps. First, total expenditure is computed by applying the observed propensities to consume from the SHIW to the endogenous real disposable income of each household. Second, total expenditure is split across 16 different consumption categories depending on the evolution of real disposable income and relative prices, according to estimated income and price elasticities using microdata from the Household Budget Survey (HBS) and the Quadratic Almost Ideal Demand System (QUAIDS) by Deaton & Muellbauer (1980). By using different wellbeing indicators as demographic shifters in the econometric model QUAIDS, it is possible to include other determinants of consumption composition in the model. Finally, the total expenditure across the 16 different consumption categories is translated into final demand for the 21 industries of the model using a bridge matrix computed based on Cazcarro et al. (2022).

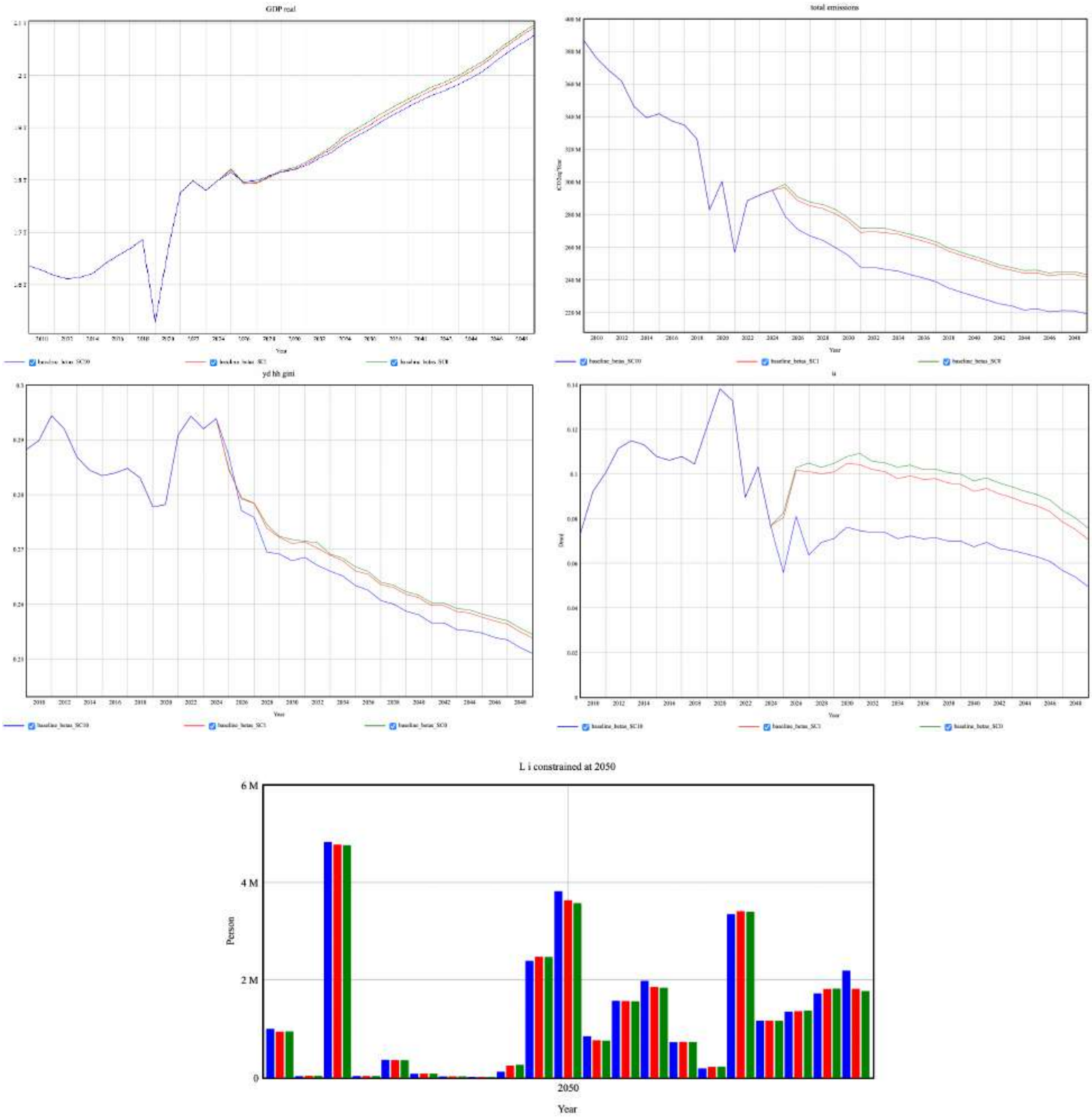
4.3 Simulation

To explore the effect of a wellbeing-enhancing policy, we introduce the wellbeing indicators in the model and their impact on consumption estimated through the QUAIDS model, and simulate an exogenous increase in social capital (the *relationships* indicator). We show the results for three scenarios: a baseline scenario with no social capital impact (green), a low impact of social capital (red), and a high impact of social capital (blue). In Figure 7 we show the simulation results on output (real GDP), greenhouse gas emissions, household income inequality, unemployment, and employment per industry (in the last period).

[7] The income sources are wages, pensions, unemployment benefits, other social transfers (sick and disability benefits, child and family benefits, social assistance), financial income and mixed income. Individuals also pay social contributions based on their occupational status, and income taxes according based on their income levels. Disposable income is computed for each individual type (excluding children) by deducting total social contributions and taxes to the sum of all the different income sources.

It can be observed that rising social capital has a negative effect on output, due to the reduction in consumption, but has positive social and environmental effects: it reduces emissions, unemployment and income inequality. Although these effects are rather small (it is necessary to induce a very strong shock to social capital to observe large effects), this nonetheless shows that improving wellbeing can lead to a more just and sustainable society in the long run.

Figure 7: Effect of an increase in social capital on macroeconomic indicators



5 Conclusions

In this document we aimed to investigate the effect of different dimensions of wellbeing on society at large, mainly by considering their effect on consumption and then linking this effect to broader macroeconomic indicators by means of macro-simulations with the Eurogreen model. To do this, we conducted extensive work of data processing, through the statistical matching among three datasets with information on household consumption (HBS), income (SHIW) and wellbeing (AVQ). Then, we investigated the effect of wellbeing on consumption through empirical estimations: first, running regressions of total household expenditure on a set of controls, disposable income and wellbeing indicators; seconf, we estimated the effect of wellbeing indicators, prices and income on consumption composition through the estimation of a QUAIDS model; and third, we simulated a counterfactual scenario that replicates the price shocks of 2021-2022 in our sample, and used the estimated parameters of the QUAIDS model to compute the cost of living losses associated with such shocks, to then analyze how these losses vary per levels of the different dimensions of wellbeing. Finally, we created a new households' module in the Eurogreen model, to increase heterogeneity and better capture the consumption process, and feed it with the estimated effects of wellbeing; with this tool, we simulated the effect of a wellbeing-enhancing policy as an exogenous increase in social capital.

Our results show that the effect of wellbeing in consumption is small with respect to factors more related to the material conditions of households, and we observe that barriers to access to public services and offices consistently has the strongest effect among the set of non-economic drivers of wellbeing considered. Regarding consumption composition, the results are mixed, sometimes pointing towards a defensive consumption effect of wellbeing, and sometimes showing that higher wellbeing is associated with higher consumption of positional and quality-enhancing types of goods. However, we also find that wellbeing indicators reduce the importance of income in the determination of consumption and can be associated with more sustainable consumption patterns, indicating their importance in this respect. With regards to their effect on the cost-of-living losses associated with price shocks, we find small effects as well, mainly related to barriers of access, which suggests that it is material conditions what counts the most in these cases. Finally, the macro-simulation shows a positive although small effect of increases in social capital on social and environmental variables. In general, our results indicate that the societal effect of wellbeing indicators through consumption is positive overall although rather small. Nonetheless, this stresses the importance of advancing wellbeing-enhancing policies for a just and sustainable society.

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Appendix: The households' module in Eurogreen

A.1 Foundations in micro and macro data

Computation of population shares

To map individuals into households we use data from the Survey of Household Income and Wealth (SHIW) by the Bank of Italy for the period 2000-2022. We classify observations in the SHIW according to the characteristics that define individual types in Eurogreen: age (5 cohorts, for the age ranges 0-14, 15-24, 25-44, 45-64, and over 65), gender (female and male), skill level (low, middle and high) and occupational category (employed, unemployed, out of labour force, and retirees). In the survey, age cohorts and gender correspond easily to age and sex variables. As in the model, children are those of the first cohort (up to 14 years old). We defined skill levels according to educational attainment level: individuals with no education, primary school, or lower secondary school certificates are classified as low skill; those with vocational or upper secondary school diplomas are middle skill; and those university degrees or postgraduate qualification are high-skill. For occupational categories we use employment status: employed and self-employed are classified as employed; those seeking first job or unemployed are classified as unemployed; the retired workers and the recipients of disability, survivors or old-age welfare benefits are classified as retired; and all the rest are classified as out of labour force. We deduct scholarships and alimony and gifts from disposable income in the survey, to harmonize this variable with the model, where such income flows are absent.

Given that the SHIW is not representative at the regional level, sample weights are adjusted to guarantee that total regional population and number of households match demographic data.[8] Being NH_R the number of households for region R in demographic data, and w_h and m_h the original sample weight and number of household members for household h in the survey, where w_h is such that their sum across individuals equals the total number of households in the sample, the adjusted sample weights are computed as $w'_h = \frac{m_h \cdot w_h \cdot NH_R}{\sum_h w_h}$, for $h \in R$.

Usign the adjusted sample weights, individuals in the sample are classified into regional quintiles of equivalized household disposable income,[9] and capitalists are defined as those in the top 1% of individual disposable income that are also in the fifth quintile of their respective region.

Once observations in the survey are classified into the 26 individual types and the 100 representative households, we pooled all the waves of the SHIW together and compute the population shares to allocate individuals into households. Denoting individual types with superscript i , region-quintiles with subscript RQ , and total population computed with adjusted sample weights by N , the share of region RQ in the poopulation of individual type i is:

$$\pi^i_{RQ} = \frac{N^i_{RQ}}{N^i}$$

For future notation, let us define $i = cap, F, (g, s, k)$, where cap denotes capitalists, F denotes children, and g, s, k all the different combinations of gender $g \in \{female, male\}$, skill $s \in \{low, mid, high\}$, and occupational category $k \in \{E, U, OLF, P\}$ (employed, unemployed, out of labour force, and retired respectively).

Adjustment to national account aggregates

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[8] We use total regional population data from Eurostat and average household members from Istat to compute total regional number of households. For years before 2009 (when Istat data on number of household members is not available), we extrapolated the average number of household members with the average annual rate of growth of this variable for the period 2009-2023.

[9] Equivalized household income is an adjusted measure to account for household composition in terms of size and age, which allows for a more accurate comparison between households. It is computed by dividing household income by its equivalent size, which is the sum of age-weighted household members. Here we use a modification of the standard *modified OECD equivalence scale*, whose weights are 1 for the household head, 0.5 for every other adult in the household, and 0.3 for every children. Our modification is the use of 18 years rather than 14 as the threshold age to define adults. This is done to make it compatible with expenditure data from the Household Budget Survey, where age is available only in ranges, the first one going from 0 to 17.

Income and expenditure aggregates computed from the SHIW are not compatible with National Accounts aggregates for a variety of reasons, so we must adjust some variables from the survey to be able to replicate such aggregates.[10] As we are interested in matching total disposable income rather than its components, we follow a simple procedure: scaling-up the mean disposble income and consumption to match the corrsponding National Accounts variables at the regional level. We use as benchmark regional accounts data for 2010 from Istat. From the *Institutional Sector Accounts* for households we use *Gross disposable income* after deducting some items to make it compatible with the income definition in Eurogreen.[11] For consumption, in turn, we use *Final domestic consumption expenditure of resident and non-resident households*.

Let us denote by YD_r^{NA} and C_r^{NA} the aggregate disposable income and consumption from National Accounts for region R, and by YD_r^{SHIW} and C_r^{SHIW} their corresponding aggregate variable in the SHIW 2010, computed using the adjusted sample weights. We thus compute the adjustment ratios as:

$$adj_R^Y = \frac{YD_R^{NA}}{YD_R^{SHIW}}$$

$$adj_R^C = \frac{C_R^{NA}}{C_R^{SHIW}}$$

Then we compute, using the adjusted sample weights, the mean household disposable income and consumption for region-quintile RQ and denote them $\overline{YD}_{RQ}^{SHIW}$ and $\overline{C}_{RQ}^{SHIW}$ respectively. Finally, using the adjustment ratios above, we obtain the per-household income and consumption variables that we use in the model, YD_{RQ}^h and C_{RQ}^h , and also the propensities to consume α_{RQ}, as:

$$YD_{RQ_0}^h = adj_R^Y \cdot \overline{YD}_{RQ}^{SHIW}$$

[10] Sources of discrepancies between survey aggregates and National Accounts data are differences in target populations, the types and definitions of income flows considered, non-response issues in the surveys, and the fact that National Accounts use harmonizes information from several sources. Moreover, the extent of such discrepancies varies across income components. For a detailed discussion see (Coli & Tartamella, 2008)

[11] The excluded items are *Other property income* of consumer households, since it is a fictitious flow attributing households income from insurance investments; net inflows from *Other current transfers*, which are non-life insurance premiums paid and claims and other miscellaneous transfers that we do not model; and the part of *social benefits received* that is not paid by the government, as we only model government benefits.

$$C^h_{RQ_h} = adj^C_R \cdot C^{SHIW}_{RQ}$$

$$\alpha_{RQ} = \frac{C^h_{RQ}}{YD^h_{RQ}}$$

Here the subscript 0 indicates that these are the initial values for income and consumption per-household in the Eurogreen model, that is, the values in the base year 2010. The superscript h, in turn, indicates that these are per-household values.

A.2 Individual-to-households integration through income pooling

Population shares are then used to pool income of the different individual types into the 100 representative households. In Eurogreen, there are different income sources, each with particular allocation rules to individuals according to their characteristics, which are the following:

- Net Wage Bill ($NWB^{g,s}$): Labour income received by the employed population (N^E) after deducting social contributions paid by workers and direct taxes on labour income, which follow a progressive marginal taxation structure. Wages are differentiated per skill, gender and industry.
- Net Pension Benefits ($NPB^{\,g,s}$): Government transfers paid to the population of cohort 5 (65 years or older, N^P), which are proportional to the current wage level of the respective gender and skill of the retired individual type, after deducting income taxes.
- Net Unemployment Benefits ($NUB^{g,s}$): Government transfers paid to a fraction of the unemployed population (N^U), after deducting income taxes.
- Net Financial Income ($NFI^{cap,(g,high)}$): Interest revenue from bonds and equity after taxes on financial income, percieved only by high-skill workers and capitalists ($N^{g,high,k}$and N^{cap}).
- Sickness and disability benefits ($SD^{\,g,s,k}$): Government transfers distributed evenly among the whole adult population, excluding capitalists ($N^{g,s,k}$).
- Other benefits ($OB^{\,g,low,OLF}$): Government transfers distributed evenly among the low-skilled population out of the labour force ($N^{g,low,OLF}$), to capture social assistance to the most disadvantaged.
- Child and family benefits (CB_{RQ}): Government transfers distributed across regions and quintiles, proportionally to the respective children shares (π^F_{RQ}).

- Mixed income (MI_{RQ}): This is a residual balancing income source, which is allocated to households to match the observed distribution of disposable income across regions and quintiles.

All income sources in Eurogreen, except child and family benefits CB_{RQ} and mixed income MI_{RQ}, accrue first to individual types and are then allocated to households using the population shares. Assuming here that a specific income source equals zero for all the individual types i for which it is not defined, total household disposable income of region-quintile RQ is thus defined as:

$$YD_{RQ} = \sum_{i} \pi_{RQ}^{i} \left(NWB^{i} + NPB^{i} + NUB^{i} + NFI^{i} + SD^{i} + OB^{i} \right) + CB_{RQ} + MI_{RQ}$$

The household specific income sources CB_{RQ} and MI_{RQ} converted into individual incomes on a per capita basis; that is, their total aggregate values are divided by the total adult population (excluding capitalists for child and family benefits) and allocated to the individual types proportionally to their shares in population.

Note that YD_{RQ} is the total aggregate income perceived by households in a specific region-quintile. The income-pooling process is based on total aggregates because we take shares of total population to define the households. Nevertheless, consumption decisions occur at the household level, so we must obtain disposable income per household, which is made equal to YD_{RQ}^{h}, the adjusted region-quintile mean income from SHIW in 2010 derived above. This variable is obtained in the model dividing total disposable income by the number of households for each region-quintile. However, we must account for the endogenous demographic dynamics.

Let NH_{RQ}^{SHIW} denote the number of households of region-quintile RQ calculated from the adjusted sample weights in SHIW 2010, and N_0 the initial total population of region-quintile RQ, obtained from applying the population shares to the initial populations of each individual category in Eurogreen:

$$N_{RQ_t} = \sum_{i} \pi_{RQ_t}^{i} N_t^{i}$$

Using the initial values we compute NHM_{RQ} the average number of household members in region-quintile RQ:

$$NHM_{RQ} = \frac{N_{RQ_0}}{NH_{RQ}^{SHIW}}$$

Note that we compute NHM_{RQ} from initial values assume it constant onwads in the model, as indicated by the absence of a time subscript for that variable. Subsequently, each period the number of households is computed using this constant number of households members and the current population per region-quintile:

$$NH_{RQ_t} = \frac{N_{RQ_t}}{NHM_{RQ}}$$

Finally, disposable income per-household is computed each period by dividing total disposable income by the lagged number of households $NH_{RQ_{t-1}}$ to avoid circularity issues.

$$YD^h_{RQ_t} = \frac{YD_{RQ_t}}{NH_{RQ_{t-1}}}$$

By setting the initial value equal to the survey one, $NH_{RQ_0} = NH_{RQ}^{SHIW}$, and given that total and mean values are computed using adjusted sample weights and adjusted to National Accounts, this procedure ensures that the initial total disposable income matches the National Accounts aggregates, and that the initial disposable incomes per household match region-quintile averages in the survey, which implies that we also match the initial income distribution between region-quintiles.

Finally, we may want to assume that population shares are constant over time, given that we do not model any mechanism of inter-regional migration. However, note that we would obtain a very different result if such shares are kept constant. Namely, when computing total population per region-quintile N_{RQ_t}, constant shares imply an expansion of the region-quintiles with higher shares of those individual categories that are also expanding and viceversa.[12] Henceforth, we adust the population shares each period to ensure that the relative size of region-quintiles is preserverd over time.

[12] For example, if occupation grows over time while unemployment falls, we would have that region-quintiles with higher shares of employed people grow in population, while region-quintiles with higher shares of unemployed shrink. Although it might make sense in this specific example, it gets more complicated if we consider population in terms of skills, gender, and other occupational categories such as the retired. Furthermore, we would have varying relative regional sizes without a detailed modeling of such a mechanism.

Let $\eta_t^j = N^j / \sum_j N^j$, so the disrepancies we want to correct for are $\eta_t^j - \eta_{t-1}^j$, the changes in the relative size of individual types j. Note that no discrepancy arises from capitalists as they are by definition the 1% of population; hence, the subscript j denotes all non-capitalists individual types, and can be read as $i \neq cap$. The adjustment thus consists in allocating this discrepancies across region-quintiles: each RQ absorbs a part of each discrepancy proportional to its share. The new share would thus be:

$$\tilde{\pi}_{RQ_{t+1}}^j = \pi_{RQ_t}^j - \sum_j \pi_{RQ_t}^j \left(\eta_t^j - \eta_{t-1}^j\right) + dz_{RQ_t}^j$$

Where $dz_{RQ_t}^j = \sum_j \pi_{RQ_t}^j \left(\eta_t^j - \eta_{t-1}^j\right)$ whenever $\pi_{RQ_{t-1}}^j - \sum_j \pi_{RQ_t}^j \left(\eta_t^j - \eta_{t-1}^j\right) < 0$, and $dz_{RQ_t}^j = 0$ otherwise. This last term ensures that the adjustment does not produce negative population shares, but it can result in a sum of shares individual type that is different than one. To correct this, such difference with respect to one is allocated evenly across all non-zero region-quintile shares per individual type. Therefore, with $nz_{RQ_t}^j = 1$ for $\tilde{\pi}_{RQ_{t+1}}^j > 0$ and $nz_{RQ_t}^j = 0$ otherwise, and $nnzRQ_t^j$ denoting the number of non-zero shares for individual type j, the final adjusted population shares are given by:

$$\pi_{RQ_{t+1}}^j = \tilde{\pi}_{RQ_{t+1}}^j - \frac{nz_{RQ_t}^j \left(\sum_{RQ} \tilde{\pi}_{RQ_{t+1}}^j - 1\right)}{nnzRQ_t^j}$$

A.3 "Mixed income" as a residual balancing item

The balancing item "mixed income" captures important components of household income that are not modeled in detail but must be included to ensure consistency with both National Accounts aggregates and observed income distribution. These components mainly comprise rents (actual and imputed) and the capital income of the self-employed. For clarity, we refer to this source of income in the Eurogreen model as *"mixed income"* (in quotation marks), to distinguish it from the corresponding item in the National Accounts, since the two do not coincide exactly.

In the National Accounts, mixed income is the residual item in the *primary income allocation account* of producer households, where labour income and capital income components cannot be distinguished, and includes the gross operating surplus of producer households, compensation of the self-employed, payment for domestic services, and actual rents (Coli & Tartamella, 2008; Eurostat, 2013).[13] In Eurogreen, however, the wage bill is computed using total employment, which includes the self-employed and domestic workers. Therefore, we treat the labour income component of mixed income as already catpured in the wage bill, leaving only the capital income component to be modelled.[14] With regards to rents, in turn, it is important to distinguish between actual and imputed rents. In the National Accounts, actual rents are treated as a remuneration for the prodcution of housing services and included in mixed income, while imputed rents are a fictional transaction aiming to capture the value of housing services produced (and consumed) by house owners, recorded in the gross operating surplus of consumer households together with the (also fictional) proceeds from own-account production. From the input-output production perspective, actual and imputed rents are recorded in the value added of the real estate industry (sector L in the NACE classification). Therefore, we treat all these residual components of household income as coming from profits.

However, a part of profits is already transfered to households as dividends, and hence captured as financial income. We therefore group all these components of household income in a single one called *mixed income* and split it into three components: imputed rents, actual rents, and capital income of the self-employed. Imputed rents are deducted from profits (of the real estate sector only) in the first place, since they are a fictional transaction that is not considered in firms accouting. Then we deduct interest payments, corporate taxes, debt repayment, and part of investment financing. Consequently, we deduct actual rents (from the real estate sector only) and self-employment capital income (proportionally to the share of self-employed in the total employment of each sector). Finally, we deduct dividends.

The total value of mixed income and the shares of its three components are obtained using regional data from Istat in the base year 2010: Institutional Sectors Accounts data for income aggregates, and Household Expenditure data for actual and imputed rents; additionally, we use as a benchmark the initial values of aggregate and regional Gross Wage Bill and Gross Financial Income implied by initial data in the Eurogreen model. We thus obtain "mixed income" as follows. First, we compute *self-employment income* from National Accounts as the sum of *mixed income from producer households* and

[13] In the National Accounts mixed income comprises the gross operating surplus from market production of producer households, compensation of the self-employed working in producer households, payment for domestic services, inside households, and actual rents.

[14] This resembles the standard method for computing the labour income of the self-employed, by imputing the unit wages of analogous employed workers with similar characteristics. D'Elia & Gabriele, (2022) propose an alternative method, by computing first the capital income part assuming the same mark-ups of non-financial companies in the same sector.

withdrawals from quasicorporations, and substract from it actual rents. Second, we add this *self-employment income* with *compensation of employees*, and substract the initial Gross Wage Bill of the model, to obtain the *capital income of the self-employed*. Third, we add this *capital income of the self-employed* with *total rents* and *net capital income* (*interests, dividends* and *rentals*), to obtain the total capital income accruing to households. Finally, we substract from this the initial Gross Financial Income in the model, to obtain "mixed income," the residual component that is not accounted for in the other income sources of households in Eurogreen.

We thus compute the shares of actual and imputed rents on national "mixed income," and obtain the share of self-employment capital income as a residual. These shares are used to deduct such components from industries' profits as described above. On the other hand, we use the variables *entrepreneurial income* (of the self-employed) and *income from real estate* from the SHIW in 2010 to obtain an measure analogous to "mixed income" in that survey, and compute the shares of each regional income quintile in the total regional aggregate of "mixed income;" with this shares we then split the regional values of "mixed income" into regional quintiles. In this way, we obtain initial values for the total aggregates of "mixed income" at the national and region-quintile level.

Using these initial values we run a preliminary simulation and then adjust the national value of "mixed income" as well as its shares across regions and quintiles to match the initial value of aggregate national households' disposable income, and the distribution of disposable income per household between regions and quintiles. In this way, "mixed income" is an additional income source for households that originates in the profits of industries and acts as a balancing item to ensure consistency with both macroeconomic and income distribution data.

The dynamic behavior of "mixed income" in the model is then made to depend on real estate prices, for the rents components, and on the wage bill, for the capital income of the self-employed component. For each region R, let us denote by MI_{R_0} the initial value of "mixed income" after all the adjustments deteiled above, and by rsh_R its share of rents (both actual and imputed). With $p_t^{RealEstate}$ the price index of the real estate sector at period t (equal to one for $t = 0$), and $rMIGWB = (1 - rsh_R)MI_{R_0}/GWB_0$ the ratio of the self-employment component of "mixed income" to the Gross Wage Bill (computed with the initial values and kept constant onwards), total mixed income at period t for region R is:

$$MI_{R_t} = rsh_R \cdot MI_{R_0} \cdot p_t^{RealEstate} + rMIGWB \cdot GWB_t$$

These regional values are then splitted across quintiles using the adjusted shares computed as explained above. In this way, "mixed income" evolves endogenously in the model.

A.4 Expected disposable income

Households make consumption decisions based on their expected income, which are formed adaptively taking the lagged values of real disposable income and its change. However, some income sources in Eurogreen are constant in real terms, so disposable income is split between "static" and "dynamic" components and expectations are formed differently for each.

The dynamic components of disposable income are wages, unemployment benefits, pensions, financial income and "mixed income." Nevertheless, the expected income includes only a fraction dfi of the difference between the current financial income and its initial value. In this way we can replicate initial total expenditure from data (since propensities to consume are computed from a value of initial disposable income that includes all financial income), but we can capture as well the lower propensity to consume of capital income, by preventing fluctuations in financial income to provoke strong changes in consumption. Therefore, dynamic disposable income for region-quintile RQ in period t is:

$$dYD^{h}_{RQ_t} = \sum_{i} \pi^{i}_{RQ_t}\left(NWB^{i}_{t} + NPB^{i}_{t} + NUB^{i}_{t} + dfi \cdot \left(NFI^{i}_{t} - NFI^{i}_{0}\right)\right) + MI_{RQ_t}$$

Static disposable income, in turn, is composed of government transfers that are indexed to inflation: child and family benefits, sick and disability benefits, and other benefits:

$$sYD^{h}_{RQ_t} = \sum_{i} \pi^{i}_{RQ_t}\left(SD^{i}_{t} + OB^{i}_{t}\right) + CB_{RQ_t}$$

To form the expectations let us define the current and lagged perceived changes in dynamic disposable income as:

$$\Delta dYD^{h,p}_{RQ_t} = \frac{dYD^{h}_{RQ_t} - dYD^{h,p}_{RQ_t}}{a}$$

$$\Delta dYD_{RQ_t}^{h,p'} = \frac{dYD_{RQ_t}^{h,p} - dYD_{RQ_{t-1}}^{h,p}}{a}$$

Where a is an adjustment time parameter for expectations. From here, the expected growth in dynamic disposable income can be computed as:

$$gyd_{RQ_t}^{h,exp} = \frac{dYD_{RQ_t}^{h,p}}{dYD_{RQ_t}^{h,p'}} - 1$$

And the expected disposable income is:

$$YD_{RQ_t}^{h,exp} = sYD_{RQ_{t-1}}^{h} + dYD_{RQ_{t-1}}^{h}\left(1 + gyd_{RQ_t}^{h,exp}\right)$$

Real expected disposable income, $yd_{RQ_t}^{h,exp}$, is computed analogously, by departing from deflated values of dynamic and static disposable incomes using region-quintile-specific price indices.

A.5 Determination of total expenditure

Finally, total consumption expenditure each period is computed from expected disposable income using the propensities to consume:

$$C_{RQ_t}^{h} = \alpha_{RQ_t} YD_{RQ_t}^{h,exp}$$

Note that we use nominal disposable income here, but also note that the propensity to consume now has a time subscript. We first determine consumption in nominal terms as it expresses the total outflow of funds from households to purchase consumption goods and services in current prices, and real consumption is computed later using the relevant price indices. However, this decision depends on real disposable income through the propensity to consume, which is mapped to real values. By interpolating the values of the initial propensities to consume for each region across its five income quintiles in the income-propensity space, we obtain functions of the propensities to consume per region in terms of real disposable income (note that, in Eurogreen, "real" means "expressed in initial period prices," so using those initial propensities gives us a mapping between income and consumption in real terms). These functions are interpolations of the pairs $\left(\alpha_{RQ}, YD_{RQ_0}^{h}\right)$, and can be expressed as:

$$\alpha_{RQ_t} = \breve{\alpha}_R\left(yd_{RQ_t}^{h,exp}\right)$$

A.6 Determination of consumption composition

Once total consumption is decided, households allocate it across 16 different consumption categories following estimated income and price elasticities. The expenditure categories follow the COICOP classification and are shown in the following table.

No.	**Name**	**COICOP code**	**Description**
1	Food	CP01	Food and non-alcohol beverages
2	Tobacco	CP02	Alcoholic beverages and tobacco
3	Clothing	CP03	Clothing and footwear
4	Rental	CP041-043	Housing (Actual and imputed rentals, maintenance, repair and security of the dwelling)
5	Water	CP044	Water supply and miscellaneous services relating to the dwelling
6	Electricity and gas	CP045	Electricity, gas and other fuels
7	Furniture	CP051-055 & part of CP056	Furnishing, household equipment, routine households' maintenance, excluding domestic work. Included expenditure items from CP056 are: non-durable household goods; household services such as window cleaning, disinfecting, fumigation and pest extermination; dry-cleaning, laundering and dyeing of household linen, household textiles and carpets; and hire of furniture, furnishings, carpets, household equipment and household linen.
8	Medical services	CP06	Health
9	Vehicles	CP071-072	Private transport
10	Public transport	CP073	Transport services
11	Communications	CP08	Communications
12	Culture	CP09	Recreation and culture
13	Education	CP10	Education
14	Restaurant	CP11	Restaurants and hotels
15	Care	CP124 & part of CP056	Social protection and domestic work. Included expenditure items from CP056 are: domestic services supplied by paid staff employed in private service such as butlers, cooks, maids, drivers, gardeners, governesses, secretaries, tutors and au pairs; and similar services, including babysitting and housework, supplied by enterprises or self-employed persons.
16	Other	CP121-123 & CP125-127	Other

Initial expenditure shares

The initial expenditure share of consumption category p is denoted β_{p_0}, for $p = 1, \dots 16$ following Table 1. Expenditure shares per household are computed for each COICOP category using HBS microdata for the period 2014-2017. Observations in each wave of the survey are classified per region and regional quintile, with quintiles defined according to equivalized household total consumption expenditure, using the same equivalence scale used for disposable income. Since HBS is representative at the regional level, there is no need to adjust the sample weights.

To obtain expenditure shares at the household level we compute aggregate expenditure—both total and for each COICOP category—per region, quintile and wave of the HBS, using sample weights. With these totals, expenditure shares are obtained for each year, and then we compute their annual average.[15] We take these initial expenditure shares as reference, but we must further adjust them to ensure consistency with National Account Aggregates.

The adjustment involves slightly modifying expenditure shares per region-quintile, so that when applied to the total expenditure of each household we obtain the aggregate values of consumption per region and per COICOP category observed in official Istat data (*Final domestic consumption expenditure of resident and non-resident households*). A suitable tool for this is the RAS algorithm, which we use in two steps.

First, we obtain total regional consumption for the three-digit COICOP subcategories that we consider in our classification, given that there is no data available for this.[16] However, there is available data for total regional consumption in the main chapters (two-digits) of the COICOP classification from Istat, and for total domestic consumption (three-digits)

[15] We use aggregate region-quintile expenditure shares rather than household averages. The latter better represents the consumption composition of the typical household in a specific region-quintile but would hardly replicate the aggregate consumption composition when multiplied by the number of households. Since we want to ensure consistency with National Account aggregates, the former method is better suited, which implies assuming that the average household behaves as the aggregate when allocating consumption across different categories.
[16] We split CP04 into CP041-043, CP044 and CP045; CP05 into CP05 without domestic work, and only the part of domestic work; CP07 into CP071-072 and CP073; and CP12 into CP124 and all the rest. Regional consumption per COICOP is available only up to two-digit COICOP classification, so we must compute and ensure aggregate consistency for these subcategories.

from Eurostat.[17] We use these two sources as row and column constraint respectively and apply the RAS algorithm to adjust initial values computed from HBS annual averages.

Secondly, we apply 16 different RAS procedures, one per each COICOP category. The data we want to adjust are our initial expenditure shares from HBS annual averages per region and quintile. We use the values of total expenditure per region and COICOP category computed above in the first RAS as row constraints, and total consumption per regional quintile from SHIW 2010 (adjusted to match National Accounts aggregates) as column constraints.[18]

Income and price elasticities and introduction of wellbeing

Elasticities are estimated following a Quadratic Almost Ideal Demand System (QUAIDS) econometric model, using 2014-2017 HBS microdata. Wellbeing indicators are introduced as exogenous variables, and their effects on consumption are simulated using the estimated parameters of such indicators on the QUAIDS model described in the empirical section. The discrepancy between the QUAIDS systems of the model and empirical analysis (one containing 9 consumption categories, and the other 16, respectively), responds to the need to maintain consistency with previous versions of the model, on the one hand, and with obtaining better and more precise indicators for the empirical analysis, on the other. Such a discrepancy is overcame by assigning the coefficients of the consumption categories in the empirical analysis to the corresponding consumption (sub)categories in the model.

[17] To compute total expenditure in domestic work (part of the CP056 category) we compute the ratio of total expenditure in domestic work to total expenditure in category CP056 from Istat, and apply this ratio to the value for CP056 from Eurostat.
[18] We use SHIW data for total expenditure per quintile rather than from HBS for two reasons. First, households in the model are defined per regional quintiles of household *income*, not *expenditure*; although both may largely coincide there still may be some discrepancies. And second, propensities to consume are computed based on NA-adjusted SHIW data, so the consumption values we want to replicate per quintiles come from SHIW.