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WHAT DO WE LEARN FROM RECALL CONSUMPTION DATA?

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Abstract

In this paper we use two complementary Italian data sources (the 1995 Istat and Bank of Italy household surveys) to generate household-specific non-durable expenditure in the Bank of Italy sample that contains relatively high-quality income data. We show that food expenditure data are of comparable quality and informational content across the two surveys, once heaping, rounding and time averaging are properly accounted for. We therefore depart from standard practice and rely on the estimation of an inverse Engel curve on Istat data to impute non-durable expenditure to Bank of Italy observations, and show how these estimates can be used to analyse consumption age profiles conditional on demographics. Our key result is that predictions based on a standard set of demographic and socioeconomic indicators are quite different from predictions that also condition on simulated food consumption, in the sense that their age profile is less in line with the implications of the standard consumer intertemporal optimization problem.

JEL classification: C24, C81, D12, E21.

Keywords: recall errors, heaping and rounding, multiple imputations and consumption.

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1. Introduction[1]

Consumption is a key quantity in economics: in standard models households are assumed to derive utility from their consumption of goods and services. In the simplest case, consumption coincides with expenditure (this is normally assumed to be true for the purchase of non-durable goods and services) and this motivates economists' interest in using survey data that contain records of expenditure by individual households. In many countries such expenditure data are regularly collected by asking households to fill out diaries covering all purchases made within a short period of time. There is a consensus that this time-consuming task produces the best quality expenditure data for small items, while recall questions should also be asked on the purchase of bulky, durable items.

The key problem with diary surveys is that the questionnaire is normally focussed on consumption alone, given time constraints and survey practice. A good example is the US Consumer Expenditure Survey (CEX): this uses two representative samples of the US household population. One sample is asked to fill out a detailed expenditure diary over a two week period and to answer a few questions on household structure (plus a single recall question on food consumption). Another sample is subject to a thorough interview on all aspects of their behavior (including work activities, ownership of major durable goods, income and wealth) that covers broad consumption groups (such as food). The former sample is only contacted once, whereas the latter is asked to participate four more times. In some countries (most notably the UK) respondents are successfully asked detailed questions on work activities and income before filling out an expenditure diary but no attempt is made to contact them again.

Given that the ideal data set for economists is a panel containing information on a number of aspects of consumer behavior (consumption, leisure and work, wealth, etc.) and covering a long period of time, and that keeping diary records is highly time-consuming in itself, the issue

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then arises of whether consumption information based on recall questions is of comparable quality to information based on diary records.

An extreme, interesting example of recall consumption questions is contained in a widely used Italian survey, the Bank of Italy Survey on Household Income and Wealth (SHIW in what follows), where respondents are asked a very broad range of questions including one on their average monthly expenditure on all items but a few listed durable goods and another on monthly expenditure on food alone. It is worth noting that SHIW contains a large panel component, even though this feature will not be used here.

This paper aims to investigate the quality of consumption data in SHIW to derive measures of non-durable expenditure alternative to the observed one. We compare the consumption information in SHIW to the corresponding information in a newly released diary-based survey run by the Italian Institute for Statistics, ISTAT, the Survey on Family Budgets (SFB). We concentrate on a single year, 1995, because for that year we gained access to the most disaggregate version of the SFB and were able to construct expenditure items in SFB that are fully comparable to the Bank of Italy definition used in SHIW.

We show that the recall consumption data in SHIW are heavily affected by heaping and rounding problems, typically characterizing retrospectively asked data. However, we also show that food expenditure data are of comparable quality and informational content across the two surveys, once heaping, rounding and time averaging are properly accounted for, whereas for other expenditure definitions (non-durable and total) there are major differences across the two surveys.

This prompts us to compare three different methods to improve the observed measure of non-durable consumption in SHIW: a straight correction for heaping and rounding that makes no use of SFB information; a standard regression-based matching method, that exploits common information on household characteristics; a more innovative matching algorithm that exploits common information on household characteristics as well as simulated food expenditure information to predict total non-durable expenditure in the SHIW sample.

We show the implications of these alternative procedures on consumption and saving age profiles in SHIW. It is in fact quite puzzling for an economist to observe that Italian households appear to be saving an increasingly larger proportion of their disposable income as they age.

This is apparently due to a marked decline in reported consumption of non-durable goods and services. Given that SHIW is known to have better income and wealth data than SFB, we try and assess whether SFB-based measures of consumption can help solve this puzzle.

The paper is organized as follows. Section 2 provides some evidence on the presence of measurement error affecting retrospectively asked questions about consumption. Section 3 describes the two data sources and compares descriptive statistics and histograms after allowance is made for sampling differences. Section 4 proposes a theoretical framework for the matching exercise that takes into explicit account the heaping and rounding problem. Section 5 describes the method used to correct for heaping and rounding in our application and presents estimation results for the conditional heaping process. Section 6 presents regression estimates for non-durable consumption in SFB. Section 7 reports estimation and prediction results of the heaping correction for both food and total non-durable consumption. Section 8 discusses the implications of the imputation exercise for non-durable consumption in the SHIW sample, with special reference to the resulting age profiles of consumption and the saving rate. Section 8 concludes.

2. The nature and consequences of recall errors

The Bank of Italy has run SHIW on a regular basis for a very long time (since 1947). Since 1987 SHIW includes a set of recall consumption questions. The survey also contains detailed information on income, real and financial wealth, work activities, family structure and, in some years, it has records of subjective expectations, risk aversion and health. The presence of information on so many aspects of household behavior has made SHIW an attractive data source for economists (see for instance the volume edited by Ando, Guiso and Visco, 1994, as well as articles by Guiso, Jappelli and Terlizzese, 1992 and 1996, Pistaferri, 2001, and many others). Nevertheless, some of these results suggest that data quality issues need to be considered, both regarding the information about consumption and the information about income.

On the one hand, the way in which information is collected suggests that SHIW data contain more reliable information about durables and income than about residual items like food and non-durables. In fact, the key reason to doubt SHIW non-durable information about consumption data is the difficulty of the question, in which households are retrospectively asked for their average monthly expenditure over the previous year. The exact wording is: 'What was your family's average monthly expenditure in 1995 for all consumption items? Consider all expenses, including food, but excluding those for: housing maintenance; mortgage installments; purchases of valuables, automobiles, home durables and furniture; housing rent; insurance premiums'. This question is then followed by a similar food question ('What was your family's average monthly expenditure for food alone? Consider expenses on all food items in grocery stores or similar food stores and expenses on meals normally consumed out') and by detailed questions on other items excluded from non-durable consumption.

On the other hand, there is also evidence on unreasonably high saving rates computed on the basis of SHIW data. The standard aggregate measure defined as (1-total expenditure/disposable income) is 23.4%, versus the National Accounts (NIPA) equivalent of 18.2 % in 1995 (see Banca d'Italia, 1999). This underestimation is not particularly large, but becomes worrying if we consider that SHIW income falls some 34.7 % below what the NIPA would imply (see Brandolini, 1999, for further details). Age profiles strongly contradict what one might expect from theory and (to a lesser extent) evidence for other countries. As shown in Brugiavini and Padula (2001), in the cross section mean individual saving rates increase from 10 % to 25 % between the ages of 25 and 60, and then stay above 20 % for all ages above 60. A slight decline after age 70 is instead observed for median saving rates, but the typical median rate still exceeds 20 %. Even if we account for a fall in the degree of consumption smoothing around the time of retirement (as pointed out by Banks, Blundell and Tanner, 1998), it is hard to understand why so much saving should take place in old age.

Retrospectively collected information of household surveys are typically characterized by recall errors. In particular, respondents are likely to round off the true measure causing abnormal concentrations of values in the empirical distribution. To illustrate this point, Figure 1 reports the histogram based on the 1995 US CEX diary sample of the answer to the question 'Since the 1st of (month) what was your usual weekly expense at the grocery store or supermarket?'. We see marked peaks at round values, particularly at $50 and $100. Similar pictures can be drawn using panel data sets, such as the US PSID and the UK BHPS, where a recall question on average monthly expenditure of food is routinely asked[2].

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[2] In the context of unemployment duration data, Torelli and Trivellato (1993) find that reported measure

As we will show in the next section, the same kind of error clearly affects consumption related variables in the SHIW sample. Such rounding and heaping process makes the relationship between what we aim to measure and what we actually observe complicated compared to classical additive error structure assumptions. The sign of the bias induced by non-classical measurement error cannot easily be assessed without imposing distributional assumptions on the process leading to the error affected measure.

Validation data, that is observations on the variables of interest collected from an independent assessment of validity study, are useful - when available - to infer on the error structure of observed variables. Bound, Brown and Mathiowetz (2001) review the state of the art about measurement error results from validation studies across a wide range of areas in economics.

Along the same lines, in what follows we aim to shed more light on the quality of information about consumption contained in the SHIW survey. The main assumption we make is that SFB reported expenditure is a reasonable benchmark for true underlying consumption of non-durable goods and services. This is consistent with the observation that SFB consumption data match the 1995 NIPA aggregate very well (less than 1 % discrepancy). In this paper we want to improve on (recall question-based) consumption information in SHIW by using diary-based information from SFB, thus using SFB information on non-durable expenditure as validation data to predict non-durable expenditure on SHIW[3].

In order for such matching exercise to be feasible, we require that surveys should be random samples from the same population and there is a common set of conditioning variables. In our case, the first condition is met by design, after allowance is made for sampling and response differences. The second condition is also satisfied after some recoding (see Rosati, 1999, for further details): the two surveys share information on household composition, region of residence, age and education of the head, that is on valid conditioning variables for the problem under investigation (consumption and savings).

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of unemployment spells from the Italian Labor Force Survey suffer from this heaping pattern. Similar problems arise with earnings data and are fully discussed in Pischke (1995).

[3] Similarly, Battistin (2001) exploits diary information from the US CEX as validation data for retrospectively asked questions about consumption habits.

As emphasized in the econometric literature, matching data sets is problem specific: the success of the matching procedure strongly depends on the parameter we aim to estimate. Typically, the parameter of interest in the economic research is the structural relationship among variables involved in the analysis; previous papers discuss issues to identify and estimate structural parameters from complementary data sources (see Angrist and Krueger, 1992, and Arellano and Meghir, 1992).

However, it is worth noting that our problem differs from a standard structural matching exercise; the point here is how to improve the quality of different measures of the same economic variable using information from complementary data sources. In particular, we use detailed information about expenditure from a household survey to impute it into another survey that has better income and wealth data. Our hope is that exploiting priors about the measurement error process and information on survey quality we can generate imputations for consumption that are more useful for economic analysis than the actual survey records.

3. Data Description

The two major sources of information on household income and consumption in Italy are the heavily used SHIW (documented in Brandolini and Cannari, 1994, and D'Alessio and Faiella, 2000) and the recently released SFB. The former has been run every second year since 1987, whereas the latter is run every year (and is available to researchers since 1985). A comparison of income data is in Brandolini (1999), that suggests that better quality data are to found in SHIW. We will come back to this point in Section 8 when discussing on the implications of our results for the saving age profiles.

As far as consumption is concerned, SFB follows the standard international procedure of exploiting both information from recall questions for more durable items bought in the quarter prior to the interview and diary-based records of purchases carried out within a twenty-day period. SHIW instead contains questions on purchases of specific durable items, and asks the average monthly expenditure on food and on non-durable items (excluding rent and housing maintenance) over the previous year.

Table 1 reports descriptive statistics of the main variables for the two surveys. Sampling differences do not disappear when we use sampling weights; this is not surprising, because the SHIW survey uses a coarser stratification scheme that does not depend on household size

Table 1: Comparisons of key indicators

Mean	**SFB**	**SHIW**
Members	2.8866	3.0170
Prop. over 60	0.2784	0.2919

Area	**SFB**	**SHIW**
Northern Italy	44.16	44.10
Central Italy	21.32	21.11
Southern Italy	34.52	34.79

Head's education	**SFB**	**SHIW**
Less than 8 years	39.87	40.69
Compulsory (8 yrs)	30.28	27.70
High school	23.12	24.45
College degree	6.72	7.15

- as discussed in Brandolini (1999) - and because response rates are different across the two surveys (57 % for SHIW, 80 % for SFB in the 1995 waves).

Table 2 presents the results from a logit regression of the binary indicator taking value 1 for observations in the SFB sample (and 0 for SHIW) over a set of common household characteristics. The explanatory variables include household composition indicators, age, employment status and education of the head dummies plus a number of interactions. The key difference across the two surveys is confirmed to lie in the SHIW relative over-sampling of households with children aged less than 18, and under-sampling of elderly households. However, significant differences are found along several dimensions, particularly in connection with wealth-related variables (that are captured here by ownership of main and secondary residence and by home surface variables)[4].

Since differences in consumption across the two surveys might reflect differences in the composition of the samples with respect to household characteristics, we re-weight SFB households on the basis of the results of the previous regression (see Appendix A for more details). This alternative weighting scheme balances the distribution of those SFB households exhibiting characteristics over-represented (or under-represented) in SHIW. Under the assumption that sampling differences are adequately captured by all the variables included in Table 2, the remaining differences between the sample distributions of expenditure in the two surveys reflect solely the different nature of measurement error[5].

To give a flavor of the magnitude of the measurement error in SHIW consumption data, Table 3 reports summary statistics of income and main expenditure categories, weighting SFB observations according to the weighting scheme defined above. The sample includes all households whose head is in the 25-80 age interval and excludes the top and bottom 1 % of the per-capita food distribution. A first comparison reveals minor discrepancies for food consumption (SFB median is 10% below the corresponding SHIW statistic - the variance is instead lower in SHIW, and so is the overall range). The picture is quite different for non-durable expenditure: mean and median are much (20-25 %) higher in SFB compared to SHIW;

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[4] As we shall discuss in Section 8, the lack of reliable income records or any other wealth information in SFB does limit our ability to further analyse sampling differences using this type of binary regression models.

[5] Anyway, such an adjustment makes very little difference to the shape of the histograms. This we take as evidence that correcting for sampling differences is not the key to explain observed differences, at least given the available common information.

Table 2: Propensity score estimates

Parameters	**Estimates**	**Std. Errors**	**t-values**	**Prob.**
Intercept	5.0451	0.4237	11.905	0.000
# members 18-26	-2.6092	0.4204	-6.206	0.000
# members 27-40	-2.6672	0.4193	-6.361	0.000
# members 41-60	-3.0434	0.4115	-7.396	0.000
# members 61-70	-3.5588	0.4111	-8.657	0.000
# members over 70	-4.4512	0.4107	-10.836	0.000
Central Italy	-0.7081	0.2165	-3.270	0.001
Southern Italy	-0.4600	0.1751	-2.626	0.009
Number of children 0-2	-3.1963	0.4061	-7.871	0.000
Number of children 3-5	-2.0456	0.4279	-4.780	0.000
Number of children 6-9	-3.2903	0.3944	-8.342	0.000
Number of children 10-13	-2.4582	0.4068	-6.042	0.000
Number of children 14-17	-2.2232	0.3941	-5.640	0.000
Number of children over 18	-0.4751	0.1481	-3.207	0.001
# retired members	0.0924	0.1056	0.875	0.382
At least 2 members	-0.2567	0.0753	-3.410	0.001
At least 3 members	-0.0295	0.0546	-0.540	0.589
At least 4 members	-0.1490	0.0454	-3.282	0.001
At least 5 members	-0.0738	0.0545	-1.354	0.176
At least 6 members	-0.1053	0.1026	-1.026	0.305
At least 7 members	-0.3614	0.1730	-2.089	0.037
Sex (male)	-0.0102	0.0584	-0.175	0.861
Age of Head ≥ 26	0.0863	0.1301	0.664	0.507
Age of Head ≥ 40	0.1853	0.0762	2.430	0.015
Age of Head ≥ 60	0.3284	0.0756	4.340	0.000
Age of Head ≥ 70	0.6674	0.0939	7.105	0.000
Head Unemployed	-0.6309	0.0734	-8.587	0.000
Head Out of the Labor Force	-0.2185	0.0436	-5.010	0.000
Education ≥ 8	-0.0172	0.0514	-0.335	0.737
Education ≥ 13	-0.1435	0.0533	-2.689	0.007
University Degree	0.1760	0.0820	2.146	0.032
Total Surface	-0.0059	0.0006	-8.764	0.000
Per-capita Surface	-0.0001	0.0013	-0.057	0.955
Homeowner	0.4885	0.0291	16.743	0.000
Owns secondary residence	-1.3874	0.0384	-36.052	0.000
Central Italy * #18-26	0.5675	0.2549	2.226	0.026
Southern Italy * #18-26	0.2487	0.2054	1.211	0.226
Central Italy * #27-40	0.6998	0.2612	2.679	0.007
Southern Italy * #27-40	0.2213	0.2145	1.032	0.302
Central Italy * #41-60	0.6079	0.2255	2.695	0.007
Southern Italy * #41-60	0.0243	0.1842	0.132	0.895
Central Italy * #61-70	0.9064	0.2115	4.285	0.000
Southern Italy * #61-70	0.1454	0.1672	0.917	0.359
Central Italy * #70+	0.8148	0.2155	3.781	0.000
Southern Italy * #70+	0.4259	0.1764	2.414	0.016
Central Italy * Educ. ≥ 8	0.2372	0.0914	2.596	0.009
Southern Italy * Educ ≥ 8	0.1673	0.0769	2.175	0.030
Central Italy * Educ ≥ 13	-0.0218	0.0953	-0.229	0.819
Southern Italy * Educ ≥ 13	0.2047	0.0829	2.469	0.014
Central Italy * Un. degree	0.2212	0.1502	1.473	0.141
Southern Italy * Un. degree	-0.1101	0.1273	-0.865	0.387
Central Italy * Sex	-0.0255	0.0911	-0.280	0.779
Southern Italy * Sex	0.1740	0.0778	2.235	0.025

Table 3: Descriptive statistics

SHIW sample (N=7502)

Variables	**Median**	**Mean**	**Std. Dev.**	**Min**	**Max**
Food	800	869.49	432.62	100	4000
Non-durable	1700	1869.46	935.26	200	10000
Total	2466.67	2841.77	1691.97	166.67	35966.67
Income	3083.17	3726.75	2871.205	-5666.67	64256.42

SFB sample (N=31400)

Variables	**Median**	**Mean**	**Std. Dev.**	**Min**	**Max**
Food	783.40	869.51	475.57	75.3	4489.09
Non-durable	2240.77	2677.74	1836.19	113.04	24542.6
Total	2899.20	3517.09	2506.93	179.85	30588.18
Income	3350.0	3844.36	2180.62	350	19919.25

variability is also higher in SFB, as for food. The comparison looks promising for income, but this might depend on heavily corrections to SFB data whose records are known to be based on total expenditure plus, where available, saving class information (see Brandolini, 1999).

Inspection of Figures 3 and 5 reveals that SHIW expenditure data suffer from severe heaping and rounding problems (all expenditure figures are in thousands Italian liras, where Lit 1000 is approximately \$0.5). For non-durable expenditure, there are spikes at all multiples of half a million (particularly at Lit 1, 1.5, 2, 2.5, 3 million), even though other spikes are found at Lit 0.8, 1.2 and 1.8 million. For food, there is a spike at Lit 1 million; smaller spikes are also found at Lit. 0.5, 1.5 and 2 million, even though all multiples of 0.1 million are well represented on the left of 0.9 million. The corresponding weighted histograms for SFB food and non-durable expenditure are presented in Figures 2 and 4.

The age profiles for non-durable consumption shown in Figure 6 also reveal that the percentage discrepancy between SHIW and SFB information is roughly constant up to age 50, but it decreases dramatically at older ages. Notably, SFB displays a sharper fall in old age: this could be due to the survey's better ability to sample the relatively poor among the old.

4. A theoretical framework

In this section we discuss the following identifying restriction to use SFB information to predict on SHIW

$$E(\ln C|X, SFB) = E(\ln C|X, SHIW), \tag{1}$$

where C represents total non-durable consumption. This conditional independence property is known in the statistical econometric literature as (weak) ignorability assumption and represents a useful tool to account for observed heterogeneity between different units.

It implies that households with same (observable) characteristics X have (on average) the same levels of (log) non-durable expenditure, no matter if they belong to the SFB or the SHIW sample. This also means that everything matters to explain heterogeneity of non-durable expenditure across households is the information contained in the set X that is common to the two samples.

In what follows we build on the following specification for the regression functions involved in (1). Let $X = [Z, \ln F]$, where Z are household characteristics recorded in both surveys and F represents food expenditure for each household. In agreement with standard models of consumer behavior, consider the following within period inverse Engel curve relating total non-durable expenditure (the budget) to food and socio-demographic variables

$$\ln C = \beta Z + \psi(\ln F) + \nu. \tag{2}$$

The function ψ is unknown and assumed suitably smooth over the support of $\ln F$[6].

As argued above, we have reliable information to estimate the regression function of (log) non-durable expenditure on (log) food expenditure and Z using SFB data. This would allow us - under condition (1) - to use the best linear predictor of (2) to impute non-durable expenditures on SHIW, exploiting the joint information on food expenditure and on household characteristics observed in this sample.

However, we have seen that the SHIW observed measure of food is affected by severe rounding and heaping problems, so that the non-classical error relationship between true and coarsened values - $\ln F$ and $\ln F^*$ respectively - could cause severe bias in the imputation step. Indeed, let

$$E(\ln C|X^*, I = SHIW) \tag{3}$$

be the imputation equation conditional on observed information $X^* = [Z, \ln F^*]$ in the SHIW sample; since $X \neq X^*$, the ignorability assumption stated in (1) fails to hold. To fix the ideas, in a fully non-parametric context we would match an household with X characteristics in the SFB sample to a Z-similar household in the SHIW sample declaring a $\ln F^*$ level of expenditure. Since the observed measure could potentially differ from the true unobserved value, this would cause a potential bias of the matching estimator procedure and - by analogy - of the estimator.

By the law of iterated expectations, the regression function in (3) can also be written as

$$E\{E(\ln C|X^*, \ln F, I = SHIW)\},$$

where the external expectation is taken with respect to the conditional distribution of $\ln F$ given X^* in the SHIW sample. If we assume that $\ln F^*$ is a surrogate of $\ln F$, that is if $\ln C$

[6] The original Engel curve relates food expenditure to income. In an intertemporal model with time-separability income is replaced by consumption or non-durable expenditure.

does not depend on $\ln F^*$ given $\ln F$, the specification (2) implies the following rule to predict on SHIW

(4) $$\beta Z + E\{\psi(\ln F)|X^*, I = SHIW\}.$$

Under such assumption, error affected values of food expenditure are 'less informative' to predict total non-durable expenditure than true unobserved values, in the sense that - conditional on $\ln F$ - $\ln F^*$ does not contain any information on $\ln C$. This corresponds to assuming non-differential measurement error characterizing reported values of food expenditure (Carroll, Ruppert and Stefanski, 1995); see Bound, Brown and Mathiowetz (2001) for a discussion on the implications of such assumption.

The last expression implies that to predict non-durable expenditure on SHIW we need to infer both (i) on the functional form of ψ and (ii) on the coarsening mechanism leading to error affected measure for food SHIW consumption data, that is the conditional distribution of $\ln F$ given $\ln F^*$ and Z. Section 5 deals with the last point while the relationship between total non-durable and food expenditure in (2) is discussed in Battistin, Miniaci and Weber (2000).

5. Accounting for heaping and rounding errors

Following Heitjan and Rubin (1990), assume that the random variable of interest W (expenditure in our case) is distributed according to a density $f(w;\vartheta)$ depending on the unknown parameter ϑ. If W was available, inference about ϑ could be drawn directly by standard methods; suppose to observe only a subset of the complete data sample space in which the true unobservable data lie. In other words, instead of observing W directly, we only observe a coarse version W^* of the variable W.

Assume that the degree of coarseness can be summarized by a continuous random variable G whose conditional distribution given W depends on γ, the parameter of the incompleteness mechanism. This means that W^* can always be expressed as a function of the pair (W, G). More formally, the conditional distribution of W^* given the true unobserved value W and the coarsening variable G is degenerate

$$f(w^*|w, g, z) = \begin{cases} 1 & \text{if } w^* = W^*(w, g) \\ 0 & \text{if } w^* \neq W^*(w, g) \end{cases},$$

where Z is an exogenous set of observable household characteristics. Let $H(w^*)$ be the inverse image of w^* with respect to this application, that is the set of couples (w, g) which are consistent with the value w^*. In what follows we assume that the variable G is not directly observed, but can at best be inferred from the observed value w^*. The likelihood function for the parameters (ϑ, γ) in the SHIW sample can be written as

$$\prod_{i \in SHIW} \int f(w_i^*|w_i, g_i, z_i) f(g_i|w_i, z_i; \gamma) f(w_i|z_i; \vartheta) dg_i dw_i,$$

or equivalently

$$\prod_{i \in SHIW} \int_{H(w_i^*)} f(g_i|w_i, z_i; \gamma) f(w_i|z_i; \vartheta) dg_i dw_i. \tag{5}$$

Moving from the evidence suggested by SHIW empirical distributions for both food and non-durables, we assume that households round off their true expenditure values to the nearest multiple of 100, 500 or 1000 (denote these three error types as R_1, R_2 e R_3, respectively) so that

$$\begin{aligned} w^* \in R_1 &\Rightarrow |w - w^*| \leq 50, \\ w^* \in R_2 &\Rightarrow |w - w^*| \leq 250, \\ w^* \in R_3 &\Rightarrow |w - w^*| \leq 500. \end{aligned}$$

Assume that disjoint regions in the domain of G uniquely correspond to different rounding errors, so that there exist two thresholds τ_2 and τ_1 ($\tau_2 > \tau_1$) with $g \geq \tau_2$ implying R_1 error, $\tau_1 \leq g < \tau_2$ implying R_2 error and $g < \tau_1$ implying R_3 error. If we define

$$\begin{aligned} H_1 &= [w^* - 50, w^* + 50) \times [\tau_2, +\infty), \\ H_2 &= [w^* - 250, w^* + 250) \times [\tau_1, \tau_2), \\ H_3 &= [w^* - 500, w^* + 500) \times (-\infty, \tau_1), \end{aligned}$$

it follows that

$$H(w^*) = \begin{cases} H_1 \cup H_2 \cup H_3 & \text{if } w^* \in R_3 \\ H_2 \cup H_3 & \text{if } w^* \in R_2 \\ H_3 & \text{if } w^* \in R_1 \end{cases}.$$

We specify an ordered (three category) probit regression model for the conditional distribution of G given W and Z

$$f(g|w,z;\gamma) \sim N(\gamma_1 w + \gamma_2 z; 1). \tag{6}$$

The heaping process in this section can be thought of as a generalization of the normal selection model widely proposed in the econometric literature: if $\gamma_1 = 0$ the true expenditure value is ignorable for the coarsening mechanism, implying exogenous rounding.

6. Estimates of the inverse Engel curve

Exploratory results based on a nonparametric estimation of the double log Engel curve using SFB data suggest that the relation between $\ln C$ and $\ln F$ is close to be linear. The linearity is confirmed by semi-parametric estimation conditional on demographics (see Battistin, Miniaci and Weber, 2000). We therefore write equation (2) as

$$\ln C = \beta Z + \alpha \ln F + \nu \tag{7}$$

and estimate it by standard parametric regression methods.

In Table 4 we present three sets of estimates of the last equation. The first set of numbers refers to parameter estimates and standard errors for a specification that linearly relates $\ln C$ to the Z variables but ignores any information about $\ln F$ (SM in the following). The explanatory variables include region of residence, household composition indicators, education, sex and age of the head and their interactions (zero-sum monthly dummies were also used, but their coefficients are not reported). Also included are some real wealth and standard of living indicators (home-ownership and the quality of housing available to the consumers, as proxied by the total surface of the dwelling and its per-capita surface). The fit of the equation is quite good ($\bar{R}^2 = 0.44$).

The second set of numbers reports OLS estimates of the Inverse Engel Curve (IEC in what follows), thus including the information on food expenditure. The addition of this single regressor makes the fit of the equation improve dramatically ($\bar{R}^2 = 0.66$), supporting the idea of including food information in the matching exercise. A reason for concern could be that the key parameter (the $\ln F$ coefficient) is estimated at 0.7362. This appears to imply that the

Table 4: Engel Curve Estimates using SFB data

$\ln C$	SM		IEC		IV	
Parameters	**Coef.**	**Std. Err**	**Coef.**	**Std. Err**	**Coef.**	**Std. Err**
Intercept	5.8614	0.1050	2.2329	0.0854	-4.7960	0.5026
$\ln F$			0.7362	0.0051	2.1842	0.0979
# members 18-26	0.1345	0.0701	0.0967	0.0545	0.0185	0.1028
# members 27-40	0.1644	0.0678	0.0600	0.0527	-0.1506	0.1003
# members 41-60	0.0930	0.0664	-0.0027	0.0515	-0.1931	0.0981
# members 61-70	-0.0484	0.0661	-0.0830	0.0513	-0.1536	0.0968
# members over 70	-0.1310	0.0675	-0.1226	0.0524	-0.1093	0.0986
Central Italy	-0.0580	0.0455	-0.0468	0.0354	-0.0235	0.0666
Southern Italy	-0.1918	0.0370	-0.1587	0.0288	-0.0931	0.0544
# Children 0-2	-0.3668	0.0666	-0.1496	0.0517	0.2847	0.1019
# Children 3-5	-0.2817	0.0694	-0.1601	0.0539	0.0831	0.1028
# Children 6-9	-0.2780	0.0639	-0.1284	0.0496	0.1670	0.0955
# Children 10-13	-0.1806	0.0666	-0.0712	0.0517	0.1459	0.0984
# Children 14-17	-0.0406	0.0632	-0.0083	0.0491	0.0586	0.0924
# Children over 18	0.1105	0.0319	0.0608	0.0247	-0.0344	0.0470
# Retired members	0.0598	0.0129	0.0497	0.0100	0.0306	0.0189
At least 2 members	0.7152	0.0337	0.1808	0.0265	-0.9579	0.0832
At least 3 members	-12.1028	0.7911	-3.1488	0.6176	16.0220	1.5905
At least 4 members	7.1227	0.6459	1.6569	0.5031	-10.0636	1.1525
Sex (male)	0.0602	0.0127	-0.0103	0.0099	-0.1478	0.0208
Age of the head	0.0123	0.0027	0.0052	0.0021	-0.0081	0.0041
Age of the head^2	-0.0116	0.0025	-0.0054	0.0020	0.0064	0.0038
Head unemployed	-0.2460	0.0191	-0.1142	0.0148	0.1455	0.0335
Head out of labor force	-0.0902	0.0107	-0.0452	0.0084	0.0442	0.0170
Education ≥ 8	0.1042	0.0111	0.0708	0.0086	0.0069	0.0169
Education ≥ 13	0.0968	0.0115	0.0637	0.0089	-0.0012	0.0177
University degree	0.1061	0.0183	0.0823	0.0142	0.0361	0.0271
Center * #18-26	-0.0272	0.0550	0.0079	0.0427	0.0789	0.0806
South * #18-26	-0.1668	0.0439	-0.0721	0.0341	0.1164	0.0655
Center * #27-40	-0.0357	0.0520	0.0114	0.0404	0.1043	0.0764
South * #27-40	-0.1496	0.0431	-0.0633	0.0334	0.1096	0.0639
Center * #41-60	-0.0474	0.0469	0.0005	0.0364	0.0926	0.0690
South * #41-60	-0.1625	0.0387	-0.0340	0.0301	0.2199	0.0590
Center * #61-70	-0.0044	0.0443	0.0201	0.0344	0.0677	0.0649
South * #61-70	-0.1313	0.0362	-0.0015	0.0281	0.2558	0.0555
Center * #70+	-0.0409	0.0474	0.0301	0.0368	0.1702	0.0700
South * #70+	-0.1672	0.0392	-0.0211	0.0305	0.2680	0.0605
Center * Educ. ≥ 8	-0.0121	0.0193	-0.0183	0.0150	-0.0311	0.0282
Center * Educ. ≥ 13	0.0257	0.0203	0.0316	0.0157	0.0446	0.0296
Center * Degree	0.0092	0.0316	0.0154	0.0246	0.0289	0.0463
South * Educ. ≥ 8	-0.0104	0.0167	-0.0013	0.0129	0.0144	0.0244
South * Educ. ≥ 13	0.0341	0.0175	0.0342	0.0136	0.0350	0.0256
South * Degree	0.0217	0.0277	0.0090	0.0215	-0.0164	0.0406
Center * Sex	0.0270	0.0193	0.0076	0.0150	-0.0308	0.0283
South * Sex	0.0230	0.0174	0.0169	0.0135	0.0035	0.0254
Total surface	0.0023	0.0002	0.0012	0.0001		
Per-capita surface	0.0008	0.0004	0.0010	0.0003		
Homeowner	0.0315	0.0066	0.0273	0.0051		
Secondary residence	0.2043	0.0120	0.1529	0.0093		
Adjusted R^2	0.4361		0.6598			
F(58, 31341)	419.67					
F(59, 31340)			1033.32			
F(55, 31344)					206.47	
Root MSE	0.4901		0.3807		0.7169	
Sample size	31400		31400		31400	

elasticity of food expenditure to total non-durable expenditure is 1.36, an implausibly high number. However, there are two reasons why OLS does not produce a consistent estimate of the reciprocal of the budget elasticity of food: first, the relation is estimated in inverse form; second, simultaneity implies that lnF in (2) correlates with the equation error ν[7].

To check whether SFB consumption data are reliable, we also estimate the IEC by instrumental variables (IV); results are reported in the last set of numbers of Table 4. We treat $\ln F$ as endogenous and we use as additional instruments four variables capturing home-ownership and quality of housing available to the consumers. The idea is that these variables correlate with the long-term standard of living the household can afford. The fact that Engel curve estimation is a well established practice in the economic literature helps us evaluate economically the success of our matching procedure (see for example Deaton and Muellbauer, 1980, for further details on Engel curves and their economic interpretation). Even though the estimated standard errors of the estimates are larger, inference can still be drawn with good confidence. The estimated elasticity of food is 0.46 and this is fully consistent with the well documented notion that food is a necessity[8].

7. Estimates of the heaping process

The error mechanism derived in Section 5 allows us to account for the heaping problems characterizing food and non-durable expenditures in the SHIW sample using predictive means derived from a fully parametric imputation model.

Exploratory plots of both $\ln C$ and $\ln F$ on the components of Z in the SFB sample suggest that a gaussian parametric specification for the conditional densities is plausible

$$f(w|z;\vartheta) \sim N(\vartheta_1 z;\vartheta_2).$$

[7] This is due to at least two reasons: food expenditure is a component of total non-durable expenditure; food and other non-durable expenditure are jointly determined and reflect the overall standard of living for each household (they both depend, via the marginal utility of wealth, on total lifetime resources available to the household).

[8] A reassuring feature of this set of estimates is that the estimated direct Engel curve also implies elasticities for food of approximately 0.45. This can be taken as evidence that our sample is sufficiently large for us to rely on asymptotic properties of the estimator (IV is not invariant to normalization in finite samples).

Exploiting the notation of Section 5, we therefore assume that the joint distributions $(\ln C, G)|Z$ and $(\ln F, G)|Z$ are both bivariate normals and specify the likelihood function (5) accordingly[9].

The conditioning set Z includes the same household characteristics described in Section 3, plus a reasonable set of interview quality indicators (such as interview length and interviewer's assessment on how well the respondent understood the questions) which we assume not to determine consumption level. For computational convenience, we also impose the exclusion restriction that the rounding process G is a function of a limited number of exogenous characteristics (namely age, education and region). It is in fact possible that response care depends on both recall ability and the shadow value of leisure, that will differ across households.

Maximum likelihood estimates of ϑ for SHIW food and non-durable expenditure together with estimates of the parameter γ in the heaping function are presented in Table 5. The adopted specification for the heaping function (6) allows us to establish that the stochastic nature of the coarsening mechanism cannot be ignored in drawing inferences about the parameter ϑ. Maximum likelihood estimates of the parameter γ support the idea that the reported expenditure is not coarsened at random[10]. We find that for food a lower expenditure level increases the probability of rounding to multiples of 1000 (γ_1 is positive and significantly different from zero) and respondents who show excellent understanding round more likely to multiples of 100. For non-durable consumption, instead, rounding errors to multiples of 1000 are associated to high expenditure levels and short interviews.

We create multiple imputations of $\ln C$ and $\ln F$ for the SHIW sample implementing an acceptance-rejection procedure based on the fitted model. Since by applying Bayes theorem we have

$$f(w, g|w^*, z; \vartheta, \gamma) \propto \begin{cases} f(w, g|z; \vartheta, \gamma) & \text{if } w^* = W^*(w, g) \\ 0 & \text{if } w^* \neq W^*(w, g) \end{cases},$$

[9] The integration sets H_1,H_2 and H_3 are $[\ln\{w^* - 500\}, \ln\{w^* + 500\})$, $[\ln\{w^* - 250\}, \ln\{w^* + 250\})$ and $[\ln\{w^* - 50\}, \ln\{w^* + 50\})$, respectively, where $W^* = C^*$ (observed non-durable expenditure) or $W^* = F^*$ (observed food expenditure).

[10] If observations were coarsened at random, the correct likelihood for ϑ would be proportional to a simple grouped data likelihood. See Heitjan and Rubin (1991) on how to extend the notion of missing at random to more complicated incomplete data problems.

Table 5: Heaping correction for SHIW data

	$\ln F$		$\ln C$	
Parameters	Coef.	Std. Err	Coef.	Std. Err
Intercept	4.7249	0.2059	5.7849	0.1965
members 18-26	0.1382	0.1691	0.1587	0.1607
members 27-40	0.1194	0.1664	0.2225	0.1581
members 41-60	0.2588	0.1623	0.2434	0.1541
members 61-70	0.1818	0.1592	0.1090	0.1512
members over 70	0.1184	0.1585	0.0286	0.1505
Central Italy	0.0130	0.0725	0.0783	0.0691
Southern Italy	-0.1576	0.0596	-0.2606	0.0572
Children 0-2	-0.0044	0.1591	-0.1481	0.1512
Children 3-5	-0.0530	0.1666	-0.1615	0.1582
Children 6-9	-0.0058	0.1548	-0.1919	0.1469
Children 10-13	0.0788	0.1584	-0.0710	0.1504
Children 14-17	0.2300	0.1546	0.0195	0.1467
Children over 18	0.0855	0.0567	0.1056	0.0544
Retired members	0.0935	0.0207	0.1197	0.0200
At least 2 members	0.6869	0.0434	0.5874	0.0417
At least 2 members	-10.249	1.0641	-9.2281	1.0179
At least 2 members	5.6535	0.8631	5.1875	0.8235
Sex (male)	0.0696	0.0218	0.0727	0.0209
Age of the head	0.0114	0.0044	0.0076	0.0042
Age of the head^2	-0.0074	0.0041	-0.0039	0.0039
Head unemployed	-0.2509	0.0246	-0.3359	0.0238
Head out of labor force	-0.0511	0.0165	-0.1117	0.0158
Education ≥ 8	0.1381	0.0175	0.1464	0.0168
Education ≥ 13	0.0362	0.0180	0.0677	0.0172
University degree	0.0638	0.0264	0.1597	0.0253
Center * #18-26	0.0001	0.0001	0.0009	0.0001
South * #18-26	-0.0001	0.0003	-0.0005	0.0003
Center * #27-40	0.0292	0.0100	0.0430	0.0095
South * #27-40	0.0527	0.0114	0.0861	0.0109
Center * #41-60	0.0494	0.0855	-0.1683	0.0814
South * #41-60	-0.0745	0.0694	-0.1784	0.0666
Center * #61-70	0.1019	0.0881	-0.1410	0.0840
South * #61-70	0.1611	0.0731	-0.0058	0.0701
Center * #70+	0.0555	0.0753	-0.0633	0.0718
South * #70+	0.0134	0.0624	-0.0196	0.0600
Center * Educ. ≥ 8	-0.0384	0.0703	-0.0973	0.0670
Center * Educ. ≥ 13	0.0766	0.0573	0.0379	0.0550
Center * Degree	0.0957	0.0739	-0.0268	0.0705
South * Educ. ≥ 8	0.1200	0.0624	0.1296	0.0599
South * Educ. ≥ 13	-0.0702	0.0312	-0.0119	0.0298
South * Degree	0.0313	0.0317	0.0123	0.0302
Center * Sex	-0.0158	0.0497	-0.0075	0.0473
South * Sex	-0.0237	0.0261	-0.0087	0.0251
Total surface	0.0871	0.0280	0.1142	0.0268
Per-capita surface	0.1239	0.0418	0.1004	0.0399
Homeowner	-0.0426	0.0324	-0.0630	0.0310
Secondary residence	-0.0192	0.0280	-0.0124	0.0271
$\ln \vartheta_2$	-0.9920	0.0087	-1.0469	0.0114
γ_1	1.7659	0.0831	-0.3195	0.0573
Fair understanding	0.0498	0.1017	0.1896	0.0626
Good understanding	-0.0172	0.0906	0.3808	0.0570
Excellent understanding	0.1964	0.0936	0.6866	0.0607
Long interview (over 1h)	-0.0402	0.0571	0.2959	0.0376
Age$>$70	-0.1031	0.1086	-0.4243	0.0616
τ_2	17.779	1.5654	-0.9110	0.4455
τ_1	12.800	0.5831	-1.9920	0.4080

for each unit we draw a couple (w, g) from the estimated distribution $f(w, g|z; \vartheta, \gamma)$ until $(w, g) \in H(w^*)$, that is until the generated couple is consistent with the observed value w^*. We then impute w as the true value of the observed (food or non-durable) expenditure. The proportion of missing values - that is the proportion of couples not consistent with observed expenditures - using 1000 drawings from the estimated distributions is always less than 1 %[11].

Validating generated values for $\ln C$ and $\ln F$ using SFB data helps us to conclude that food data are of comparable quality and information content across the two surveys, once heaping and rounding are accounted for. A different conclusion must be drawn for non-durable expenditure. Average histograms of 100 imputations are shown in Figures 7 and 8 and can be compared to the corresponding distributions of food and non-durable expenditure for the SFB sample (Figures 5 and 4). Different composition with respect to observable characteristics is corrected by weighting SFB observations to obtain the same distribution of observable characteristics for the two samples.

To assess the effectiveness of the error correction procedure, Table 6 reports descriptive statistics for the absolute differences between the SFB empirical and the SHIW estimated density functions, both for $\ln C$ and $\ln F$. For the food measure, the imputation procedure fails to recover the lower tail of the distribution but is globally close to the one observed for the SFB sample (differences between histograms shift significantly towards zero with a mean reduction of about 80 %). Instead, the SHIW empirical distribution for non-durable expenditure is based on much lower values than the SFB one and lies at its left. The under-reporting pattern showed in Table 3 is not accounted for by the heaping process alone.

8. Prediction results

Before commenting on the estimation results, it is worth summarizing the steps we have followed to impute alternative measures of non-durable consumption for the SHIW sample. We at first have argued that SFB data contain reliable information on expenditure items; we have then constructed food and total non-durable expenditure aggregates that are diary-based

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[11] Note that - given the parametric rule to impute $\ln F$ on SHIW - the regression function (3) can be estimated in a fully nonparametric context without exploiting the linear specification (7). For any given household with X^* characteristics in the SHIW sample we can replicate the following two steps: (i) generate $\ln F$ from its conditional distribution given X^*, as determined by the error structure assumed in Section 5 (ii) generate non-durable expenditure sampling from the SFB empirical distribution of $\ln C$ for households with Z characteristics and observed food expenditure in a neighborhood of the SHIW food measure in the previous step. Averaging over the set of non-durable expenditures imputed to SHIW would consistently estimate (3).

Table 6: Imputations

	Food		Non-durables	
	Observed	**Imputed**	**Observed**	**Imputed**
min	0.0003	0.0000	0.0002	0.0002
max	0.0901	0.0141	0.0976	0.0438
mean	0.0144	0.0027	0.0133	0.0086
5%	0.0006	0.0000	0.0003	0.0005
25%	0.0023	0.0006	0.0014	0.0016
50%	0.0044	0.0013	0.0046	0.0042
75%	0.0159	0.0036	0.0142	0.0117
95%	0.0503	0.0100	0.0449	0.0355

and are defined in a way that is fully comparable to SHIW corresponding items. Also, we have seen that an inverse Engel curve can be successfully estimated exploiting such data.

Hence, exploiting SFB as validation data for the consumption information, we have shown that the type of rounding and heaping errors characterizing SHIW can be dealt with in estimation. In particular, the underlying density function is comparable for food expenditure, but differs markedly for total non-durable expenditure.

We therefore present three alternative estimates of $E(\ln C)$ for the SHIW sample. The first one builds on error corrected values for $\ln C$ exploiting results from the multiple imputation procedure described in the previous section. The effectiveness of this correction has already been discussed in Table 6. The second correction we propose builds on IEC prediction by means of the error corrected values for $\ln F$ generated in the SHIW sample. The third one neglects information on food expenditure - thus imposing $\alpha = 0$ in equation (7) - and is therefore both robust to potential mis-specification in the multiple imputation procedure and unaffected by imputation variability.

Clearly, the first and the second procedures rely on our ability to correctly generate total non-durable and food measures in the SHIW sample, respectively, and their precision is affected by the random nature of the imputation technique. In what follows, we discuss the implications of the SM and the IEC estimation procedures to derive consumption age profiles (Section 8.1) and saving age profiles (Section 8.2) for the SHIW sample.

8.1 *Consumption profiles*

Given the results presented in Table 6, we resort to the SM and the IEC methods to impute non-durable expenditure in the SHIW sample. Table 7 reports the distributions of non-

Table 7: Descriptive statistics for ln(nd)

	SFB	**SHIW**		
	p-score adjusted	Observed	SM	IEC
5%	6.4871	6.4922	6.7957	6.8075
25%	7.2659	7.0900	7.4174	7.3693
50%	7.7146	7.4383	7.7529	7.7307
75%	8.1430	7.8240	8.0057	8.0606
95%	8.7116	8.1605	8.3861	8.5136
Mean	7.6814	7.4131	7.6917	7.7097
Variance	0.4480	0.2530	0.2232	0.2657
SE of the mean			0.0065	0.0076

durable consumption (in logs) based upon observed and predicted values. The table reveals that both mean and median $\ln C$ are higher in the SFB sample (after allowance is made for sampling differences) compared to the SHIW sample observed data, as we already pointed out. After correction, these differences all but disappear: median consumption (in logs) is now 2-4% higher in the SHIW sample, while mean consumption is again 1-2 % higher. The variance is much higher in SFB than in SHIW (44.8 % as opposed to 25.3 %); SM predictions have lower variance (22.3 %) while IEC imputations display some more variability (26.6%). A similar picture emerges when we consider interquartile differences[12].

Table 7 also reports standard errors for the mean prediction of $\ln C$, based upon prediction error variances. The SM prediction error variance is the sum of the variance of the disturbance and the variance of the parameter estimates, as usual. With the IEC method - thus conditional upon Z and $\ln F$ - a third variance component comes into play, reflecting the variability induced by the imputation procedure (see Appendix B for further details). The standard errors are of comparable magnitude, but the IEC standard error is larger than the SM standard error, indicating that imputation variance is of non-negligible magnitude.

Figure 9 presents age profiles for consumption corresponding to the last three columns of Table 7: observed consumption, SM predictions and IEC predictions.[13] All 100 IEC predictions are shown as individual points, to highlight the variability in the predicted profile

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[12] The statistics referred to the IEC method are calculated as the average of the sample statistics obtained using the 100 imputations of food expenditure for SHIW households.

[13] The age profile based on the measure of $\ln C$ derived from the heaping correction of Section 7 is extremely close to the observed profile, and therefore is not reported. The profile of observed data is the one already reported in Figure 6.

that is attributable to the imputation method (there 100 food imputations per household, and thus 100 lnC profiles). The solid line passing through these points is the median IEC profile.

As previously noted looking at the overall sample, both the SM and the IEC profiles are markedly above the observed profile, so that the their level is of magnitude similar to the one observed for SFB (see Figure 6)[14]. Their shape remains basically the same between ages 42 and 56 but is different outside this interval. We notice that the key difference between the two lies in the shape for households aged less than 35 and over 60: the inverse IEC method predicts a sharper rise early in life and a much smaller fall in old age than the standard method.

The question remains of whether these profiles are statistically different. This requires computing the confidence interval of the difference, something that is most easily done by bootstrapping methods (the variance of the difference is not simply the sum of the variances here. Given that we predict over the same sample using at least some common information, the prediction errors are positively correlated). In Figure 10 we report the difference between SM and IEC saving age profiles together with the corresponding bootstrap confidence bands of ± 2 standard errors We can see the two profiles are statistically different over most of the age range, with the notable exception of some ages in the $45-55$ interval.

8.2 *Saving profiles*

Much of the literature on savings is interested in the age profile of the saving rate, as the leading economic theory (the life-cycle model of consumption) predicts a hump-shaped age profile for individual households. It is well known that cross-section profiles do not correct for cohort effects, and therefore may provide a misleading picture of the true underlying age profile for each cohort. However, the cross section plot of our different measures may still be interesting if we believe cohort effects to be zero for the saving rate (as assumed by Paxson, 1996) or unaffected in imputation.

The standard definition of the personal sector saving rate in aggregate data is given by

$$1 - \frac{total\ consumption}{income},$$

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[14] When we compute analytic standard errors as shown in Appendix B, we find that the observed profile lies significantly below the IEC confidence interval throughout, and below the SM confidence interval for all ages below 75.

where income refers to disposable income and total consumption is either the sum of spending on durable goods and non-durable goods and services, or just expenditure on non-durable goods and services. Note that in both cases, contrary to the definition of consumption we followed to derive $\ln C$ in the previous section, consumption includes rent (that we observe in SHIW).

If we wish to produce evidence on a saving rate definition that is comparable to the aggregate measure, we need to generate predictions for the levels. To do this, we can resort to the following relationship between moments of logs and levels

$$\ln E(C) - E(\ln C) = \frac{1}{2} Var(\ln C) \tag{8}$$

that holds true if $\ln C$ is normally distributed. In Section 7 we have already used the fact that such an assumption is reasonable in our data. Indeed, Figure 11 reports the left hand side - sometimes referred to as entropy - and the right hand side of equation (8) against age for SFB data[15]. We see that the difference is minor for all ages and does not display a strong age pattern.

A close approximation for the first moment of C at any age can therefore be obtained as

$$E(C) = \exp\{E(\ln C) + \frac{1}{2} Var(\ln C)\}.$$

This can be used to generate predictions for the first moment of C in the SHIW sample if we replace the unobserved first and second moments of $\ln C$ with their consistent estimates[16].

This approximation allows us to compute average spending by age in the SHIW sample. We alternatively define spending as (i) the sum of C and rent, that is treating spending on durable goods as saving, and (ii) the sum of C, rent and durables, that is treating spending on durables as consumption. Given that we base our estimates for expenditure on SFB information and the same information is used to generate aggregate statistics for the NIPA, we expect our consumption data to be in line with the corresponding NIPA aggregate.

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[15] A similar plot is shown in Attanasio and Weber (1993).

[16] For the first moment, we take the SHIW sample mean of the imputed $\ln C$. The variance of $\ln C$ is instead estimated as the sum of the SHIW sample variance of the imputed $\ln C$ and the variance of the residuals from the regressions in Table 5. An alternative, equivalent estimator is given by the SFB sampling variance of the observed $\ln C$.

To compute a measure of saving, we also need an estimate of average income by age that is consistent with the NIPA figure. Income is poorly measured in SFB as responses are based on a single question about normal monthly income, and (see Brandolini, 1999) in some 40 % of cases the SFB figure has been revised upwards by exploiting information on total expenditure (plus, where available, saving class information). SHIW contains a number of detailed questions on income and is therefore a more promising source of information. However, we know from Brandolini (1999) that in 1995 SHIW income data fall short of national accounts estimates by 34.7 %; thus we could produce a grossed-up income profile by multiplying each household's income by 1/(1-.347)=1.53. More importantly, Brandolini provides information on proportional shortfalls by income type: for employment income, this is 18.4 %, while for transfer income (including pensions) it rises to 25.7 %. The larger shortfall in transfer income compared to employment income is to some extent surprising, and may reflect failure to report secondary transfers (such as invalidity pensions and supplementary occupational pensions) rather than primary pensions[17]. The SHIW is found to overestimate the rent component of income compared to the National Accounts by 10.6 %. Severe underestimation affects instead interest income (80.1 %) and self-employment income (63.8 %).

Underestimation of interest income is common in household surveys, and its correction is relatively straightforward and of little consequence for the income age profile in our data. The underestimation of self-employment income is also relatively common, but the size of the required correction (the grossing up factor is 2.76 in this case) and its application to a relatively small sub-sample (in SHIW only 18.2 % of all households can be classified as self-employed) produces major differences between corrected and original income age profiles.

However, there are good reasons to doubt the grossing up procedure; first, because the NIPA statistic is at best an educated guess and secondly because the correction falls heavily on too small a number of households (unit non-response in SHIW appears to be higher among the self-employed). For this reason we compute the saving rate age profiles for that part of the SHIW sample that excludes the self-employed households (defined as those households where the head is self-employed or at least a fourth of reported household income is from self-employment).

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[17] This conjecture is supported by the analysis of the raw data. For instance, the histogram for pension income displays a peak at Lit 736000, that was the standard Social Security minimum pension for the year.

In Figure 12 we show the saving rate age profile corresponding to the standard NIPA aggregate, thus treating spending on durable goods as consumption. The income measure is corrected using the grossing up factors described above. The top line corresponds to reported expenditure ("observed") and rises from values around 25% for young households to values in the 45% region around age 65 (statutory retirement age was 60 in 1995 for males, 55 for females). After that age, the saving rate profile flattens out. The same statistic taken over the whole sample is 43.4%.

The line corresponding to SM predictions is much lower overall (its value over the whole sample is 26.7%), and it monotonically increases from 2% at age 25 to 40% at age 80. Finally, we report the 100 consumption profiles by age corresponding to the 100 food imputations per household using the IEC method. The median profile makes up the third line and we take it as representing the IEC age profile. Such line is still monotonically increasing, albeit with a lower slope than the one corresponding to the SM method (from 5% at 25 to 35% at 80 years of age). Its overall value is 24.6%.

To understand these findings we can go back to Figure 6. This shows that the SFB age profile of non-durable consumption lies all above the corresponding SHIW profile, but the SHIW profile falls more gently with age. The former feature accounts for the higher level of the saving rate based on observed SHIW consumption; the second feature for its less steep ascent with age compared to the standard method predictions. The IEC method further exploits SHIW information on food consumption and therefore does not generate as steeply decreasing consumption levels in old age as the standard method (see Figure 9 for similar evidence on $\ln C$).

A question worth asking is to what extent our treatment of durable spending as consumption is responsible for the shape of the age profile. In Figure 13 we show similar age profiles for the saving rate where spending on durable goods is treated as saving. Saving rates are overall higher, and the age profiles for observed consumption and IEC imputations are no longer monotonically increasing with age. But the overall pattern of high positive saving rates in old age is confirmed.

9. Conclusions

In this paper we compare food and non-durable expenditure data across two Italian surveys: the widely-used, recall-questions-based Survey of Household Income and Wealth (SHIW) and the newly released diary-based Survey of Family Budgets (SFB). The former contains detailed income and wealth information, but only a few, broad consumption questions; the latter contains accurate records on consumption, but little (if any) income and no wealth information. The two surveys share information on social and demographic household characteristics.

We have argued that the consumption data in SHIW are questionable because of the non-standard nature of recall measurement error and that a matching technique should be used to generate predictions for total non-durable expenditure in SHIW.

In a first step we have analyzed the nature of the recall error process. When we compare marginal densities for food expenditure and total non-durable expenditure, modelling the heaping and rounding process as a function of interview quality information, observed characteristics and the true expenditure level, we find that:

- the SHIW reported food expenditure measure is comparable to the SFB measure once heaping and rounding errors are taken into account

- the SHIW reported non-durable expenditure measure is instead more seriously affected by recall error.

On the basis of the above, we have argued that it makes sense to use inverse Engel curve estimates from the SFB to generate an imputation for non-durable expenditure in SHIW. In a second step, we therefore estimate a double-log inverse Engel curve and show that parameter estimates agree well with standard findings on consumer behavior.

We then discuss the relative merits of two prediction techniques: the standard method (SM) that makes no use of food information in the SFB sample and an Inverse Engel Curve (IEC) method that uses food records from both SFB and SHIW samples. This latter method exploits information on reduced form variables and from imputations on SHIW food consumption that are consistent with the estimated heaping and rounding process. Even though more information is used in estimation, the overall precision of the IEC predictions is potentially reduced because of imputation errors.

We assess the quality of the prediction methods by plotting age profiles for the logarithm of non-durable consumption and for the corresponding saving rate. We show that the age profile for observed log consumption in SFB is more hump-shaped and uniformly higher than in SHIW. When the standard method is used to predict log consumption in SHIW the profile is pushed up, but we get the same steep fall in old age as in SFB. The inverse Engel curve method generates a higher profile than in the raw data, that declines in old age more gently (as in SHIW original data). We also derive some implications for the saving rate by using SHIW income data (after implementing differential corrections for income under-reporting by income type). The observed SHIW expenditure data imply a very high saving rate overall, monotonically increasing with age. The standard method produces a more sensible aggregate saving rate measure, but an even more steeply ascending age profile. The inverse Engel curve method also produces a reasonable aggregate measure, but an age profile that increases less steeply with age than the profile of the standard prediction method. In all cases, however, there is strong evidence of active saving behavior after retirement.

Appendix A: Correcting for sampling differences

We account for differences in the composition with respect to observable characteristics z common across the two surveys using the following weighting procedure. Let $F_{W|SFB}$ and $F_{W|SHIW}$ be the cumulative marginal distribution functions for the variable W in the SFB and SHIW data, respectively.

Differences between $F_{z|SFB}$ and $F_{z|SHIW}$, the cumulative distribution functions of z in the two samples, can be controlled for by choosing as reference population the one described by the SHIW sample and comparing $F_{W|SHIW}$ to

(9) $$F_{W|SFB}^{SHIW} = \int F_{W|z,SFB}\, dF_{z|SHIW} = \int F_{W|z,SFB}\, \frac{dF_{z|SHIW}}{dF_{z|SFB}} dF_{z|SFB},$$

that is to the conditional distribution of W in SFB integrated with respect to $F_{z|SHIW}$. This expression defines the weighting function

$$\delta(z) = \frac{dF_{z|SHIW}}{dF_{z|SFB}},$$

whose role is to down-weigh (up-weigh) those households in the SFB sample exhibiting characteristics z over represented (under represented) with respect to the reference population (SHIW). Applying Bayes theorem, the weights can also be written as

(10) $$\delta\left(z\right) = \frac{e\left(z\right)}{1-e\left(z\right)} \frac{\Pr\left(SFB\right)}{\Pr\left(SHIW\right)},$$

where $e\left(z\right)$ is the propensity score as defined by Rosenbaum and Rubin (1983), that is the conditional probability of observing characteristics z in the population represented by the SHIW sample.

Notice that if the two groups were balanced with respect to z, then the propensity score would not depend on z, $\delta(z)$ would be constant over households and the corrected distribution function for the SFB sample (9) would collapse to the standard one. See Heckman, Ichimura, Smith and Todd (1998) for a review of propensity score based estimators to control for systematic differences with respect to observable characteristics between different groups.

We replace $\delta\left(z\right)$ by its sample counterpart assuming a logistic specification for $e(z)$ depending on a large number of demographic indicators and their interactions; $F_{W|SHIW}$ is then estimated by the empirical distribution function while the corresponding estimate for the SFB sample is obtained by the ratio

$$\widehat{F}^{SHIW}_{W|SFB}(\cdot) = \frac{\sum_{i \in SFB} \widehat{\delta}_i \mathbb{1}\left(w_i \leq \cdot\right)}{\sum_{i \in SFB} \widehat{\delta}_i},$$

where $\mathbb{1}(A)$ is the index function of event A.

Appendix B: Standard errors of imputed lnC

In this section we formally derive the asymptotic standard errors for mean predicted saving rates reported in Table 7. Let

$$\widehat{\mathbf{y}}_j = \widetilde{\mathbf{X}}_j \widehat{\boldsymbol{\beta}} \tag{11}$$

be the predicted non durable expenditure based on the j-th imputed food measure in the SHIW sample, where $j = 1, \ldots, m$. The matrix $\widetilde{\mathbf{X}}_j = \left[\widehat{\ln F_j}, \mathbf{Z}\right]$ contains the observed SHIW information about household demographics considered in equation (7) $(\mathbf{Z})$, together with the SHIW j-th imputed measure of food obtained as explained in Section 7 $\left(\widehat{\ln F_j}\right)$.

We predict non-durable expenditure in SHIW for each of the m sets of regressors $\widetilde{\mathbf{X}}_j$ and combine the results to produce final estimate properly adjusted for the multiple imputation context. Given that $\widehat{\ln F_j}$ are uncorrelated with $\widehat{\boldsymbol{\beta}}$, then, conditional on the generic imputation, standard econometric results can be applied to prove that the covariance matrix of the forecast in (7) can be easily estimated by

$$\widehat{\boldsymbol{\Psi}}_j = \widehat{\sigma}^2 \left[\mathbf{I} + \widetilde{\mathbf{X}}_j \left(\mathbf{X}'\mathbf{X}\right)^{-1} \widetilde{\mathbf{X}}_j'\right] + \hat{\alpha}^2 \left[\hat{\vartheta}_2 \mathbf{I} + \mathbf{Z} Var\left(\hat{\vartheta}_1\right) \mathbf{Z}'\right]$$

The terms $\widehat{\sigma}^2 \left(\mathbf{X}'\mathbf{X}\right)^{-1}$ and $\hat{\alpha}$ are the best unbiased estimates for the variance matrix of $(\widehat{\boldsymbol{\beta}} - \beta)$ and for the $\ln F$ parameter obtained from the structural equation estimation step in the SFB sample, $\left(\hat{\vartheta}_1, \hat{\vartheta}_2\right)$ are the estimates of the parameters of the conditional distribution of $\ln F$ in SHIW obtained in Section 7. The estimated variance of the mean predicted expenditure

$$\widehat{\mu}_j = \frac{1}{n} \sum_{i \in SHIW} \widehat{y}_{ij}$$

can be written as

$$\widehat{\tau}_j^2 = \frac{1}{n^2} \mathbf{1}' \widehat{\boldsymbol{\Psi}}_j \mathbf{1}.$$

Pooling the information from the m imputed data sets, the combined estimate and its associated variance are

$$\overline{\mu}_m = \frac{1}{m} \sum_j \widehat{\mu}_j,$$

$$T_m = \overline{W}_m + \frac{m+1}{m} B_m, \tag{12}$$

where

$$\begin{aligned}
\overline{W}_m &= \frac{1}{m} \sum_j \tau_j^2, \\
B_m &= \frac{1}{m+1} \sum_j \left(\widehat{\mu}_j - \overline{\mu}_m\right)^2
\end{aligned}$$

are the within imputation and the between imputation sources of variability, respectively, and $(m+1)/m$ is an adjustment for finite m. Interval estimation and significance tests are based on the statement

$$(\overline{\mu}_m - \mu) T_m^{-1/2} \sim t_\rho,$$

where t_ρ is the t reference distribution with

$$\rho = (m-1)\left[1 + \frac{1}{m+1} \frac{\overline{W}_m}{B_m}\right]^2$$

degrees of freedom (see Little and Rubin, 1987, for more details).

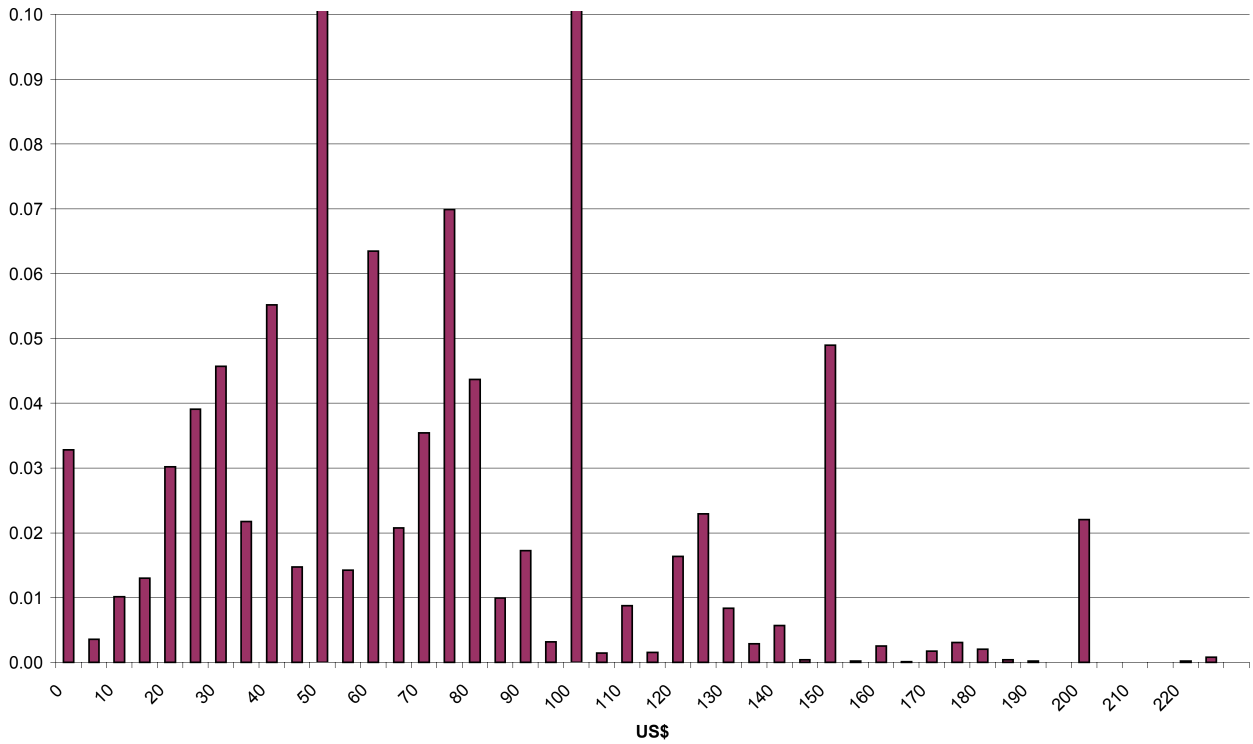

Figure 1: CEX data - Weekly spending at grocery store

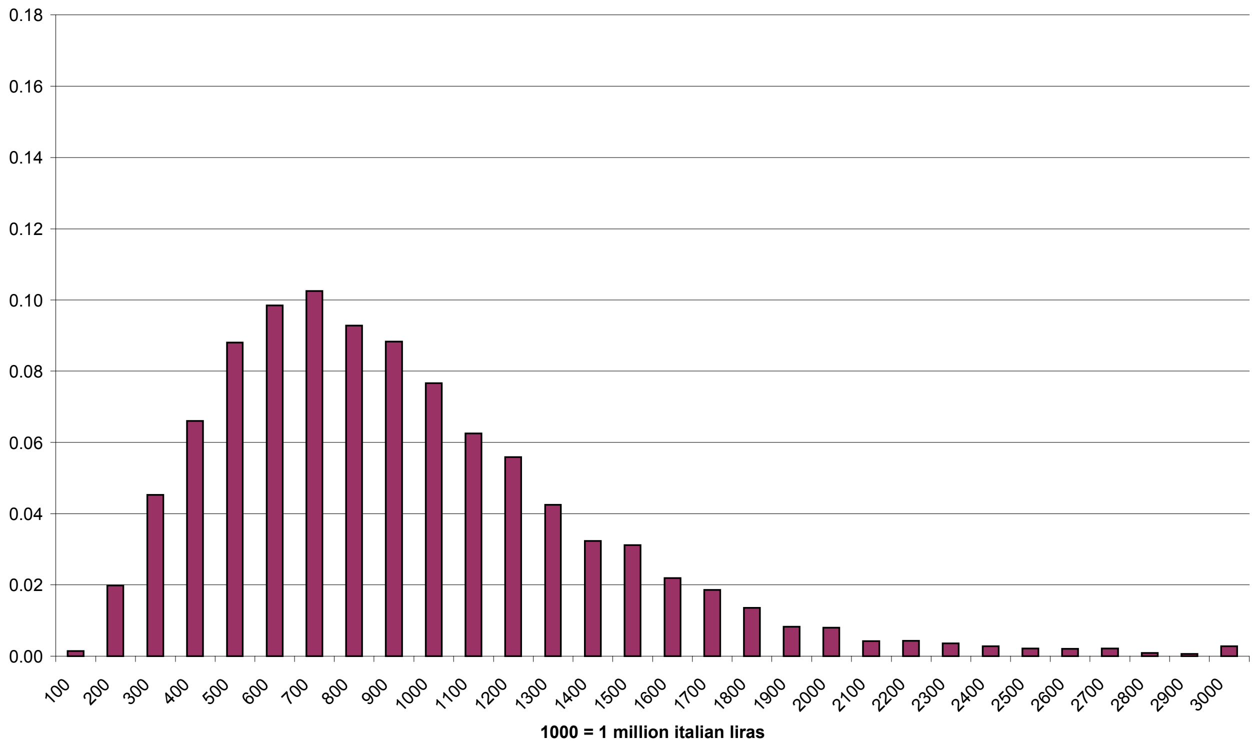

Figure 2: Observed (weighted) food expenditure for SFB data

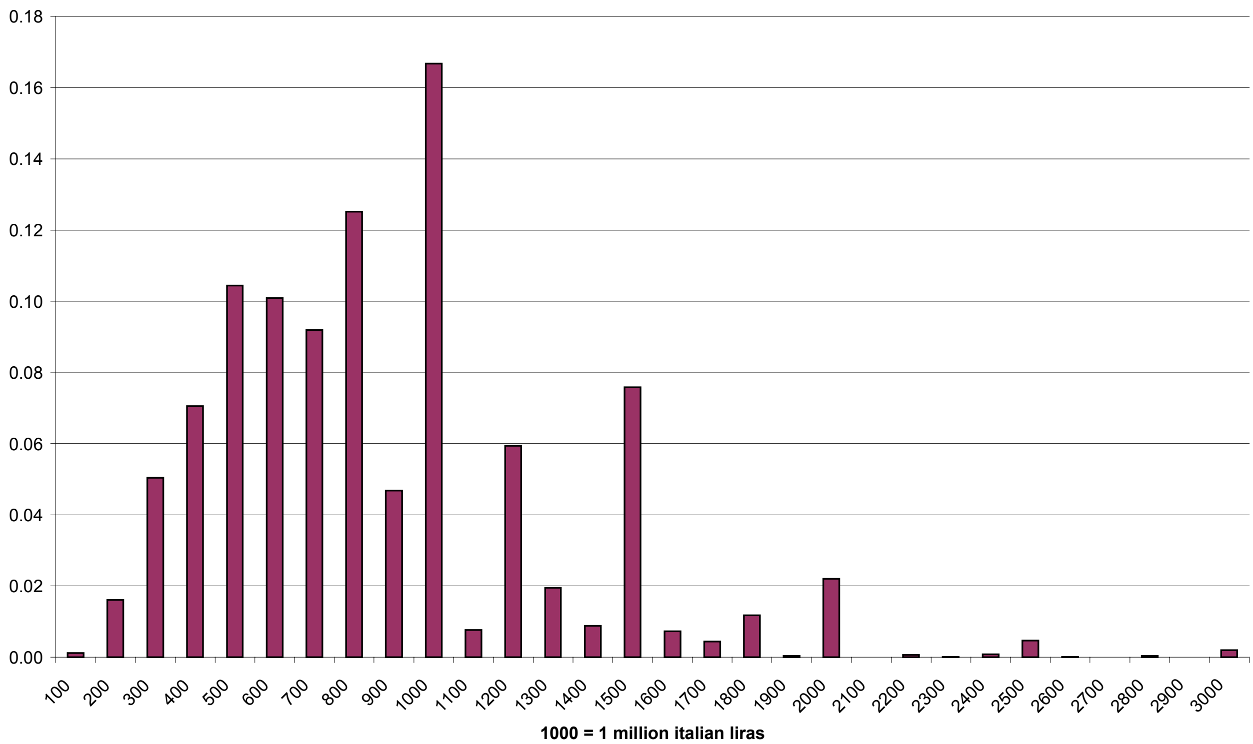

Figure 3: Observed food expenditure for SHIW data

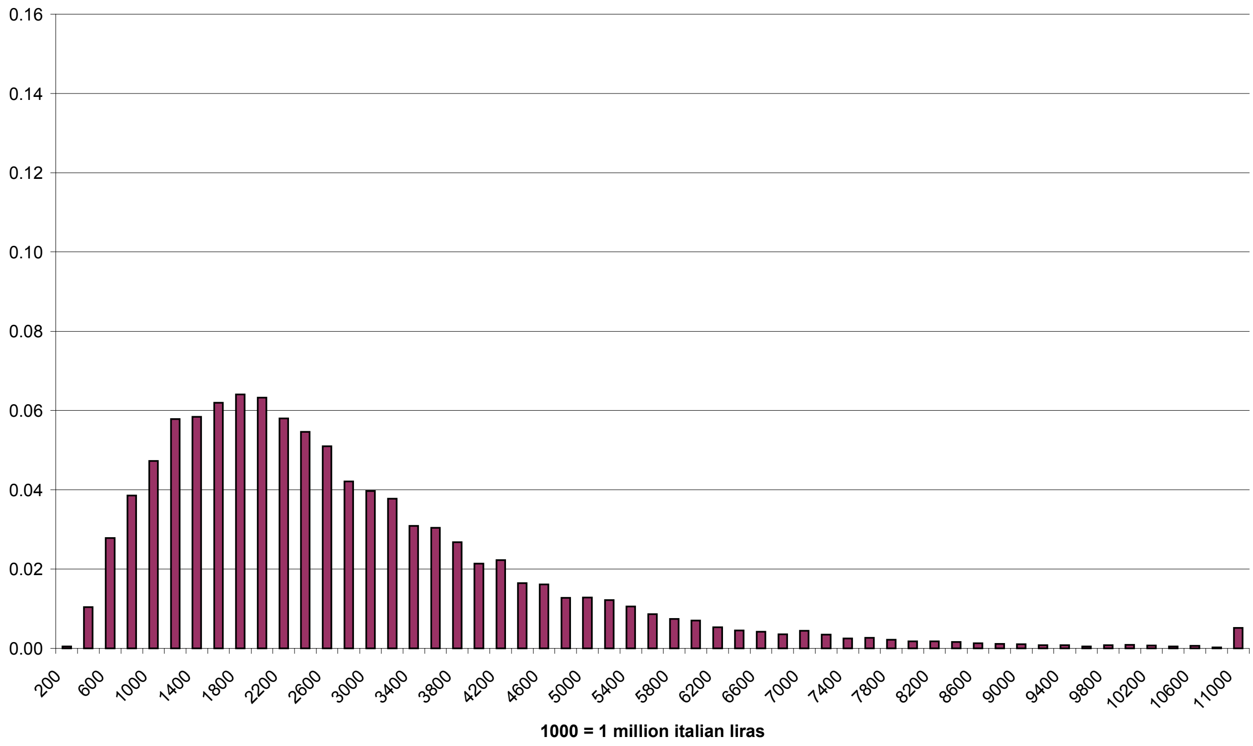

Figure 4: Observed (weighted) non-durable expenditure for SFB data

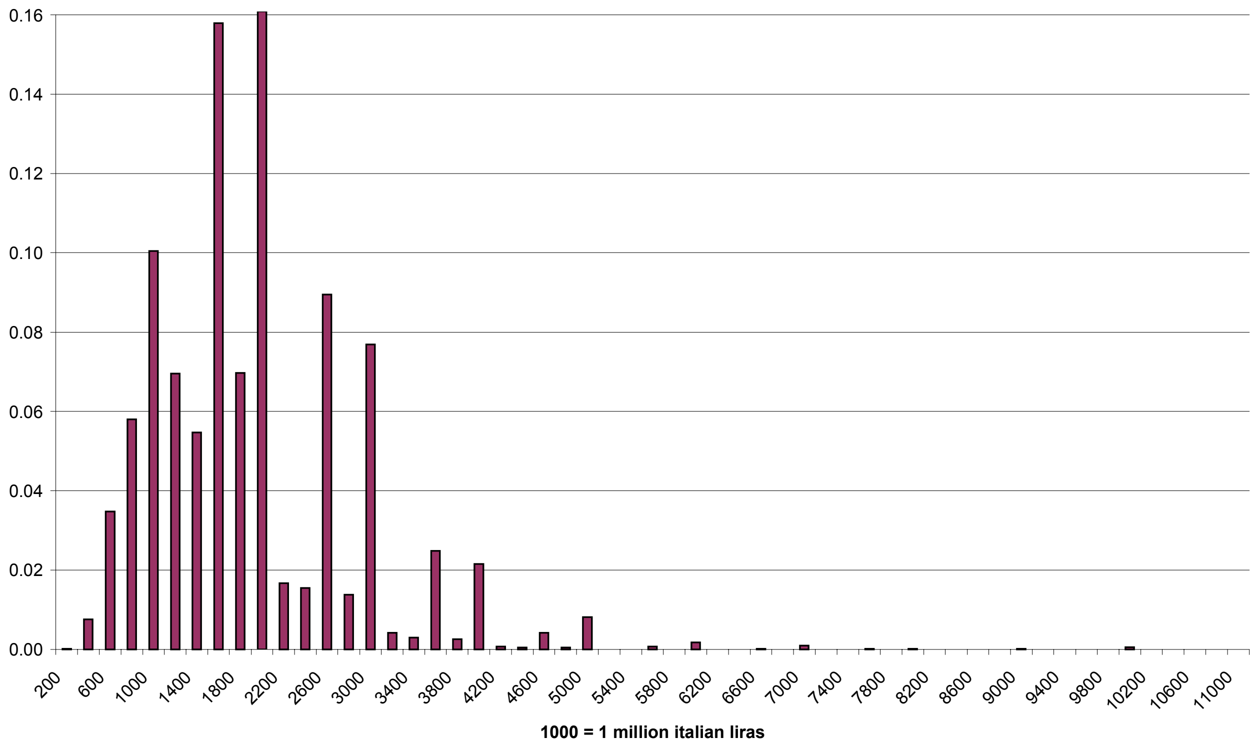

Figure 5: Observed non-durable expenditure for SHIW data

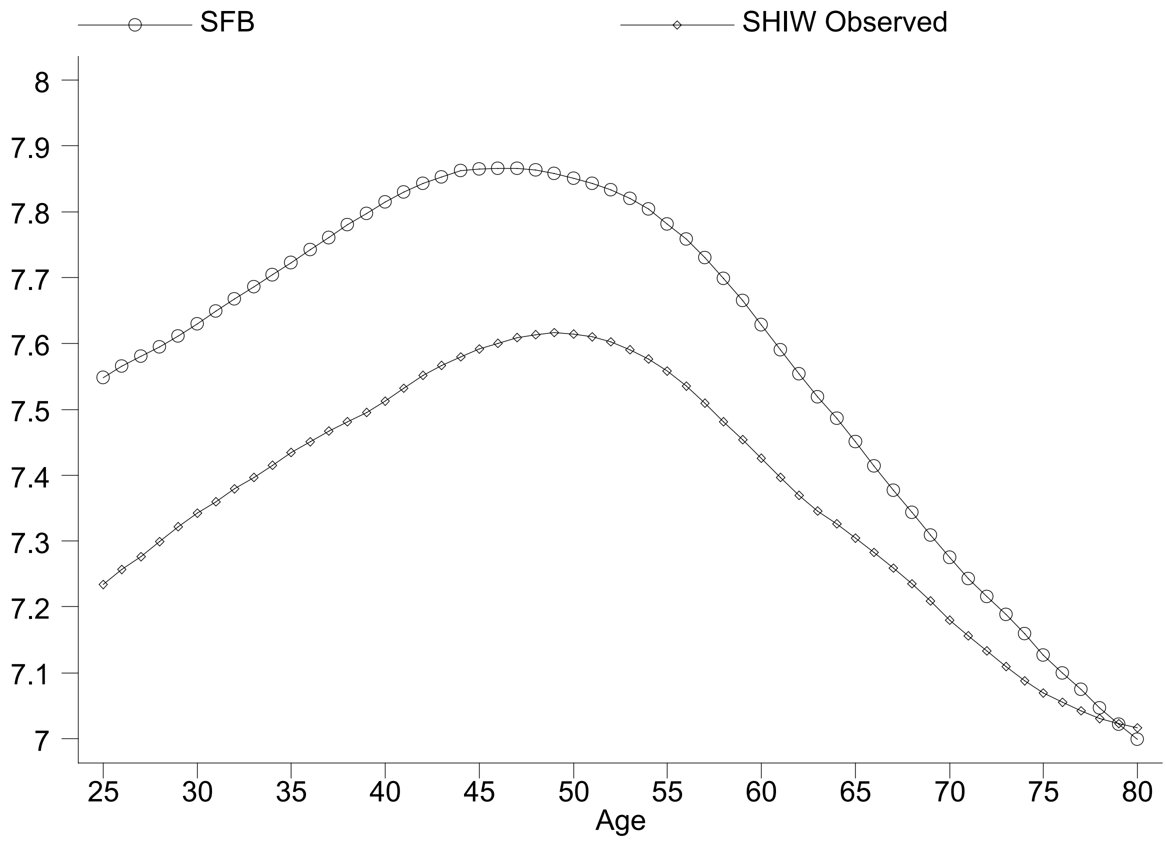

Figure 6: Age profile for non-durable consumption

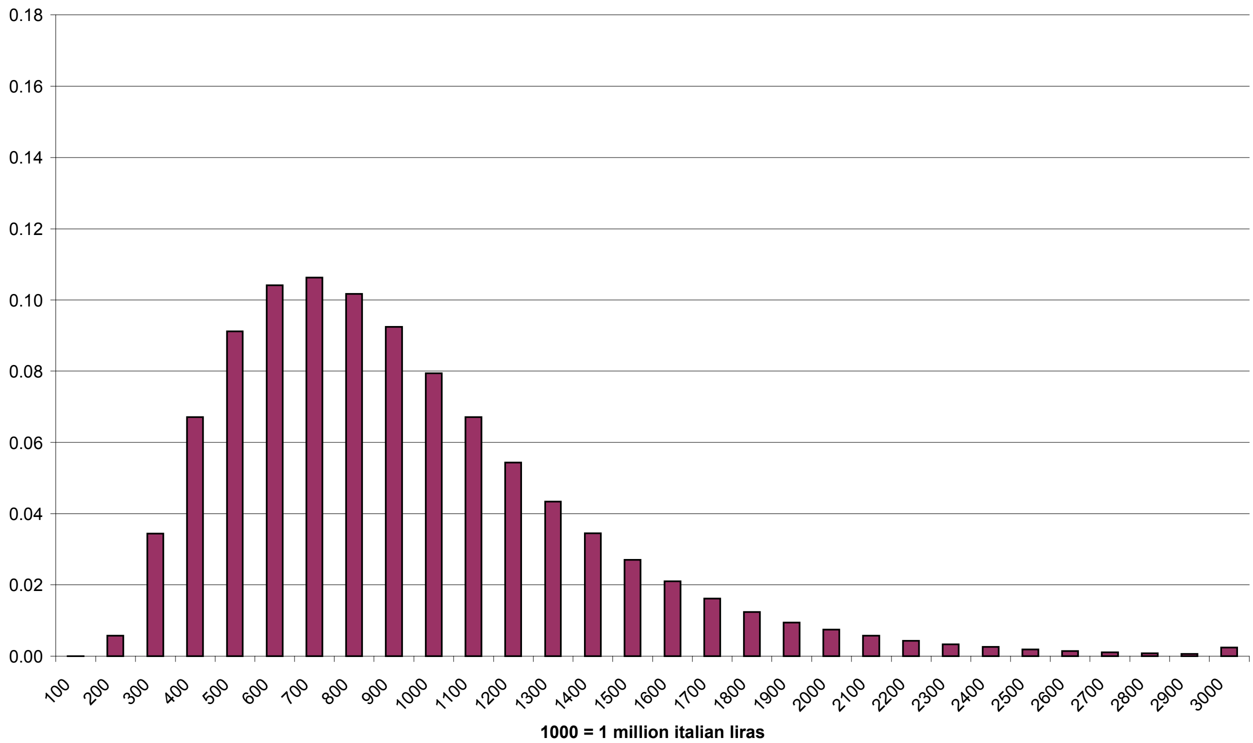

Figure 7: Imputed food expenditure for SHIW data

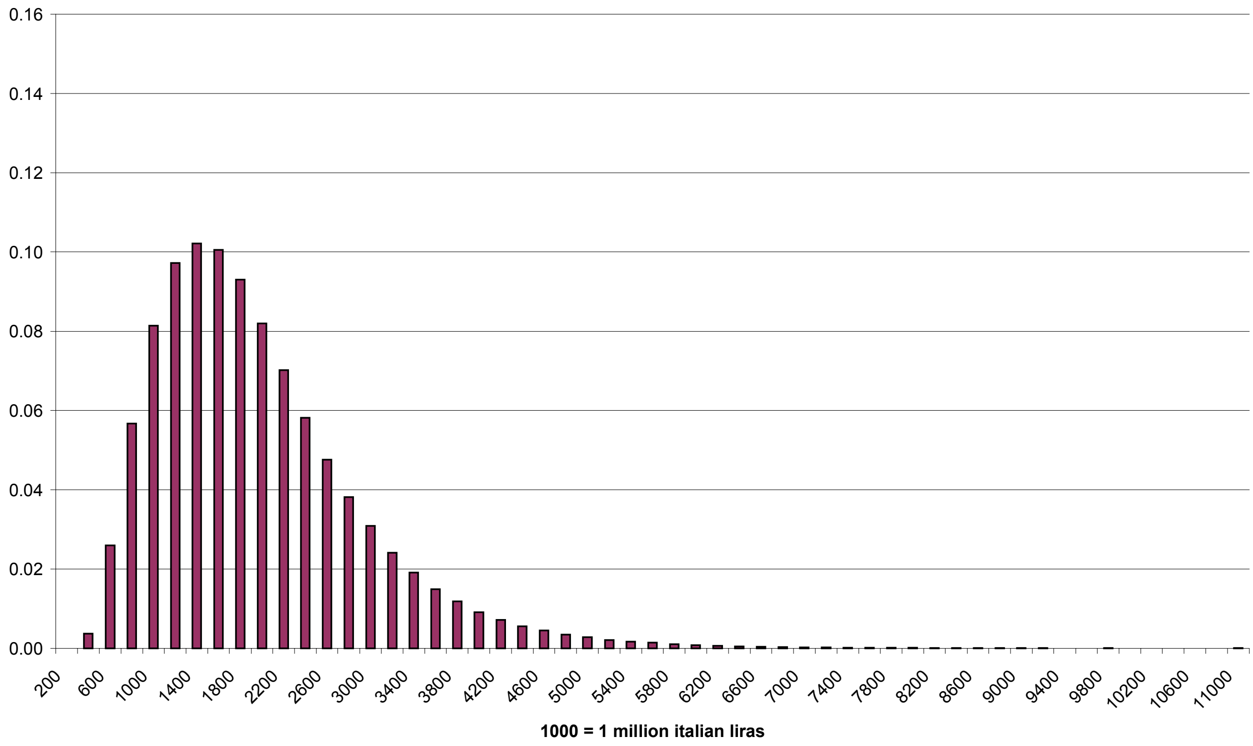

Figure 8: Imputed non-durable expenditure for SHIW data

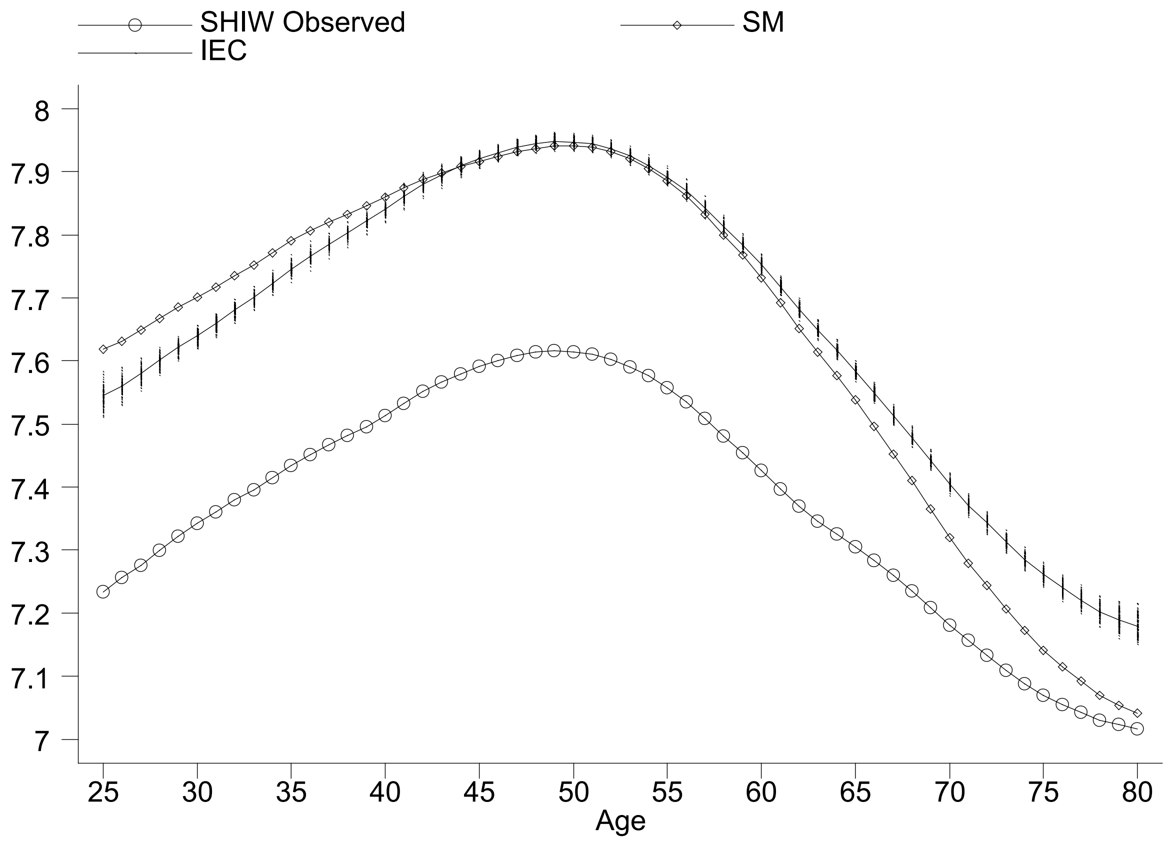

Figure 9: Predicted and actual lnC age profiles

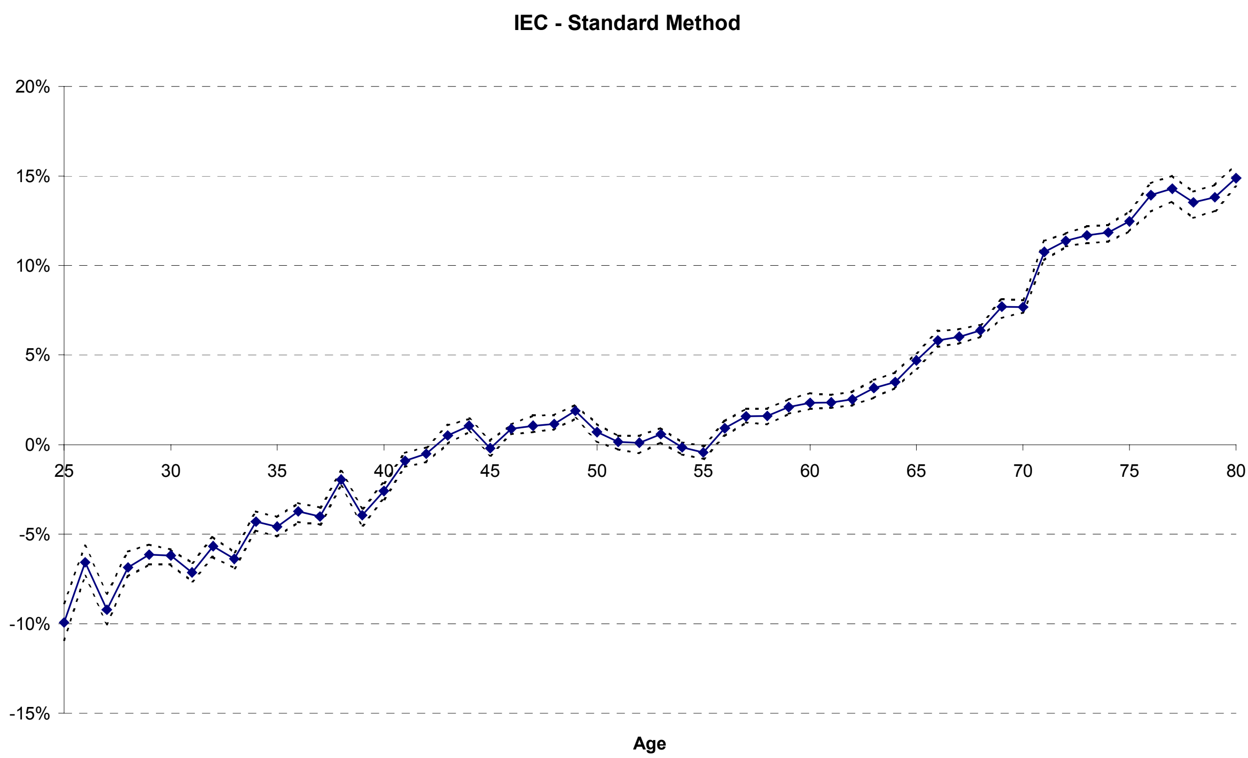

Figure 10: Difference in predicted lnC profiles and confidence interval

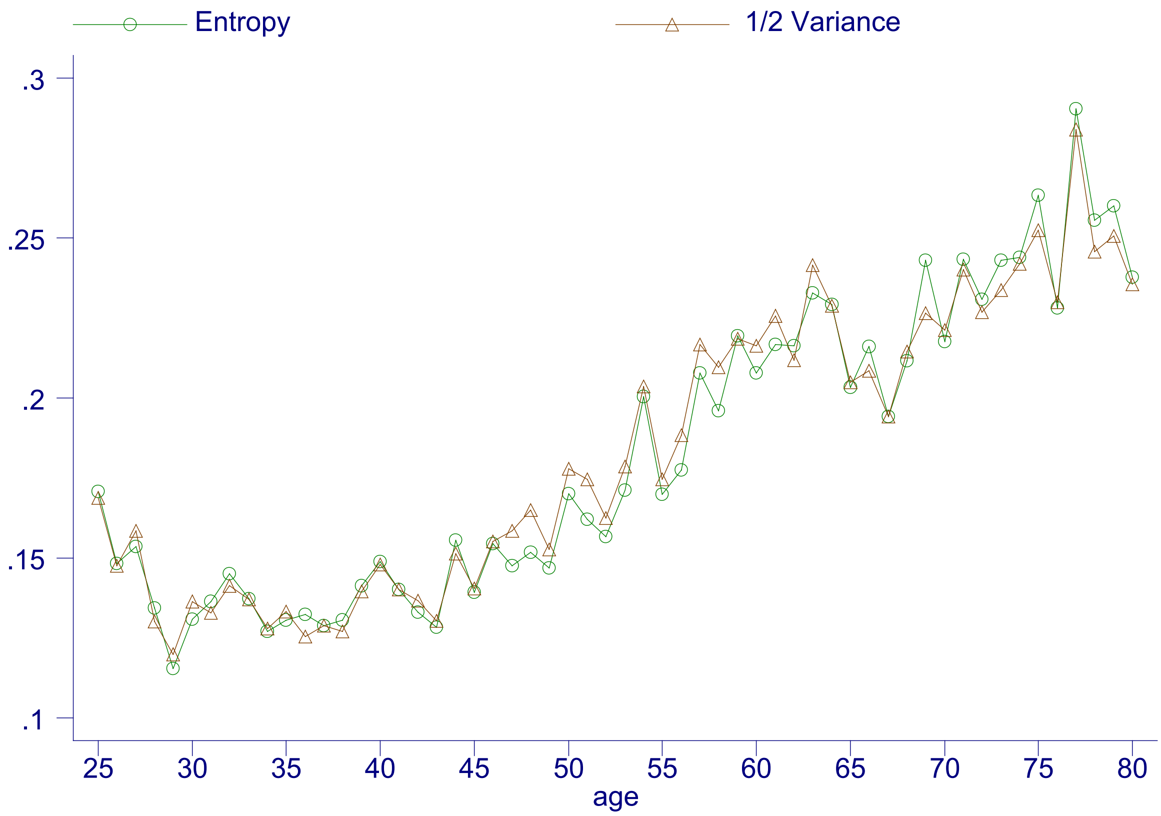

Figure 11: Relation between entropy and variance of lnC

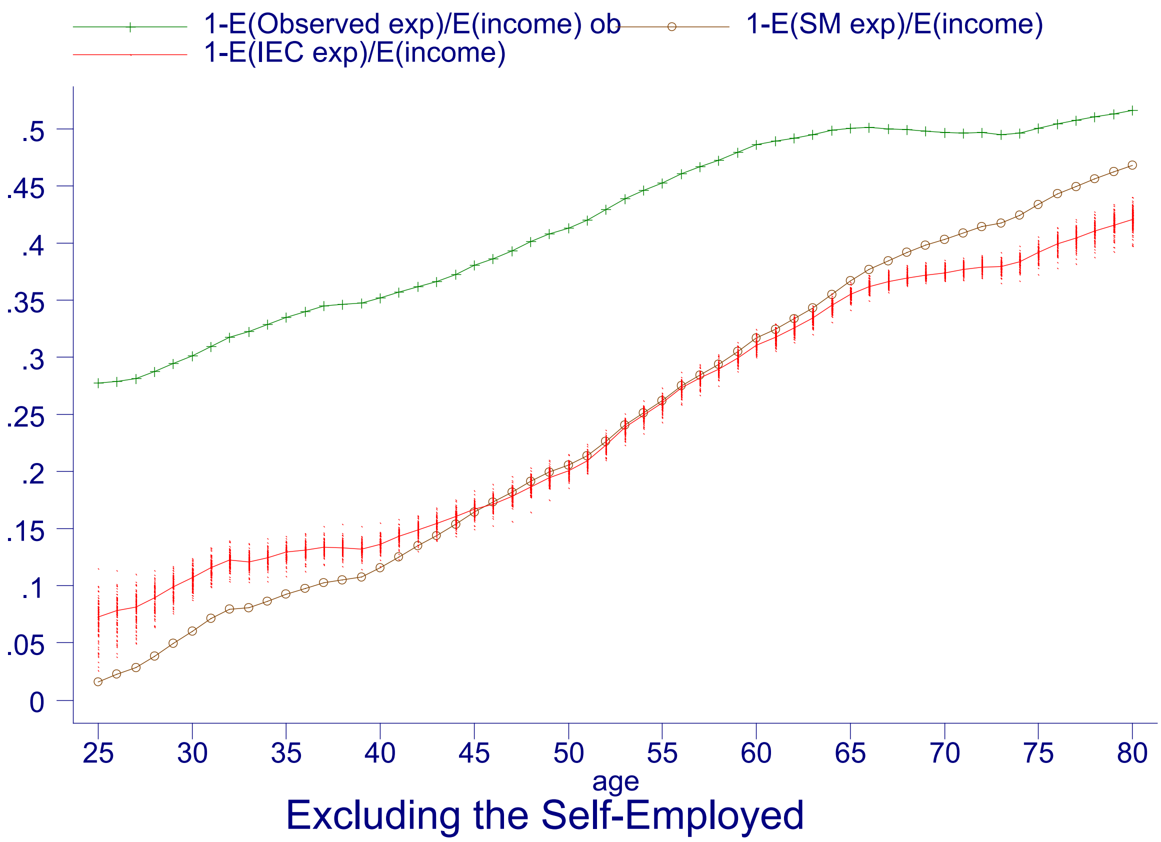

Figure 12: Saving Rate - consumption includes durables

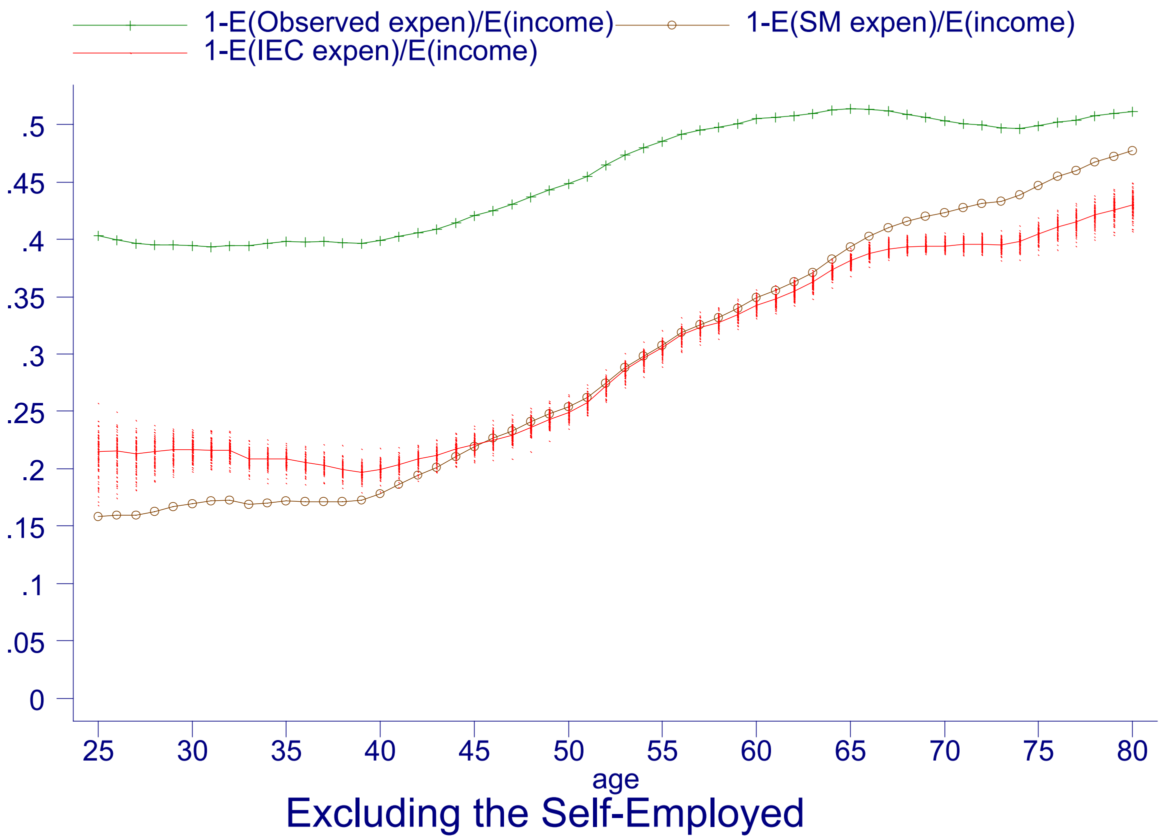

Figure 13: Saving Rate - no durables spending in consumption

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