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Item-non-response and Imputation of Labor Income in Panel Surveys: A Cross-National Comparison

by Joachim R. Frick (DIW Berlin, TU Berlin & IZA Bonn) and Markus M. GRABKA (DIW Berlin)

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Abstract:

Using data on annual individual labor income from three representative panel datasets (German SOEP, British BHPS, Australian HILDA) we investigate a) the selectivity of item-non-response (INR) and b) the impact of imputation as a prominent means to cope with this type of measurement error on prototypical analyses (income inequality, income mobility and wage regressions) in a cross-national setting. Given the considerable variation of INR across surveys as well as the varying degree of selectivity build into the missing process, there is substantive and methodological interest in an improved harmonization of (income) data production as well as of imputation strategies across surveys. All three panels make use of longitudinal information in the imputation procedure, however, there are marked differences in the implementation.

Our empirical investigation provides evidence for the probability of INR to vary across countries and to depend on survey-related aspects as well as on indicators for variability and complexity of labor income composition. Longitudinal analyses yield a positive correlation of INR on income data over time as well as provide evidence of INR being a predictor of subsequent unit-non-response, thus supporting the "cooperation continuum" hypothesis in all three panels. Applying various mobility indicators there is a robust picture about earnings mobility being significantly understated using information from completely observed cases only. Regression results for wage equations based on observed ("complete case analysis") vs. all cases and controlling for imputation status, indicate that individuals with imputed incomes, ceteris paribus, earn significantly above average in SOEP and HILDA, while this relationship is negative using BHPS data.

Concluding, we argue for improved cross-national harmonization of imputation techniques.

Theme Wage inequality and mobility

Keywords: Item-non-response, imputation, income inequality, income mobility, panel data, SOEP, BHPS, HILDA

JEL-code: J31, C81, D33

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1 Motivation

A common phenomenon in population surveys is the failure to collect complete information due to respondent's unwillingness or lacking capability to provide a requested piece of information. This non-response behavior is called item-non-response (INR). INR may be caused by a respondent's reservation to answer to a question that appears to be too sensitive, or that affects confidentiality and privacy or simply from the fact that the correct answer is not known (given the underlying complexity of the surveyed construct). In general, simple demographic information such as sex, age or marital status is not very sensitive to ask for, leading to low incidence of INR. Wealth or income questions, however, are typically associated with higher rates of INR (e.g. Riphahn and Serfling 2005). There is increasing literature which explicitly acknowledges this phenomenon in micro-economic research as a specific form of measurement error (e.g. Cameron & Trivedi 2005). Most importantly, INR on income questions has been found to be selective with respect to inequality as well as to mobility (e.g., Jarvis & Jenkins 1998, Biewen 2001; Frick & Grabka 2005).

In recent years there is a increasingly large body of empirical literature focusing on cross-national comparisons. Databases such as the European Community Household Panel (ECHP) provide the empirical basis for comparative research across countries or welfare-regimes with harmonized (or functionally equivalent defined) micro-data. A typical application in welfare economics comes with the need to empirically shadow the harmonization of social politics in the EU e.g. by using harmonized pre- or post-government income measures in order to shed light on the national redistribution policies. Obviously, in order to optimize comparability, the harmonization of micro-data (e.g. income measures) is a most relevant issue in this context, however, the same is true for other methodologically relevant decisions in pre- and post-data collection phase: for example, the definition of the relevant population, the means of data collection (e.g. interview or register data), and the management of attrition.

This paper deals with the handling of missing (annual gross) labor income information caused by INR in three major national panel data sets, the British Household Panel Study (BHPS), the German Socio-Economic Panel Study (SOEP), and the Survey of Household, Income and Labour Dynamics in Australia (HILDA). Assuming that the underlying missing process in general is not MCAR (missing completely at random, see Rubin, 1976), a popular way of dealing with INR is imputation. This strategy is applied in all three datasets considered here. However, while all three surveys take advantage of the longitudinal character of data, the actual implementation of the respective imputation strategies differs. This aspect might be of particular importance for cross-national comparability. Following the postulation of the "Canberra Group on Household Income Measurement" for harmonized national household income statistics (Canberra Group, 2001) it appears to be relevant, not only to harmonize the income measurement but also the procedure to handle, and eventually to impute, INR.

The paper is organized as follows: Chapter 2 briefly sketches basic characteristics of the three panel surveys including the incidence of INR (with respect to labor income). We demonstrate the selectivity for INR and investigate the longitudinal relationship of item- and subsequent unit non-response. Chapter 3 describes the imputation methods applied in the three surveys. Based on rather typical empirical research questions using labor income, Chapter 4 demonstrates the impact of imputation on earnings inequality and mobility, as well as on wage regressions. Finally, chapter 5 concludes from the perspective of cross-nationally comparative research.

2 Data and Incidence of INR

2.1 The three panels

The following section will briefly describe the underlying panel dataset, two of which are included in the Cross-National Equivalent File (CNEF; see Burkhauser et al. 2001), namely the German SOEP and the British BHPS. The annual labor income information as well as the accompanying information on imputation status (flag) which is used in this paper is included as a standard variable in the CNEF.

2.1.1 SOEP

The German SOEP is the longest running household panel study in Europe (cf. Haisken-DeNew and Frick 2005; http://www.diw.de/gsoep). All household members aged 17 and over are surveyed individually each year, and an additional household interview is conducted with the head of household. Interviews usually take place face-to-face with the interviewer filling in the questionnaire. Although Computer Assisted Personal Interviewing (CAPI) was introduced in 1998, paper and pencil interviews are still a most relevant interview mode. In order to keep the survey sample representative, various new sub-samples have been incorporated since the initial start in 1984. In 1990 and 1995 new samples were introduced to capture the effects of unification with East Germany and recent immigrants, respectively. A major “refreshment sample” (called sample F) was started in 2000. In this paper, we will show results based on the entire SOEP sample (survey years 1992 to 2004) as well as separately for the new sample F (survey years 2000 to 2004), in order to control for eventual panel effects in the old sample. Moreover, sample F may be more comparable to the rather young HILDA sample which was started in 2001, while the results based on the overall

SOEP-sample may be better comparable to the BHPS results which capture the period 1991-2002. The SOEP sample as of 2004 includes about 11,800 households, thereof 4,200 in Sample F.

Information about gross annual labor income is gathered from 10 different single questions. In principle, from each individual labor income for the previous calendar year is asked separately for dependent employment as well as self-employment. In each case, the average monthly amount is collected as well as the number of months with receipt of this income type. Additionally, one time or irregular payments like 13th or 14th monthly salary, holiday pay or bonuses are separately asked for and added together (see appendix B for the exact wording of the respective income questions in the SOEP).

2.1.2 BHPS

The British Household Panel Survey (BHPS) is carried out by the Institute for Social and Economic Research (ISER) at the University of Essex (see Taylor 2005; http://www.iser.essex.ac.uk/ulsc/bhps/doc/vola/contentsI.php). It was started in 1991 with about 5,500 households and roughly 10,300 individuals surveyed in England. The sample was extended in 1999 with about 1,500 households in each, Scotland and Wales. In 2001 a further sample of 2,000 households in Northern Ireland was added, supporting panel research for all of the UK. However, the following analyses are based on the original sample only, including data for waves 1991 through 2002. In 1999, the interview mode was entirely changed for the whole sample from Paper and Pencil to CAPI. Annual gross labor income in the BHPS is surveyed via only one single question where the amount of the last gross pay including any overtime, bonuses, commission, tips or tax refund is asked (see appendix B).

2.1.3 HILDA

The “Household, Income and Labour Dynamics in Australia” (HILDA) Survey started in 2001 with about 7,700 participating households (Watson 2005; http://www.melbourneinstitute.com/hilda/). HILDA, compiled by the Melbourne Institute of Applied Economic and Social Research, provides information on living conditions of private households in Australia. By and large, the panel design used in HILDA resembles the one of BHPS. The sampling unit is the private household, and only original members of those households are to be tracked in case of residential mobility.

Annual gross labor income in HILDA comes from three sources of information. Firstly, all respondents are asked for their total wages and salaries from *all* jobs over the last financial year (July 1st of the previous year to June 30st of the survey year). Secondly, income from own business or farming from incorporated businesses were added and finally the total share of profit or loss from unincorporated businesses or farms are summed-up (see appendix B). One time payments and irregular payments are not explicitly surveyed. Data from waves 2001 through 2003 is used in this paper.

2.2 Incidence of INR and the "cooperation continuum"

We find striking differences in the incidence of gross annual labor earnings in the three panels (Figure 1): While in HILDA less than 10% of the observations suffer from INR, the corresponding shares in SOEP and BHPS are about 14% and 15%, respectively. In case of the SOEP this high share might be related to the fact that up to ten different income items were collected which most likely raises the odds of at least one missing component, while this finding for the BHPS is rather unexpected, given that merely one question is asked for[1]. On the other hand, the HILDA and BHPS questioning offers a "Don't know" category, which may as well tempt respondents to refrain from giving a positive value instead (see Schräpler 2003b). Finally, one should note that any seemingly valid observed income information may be affected by measurement error as well, e.g. by rounding or rough estimation (see e.g. Hanisch 2005).

Conditional on the applied imputation (to be described below), the incidence of INR in annual labor earnings appears to follow a somewhat u-shaped pattern (see also Biewen 2001) over the income distribution with INR, in principle, being most prominent in the lowest income decile. An exception is the rather young sub-sample F in the SOEP. Here a undulated distribution can be observed with the highest decile showing the highest share of INR.

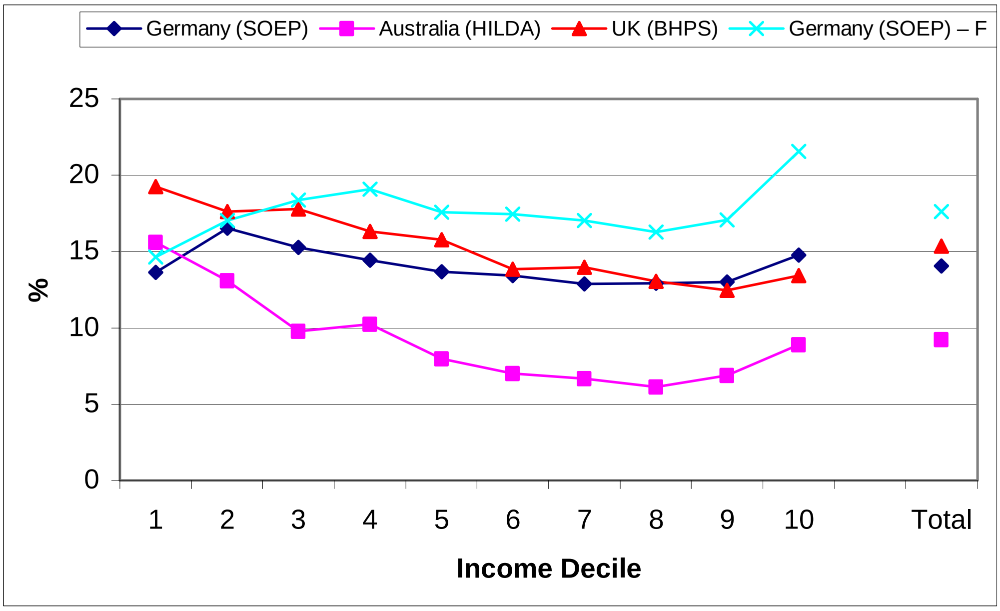
Given our substantive analytical interest in inequality and mobility analyses, there is an inherent need to control for eventual time-dependence of INR. Separating individual observations by imputation status at time t_0 (i.e., "valid" income vs. INR)[2], Figure 2 differentiates four potential outcomes at time t_1, namely "valid earnings information", "imputed due to INR", "zero labor income due to leaving the labor force" and "attrition". In all panel studies, we do not only find state-dependence of INR, but also clear support for the "cooperation continuum" hypothesis (see Loosveldt et al 2001, Schräpler 2004), according to which INR is a valid predictor of subsequent unit-non-response, namely attrition.[3]

1 However, there is information available on earnings received on September, 1st of the previous as well as of the current year in case of any variation across time. This is eventually considered in the generation of the annual income measure used here.

2 Leaving out observations out of the labor force, i.e., those with zero labor earnings.

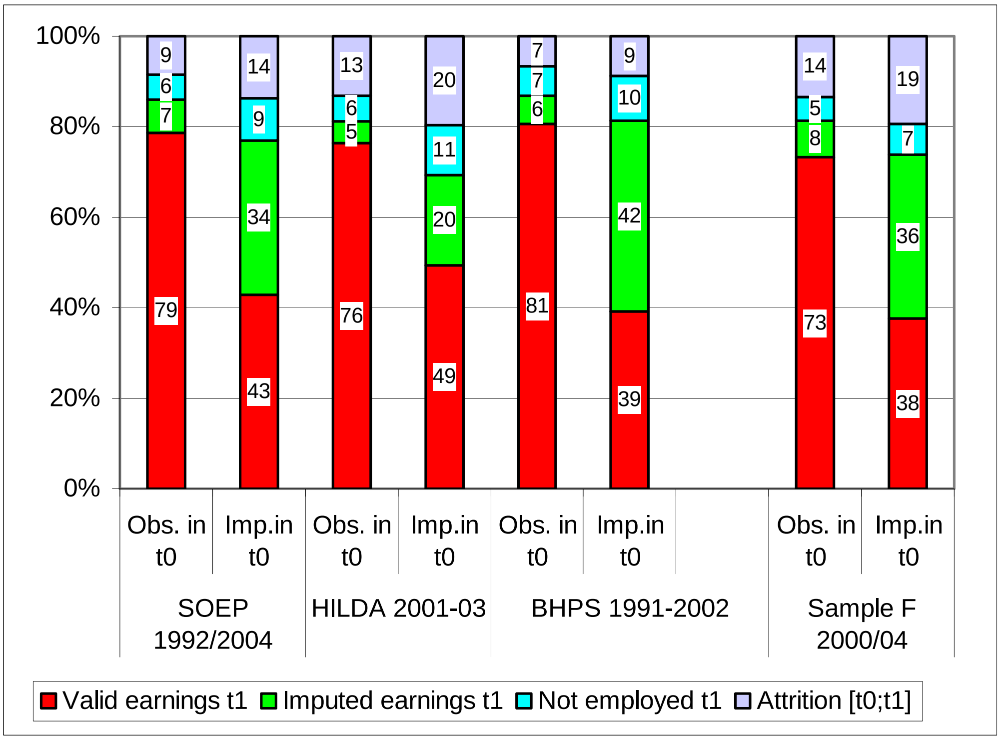
3 Figures A-1a-d in the appendix provide a more differentiated picture of theses processes across the income distribution. There is a stable finding of unit-non-response being higher at all income levels among those with INR in

Figure 1: Observations with INR on labor income by deciles (in %)



Note: Contingent on the imputation as described in Section 3.
Source: SOEP survey years 1992-2004; HILDA survey years 2001-2003; BHPS survey years 1991-2002.

Figure 2: Item-Non-Response in a longitudinal Perspective: The Case of individual labor earnings



Source: SOEP survey years 1992-2004; HILDA survey years 2001-2003; BHPS survey years 1991-2002.

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the previous wave as compared to those with valid income information. However, for those with INR in the previous wave, we find INR to increase with income in the current wave. Separating "refusals" from "don't know" as the underlying motivation for INR, Schräpler (2003b) finds attrition in the subsequent wave only to be significant among refusing respondents while there is no such strong relationship among those who answer "don't know".

2.3 Selectivity of INR

As mentioned above, INR may be a function of various factors such as the respondent's unwillingness to answer questions that are perceived as highly sensitive or in violation of confidentiality and privacy, the fact that the requested information is too complex or simply that the answer is not known (e.g., Schräpler 2003, 2004). Also the formulation of a given question may matter (Hill & Willis 2001). A strand of research found the interview situation and eventual interviewer effects, including change of interviewers in panels studies, to be relevant determinants of INR (e.g. Rendtel 1995, Pickery et al. 2001, Riphahn & Serfling 2005).

For the sake of cross-national comparability it is most relevant to control whether the missing mechanisms coincide for the datasets considered here. Separately for each of those panels and making use of the panel nature of the underlying data, we specify a random effects model estimating the probability of INR on our measure of annual labor earnings.[4] Based on currently employed individuals (including self-employed) aged 20 to 65 years, we control for socio-demographic characteristics, the interview situation, the survey experience of the respondent, as well as for the complexity of the income receipt. The latter is operationalized by various dummy-variables indicating changes in an individual's labor market career over the previous (calendar or financial) year by identifying experience of unemployment and exit from education (see Table 1). In brief, INR on previous year's labor income is clearly more common among self-employed, while it is less likely with increasing number of months in (full- or part-time) employment. As expected, one finds a higher probability of INR among those with unemployment experience during the last year in SOEP and HILDA, however, this effect is reverted in BHPS. Inconsistent findings are also found with respect to gender (SOEP and BHPS showing more INR among men, while women in the HILDA survey provide more valid answers to labor income questions). In case of HILDA and BHPS there is a negative education effect, i.e., higher educated individuals are less likely not to respond – there is no such effect in the SOEP. Controlling for long-term employment patterns, it appears that INR is reduced with tenure, however, at a reduced pace. Ceteris paribus, foreigners in the SOEP are more likely to provide valid income data, while this is the opposite in the BHPS. We find an expected result for public servants in BHPS and HILDA, being more likely to respond. In Germany, there is a most pronounced negative effect on INR among East Germans. The results for

[4] All empirical results presented in this paper are based on calculations using Stata (version 8.2), including the ado-modules INEQUAL7, INEQDECO, IMOBFOK, FOKMOB, SHORMOB authored by Stephen P. Jenkins and Philippe van Kerm, respectively.

the INR-reducing effect of survey experience, here measured by the number of interviews, are consistent across all panels.

Table 1: Estimating the probability for INR on labor income – Results from random effects models

	Germany (SOEP)		**Australia (HILDA)**		**UK (BHPS)**		**Germany (SOEP) – F**	
Age	-0.000	*(0.006)*	-0.002	*(0.013)*	0.004	*(0.007)*	-0.011	*(0.015)*
Age squared	0.000	*(0.000)*	0.000	*(0.000)*	0.000	*(0.000)*	0.000	*(0.000)*
Male	0.044*	*(0.021)*	-0.229**	*(0.039)*	0.087**	*(0.032)*	-0.012	*(0.047)*
edu1==2	0.058*	*(0.026)*	-0.101*	*(0.048)*	-0.067*	*(0.034)*	-0.052	*(0.069)*
edu1==3	0.052	*(0.033)*	-0.287**	*(0.057)*	-0.142**	*(0.034)*	-0.105	*(0.085)*
edu1==4	-0.003	*(0.032)*	-0.287**	*(0.078)*	-0.218*	*(0.088)*	-0.055	*(0.079)*
Disability status	0.031	*(0.039)*	0.037	*(0.049)*	-0.027	*(0.033)*	-0.020	*(0.088)*
Married	-0.005	*(0.021)*	-0.109*	*(0.045)*	-0.007	*(0.027)*	0.030	*(0.049)*
# HH members aged 0-14	-0.001	*(0.011)*	0.023	*(0.019)*	0.016	*(0.013)*	-0.002	*(0.026)*
Metrop. area	-0.036	*(0.028)*	0.007	*(0.040)*	-0.093**	*(0.030)*	-0.191**	*(0.068)*
Remote area	0.040*	*(0.019)*	-0.186+	*(0.112)*	-0.075+	*(0.040)*	0.091*	*(0.043)*
Tenure	-0.003	*(0.003)*	-0.026**	*(0.006)*	-0.067**	*(0.004)*	0.009	*(0.006)*
Tenure squared	0.000+	*(0.000)*	0.001**	*(0.000)*	0.002**	*(0.000)*	-0.000	*(0.000)*
Foreigner	-0.064*	*(0.032)*	0.006	*(0.048)*	0.211**	*(0.038)*	-0.281**	*(0.094)*
Public service	0.027	*(0.021)*	-0.245*	*(0.099)*	-0.079**	*(0.024)*	-0.007	*(0.046)*
Firm size: small	-0.013	*(0.019)*	0.319**	*(0.043)*	0.017	*(0.023)*	0.014	*(0.042)*
Firm size: large	-0.008	*(0.021)*	-0.086	*(0.074)*	0.003	*(0.039)*	0.019	*(0.048)*
East Germany	-0.216**	*(0.024)*	-	-	-	-	-0.228**	*(0.055)*
Months full-time (last year)	-0.022**	*(0.003)*	-0.051**	*(0.010)*	-0.016**	*(0.004)*	-0.015*	*(0.008)*
Months part-time (last year)	-0.020**	*(0.003)*	-	-	-	-	-0.025**	*(0.008)*
Months in unemployment (last year)	0.090**	*(0.031)*	0.247**	*(0.078)*	-0.077*	*(0.037)*	0.099	*(0.076)*
Left educ. system during last year	0.007	*(0.033)*	-0.062	*(0.058)*	-0.098	*(0.081)*	-0.151+	*(0.090)*
Self employed	0.468**	*(0.028)*	1.218**	*(0.051)*	1.038**	*(0.032)*	0.624**	*(0.062)*
Problems during Interview	0.212**	*(0.016)*	-0.249*	*(0.108)*	0.138+	*(0.079)*	0.133**	*(0.036)*
# Interviews = 2	-0.125+	*(0.065)*	-0.250**	*(0.068)*	0.041	*(0.086)*	-0.161	*(0.103)*
# Interviews = 3+	-0.353**	*(0.047)*	-0.408**	*(0.059)*	-0.221**	*(0.062)*	-0.301**	*(0.075)*
Constant	-1.297**	*(0.132)*	-0.349	*(0.342)*	-1.013**	*(0.150)*	-0.800**	*(0.310)*
Obs.	120818		21304		63353		22456	
N	24178		9354		10606		7063	
-2 Log-Likelihood	-36493.31		-5151.03		-21216.79		-8807.08	
Pseudo-R-squared	.1254		.1609		.2036		0.1261	

Note: Time effects controlled, but not reported. Standard errors in parentheses;
Significance level: + significant at 10%; * significant at 5%; ** significant at 1%.
Source: SOEP survey years 1992-2004; HILDA survey years 2001-2003; BHPS survey years 1991-2002.

Summing up the results of this section, we observe profound differences with respect to the incidence of INR across surveys. With respect to the selectivity of INR in the three panels, we do find some similarities, however, against the background of the above mentioned varying incidence of INR there emerge country-specific reasons for INR as well.

Even the two relatively young panels (HILDA and the SOEP sub-sample F) are not congeneric, which supports the importance of such cross-country analyses.

3 Imputation rules in the three surveys

Imputation is a most prominent way to handle INR in micro-data. An exhaustive description of such procedures other than the one used in SOEP, BHPS and HILDA is beyond the scope of this paper. However, it should be noted that even a very sophisticated approach of substituting for non-response may not completely eliminate any bias resulting from it. As such, the choice of the adequate imputation technique is a problem in itself. Potential bias due to imputation may creep in due to "regression-to-the-mean effects" and a potential change in total variance – most likely a decline – may occur.[5]

Annual individual labor income in the BHPS is imputed using a regression based predictive mean matching (PMM) procedure proposed by Little (1988) also known as regression hot deck. The basic idea of the PMM is the use of observed predictor variables from a linear regression to predict variables with missing values. The advantage of this method is, that a possible real value is imputed and that a random error component is added to preserve variance. The PMM method adopted in the BHPS also considers longitudinal information from a shifting three-year window. Depending on the availability of valid information about labor income in previous and subsequent waves as well as eventual job changes, either forward or backward imputation is applied resulting in 14 different regression models (ISER 2002). An indication for the imputation quality is given by the corresponding R-squares of the underlying regression estimations. In the first three waves of the BHPS, the share of explained variance of gross usual pay – which is the main income component for annual individual labor income – varies between 0.78 and 0.94 (ISER 2002: A5-27).

HILDA and SOEP are both using a two-step procedure to impute any income information missing due to INR. The primary method is based on the "row-and-column-imputation", described by Little & Su (1989) (hereafter L&S). The row-and-column-imputation takes advantage of cross-sectional as well as individual longitudinal information – using income data available from the entire panel duration – by combining row (unit) and column (period/trend) information and adds a stochastic component resulting from a nearest neighbor matching, i.e.,

*imputation = (row effect) * (column effect) * (residual).*

[5] See Rubin (1987) for a discussion of imputation methods and the advantages of *multiple* imputation which allow to assess the degree of variation added to parameter estimates as a result of imputation. However, most producers of micro-data (including those of the three panel datasets used in this paper) do not (yet) provide *multiply* imputed information. One exception is the US Survey of Consumer Finances (Kennickell & McManus 1994).

Using an exemplary panel with 20 waves of data, the column effects are given by

(1) $$c_j = (20 * \bar{Y}_j) / \sum_{k=1}^{20} \bar{Y}_k$$

and are calculated for each of the 20 waves of data, where j = 1, ..., 20 and $\bar{Y}_j$ is the sample mean income for year j. The row effects are given by:

(2) $$r_i = m_i^{-1} * \sum_{j=1}^{20} (Y_{ij} / c_j)$$

and are computed for each sample member. Y_{ij} is the income for individual i in year j and m_i is the number of recorded periods. Sorting cases by r_i and matching the incomplete case i with information from the nearest complete case, say l, yields the imputed value

(3) $$i = [r_i] * [c_j] * [Y_{lj} / (r_l * c_j)]$$

The three terms in brackets represent the *row*, *column*, and *residual* effects. The first two terms estimate the predicted mean, and the last term is the stochastic component of the imputation stemming from the matching process. While the SOEP applies this L&S-procedure to the entire population (Grabka & Frick 2003) as described above, HILDA uses a modification of this technique by matching donors and recipients within imputation classes defined by seven age groups (Starick 2005).

A secondary method is needed whenever longitudinal information is lacking. This includes not only first time respondents, but all those observations for whom a given income variable has been surveyed for the very first time. Hence, a purely cross-sectional imputation method needs to be applied. In the case of HILDA a nearest neighbor regression method (similar to that used by the BHPS) is deployed. In the SOEP, this is accomplished by means of a hot-deck regression model supplemented by a residual term retrieved from a randomly chosen donor with valid income information in the regression model.[6]

In an evaluation of various imputation methods, Starick (2005) argues that “in a longitudinal sense, the Little and Su methods perform much better when compared to the nearest neighbour regression method. Evidence shows that the Little and Su methods preserve the distribution of income between waves. Furthermore, the Little and Su methods perform better in maintaining cross-wave relationships and income mobility” (Starick 2005: 31). This finding is also confirmed by Frick and

[6] An indication for the quality of the secondary imputation in SOEP is given by the R-squares of gross annual labor income which varies between 0.48 and 0.66.

Grabka (2005) for the SOEP by showing that the L&S-imputation performs better in terms of preserving the distribution than a regression based imputation strategy.[7]

4 Empirical application on the impact of imputation

Keeping in mind the above mentioned variation in incidence and selectivity of INR across panels as well as the differences and commonalities in the respective imputation process, the following analyses focus on the impact of imputation on prototypical applications. We will first concentrate on distributional aspects (measured by various income inequality indicators) and on earnings mobility derived from wave-to-wave comparisons (again applying various mobility indicators in order to control for robustness of our results (section 4.1)). In section 4.2, we investigate whether imputed observations "behave" differently in a wage regression model, i.e., whether correct inferences can be drawn from a dataset excluding observations with INR.

4.1 Imputation and the analyses of earnings inequality and mobility

Accepting the applied imputation strategies, i.e., assuming that these correctly identify the underlying missing mechanism, obviously any increase in selectivity of non-response will be reflected in the deviation of empirical results based on truly observed cases ("complete case analyses") from those derived on the basis of all observations (i.e., observed plus imputed cases).

A comparison of basic statistics of annual gross labor income (top panel of Table 2) shows income levels (given by mean and median) to be clearly lower among the population with imputed values in the case of BHPS and HILDA, while in the SOEP a reverted tendency can be observed.[8] The result for the overall population ("all cases") thus deviates from the one for the observed cases, e.g. the overall median in HILDA is about 2,2% lower than the value resulting from "observed cases" only. Extending the focus on cross-sectional measures of inequality, there is a robust picture of understating inequality when using "complete case" analysis, which is especially true in the case of HILDA and BHPS. E.g. the 90:10 decile ratio for the observed cases in HILDA understates

[7] In a simulation study, Frick and Grabka (2005) use a random sample of approx. 1,000 observations for which a positive value of "labor income from first job" has been observed and who provide longitudinal information as a prerequisite for the L&S procedure. While the L&S procedure overstates inequality by about 9%, the cross-sectional approach understates the Gini by about 18%. This finding is in line with those of Spiess and Goebel (2003) based on survey and register data for Finland.

[8] The analysis of income inequality is based on pooled, deflated income data for all available years as described in section 2. In case of Australia inequality is rather stable over the 3-year period, whereas in Germany we observe an increase in earnings inequality over the recent years, and in Britain a slight reduction (see appendix Table A-1).

inequality by about 7%. Our findings point to a more pronounced relevance of imputation at the upper tail of the income distribution as indicated by the results for the top-sensitive SCV (Squared coefficient of variation). On the other hand, in BHPS and HILDA imputation appears to have a stronger effect at both ends of the distribution as indicated by both, the SCV and the MLD (mean logarithmic deviation).

Following from the varying degree of INR-incidence across panels, the (weighted) population share containing imputed data is as high as 10% in HILDA, 13% in SOEP, 18% in BHPS and even 20% in SOEP's newest sub-sample F.

Table 2: Income inequality and income mobility by imputation status

	Germany (SOEP)				**Australia (HILDA)**			
	Imputation status			*Deviation: "All" vs. "Observed" (%)*	Imputation status			Deviation: "All" vs. "Observed" (%)
	"All cases"	"Observed cases"	"Imputed cases"		"All cases"	"Observed cases"	"Imputed cases"	
Basic statistics*								
Mean	24408	24401	24455	*+0,03*	27407	27691	24615	*-1,03*
Median	21940	22077	21010	*-0,62*	23256	23772	17998	*-2,17*
Income inequality								
Theil 0 (Mean log deviation)	0,40964	0,40563	0,43416	*+0,99*	0,46602	0,44362	0,68033	*+5,05*
Gini	0,41405	0,41006	0,43769	*+0,97*	0,43264	0,42270	0,52649	*+2,35*
Half-SCV (top-sensitive)	0,34880	0,33692	0,42106	*+3,53*	0,49578	0,46483	0,86711	*+6,66*
Decile ratio 90:10	13,71	13,66	14,17	*+0,37*	14,77	13,78	32,38	*+7,18*
Decile ratio 90:50	2,13	2,11	2,27	*+0,95*	2,22	2,17	2,82	*+2,30*
Decile ratio 50:10	6,45	6,49	6,25	*-0,62*	6,67	6,36	11,49	*+4,87*
Average N per cross-section	***10773***	***9501***	***1272***	*+13,39*	***8703***	***7887***	***816***	*+10,35*
Income mobility								
Quintile matrix mobility: Average jump	0,448	0,376	0,713	*+19,1*	0,503	0,468	0,763	*+7,5*
Quintile matrix mobility: Normalized average jump	0,179	0,150	0,285	*+19,3*	0,201	0,187	0,305	*+7,5*
Fields & Ok: Percentage income mobility	24,38	18,89	42,94	*+29,1*	27,86	24,99	48,26	*+11,5*
Fields & Ok: Non-directional	0,333	0,301	0,460	*+10,6*	0,426	0,385	0,683	*+10,6*
Shorrocks: Using Gini Coefficient	0,0290	0,0242	0,0465	*+19,8*	0,0400	0,0354	0,0619	*+13,0*
Average N per 2-wave balanced panel	***9878***	***7554***	***2324***	***+30,8***	***7152***	***6143***	***1009***	***+16,4***

* Germany in 2000 Euro; UK in 1996 GBP; Australia in 1989/90 AUD.

…

contd. Table 2

	UK (BHPS)				Germany (SOEP) – Sample F			
	Imputation status			Deviation: "All" vs. "Observed" (%)	Imputation status			*Deviation: "All" vs. "Observed" (%)*
	"All cases"	"Observed cases"	"Imputed cases"		"All cases"	"Observed cases"	"Imputed cases"	
Basic statistics*								
Mean	13207	13399	12149	*-1,43*	24695	24309	26504	*+1,59*
Median	11051	11297	9622	*-2,18*	21781	21774	22245	*+0,03*
Income inequality								
Theil 0 (Mean log deviation)	0,44428	0,41594	0,59663	*+6,81*	0,44672	0,44613	0,44630	*+0,13*
Gini	0,42967	0,42304	0,46457	*+1,57*	0,43357	0,43012	0,44727	*+0,80*
Half-SCV (top-sensitive)	0,45944	0,43255	0,63114	*+6,22*	0,38577	0,36422	0,46560	*+5,92*
Decile ratio 90:10	13,09	12,62	16,18	*+3,72*	15,43	15,40	14,89	*+0,19*
Decile ratio 90:50	2,34	2,30	2,54	*+1,74*	2,20	2,17	2,33	*+1,38*
Decile ratio 50:10	5,61	5,49	6,38	*+2,19*	7,00	7,10	6,39	*-1,41*
Average N per cross-section	***5098***	***4314***	***784***	*+18,17*	***6790***	***5641***	***1149***	*+20,37*
Income mobility								
Quintile matrix mobility: Average jump	0,442	0,350	0,792	*+26,3*	0,455	0,371	0,677	*+22,64*
Quintile matrix mobility: Normalized average jump	0,177	0,140	0,317	*+26,4*	0,182	0,149	0,271	*+22,15*
Fields & Ok: Percentage income mobility	25,17	18,16	49,30	*+38,6*	26,78	20,49	42,81	*+30,70*
Fields & Ok: Non-directional	0,356	0,288	0,613	*+23,6*	0,348	0,316	0,447	*+10,13*
Shorrocks: Using Gini Coefficient	0,0288	0,0214	0,0551	*+34,6*	0,0302	0,0239	0,0472	*+26,36*
Average N per 2-wave balanced panel	***4824***	***3530***	***1294***	***+36,7***	***4928***	***3453***	***1475***	*+42,72*

* Germany in 2000 Euro; UK in 1996 GBP; Australia in 1989/90 AUD.
Source: SOEP survey years 1992-2004; HILDA survey years 2001-2003; BHPS survey years 1991-2002.

With respect to labor income mobility, as is true for any longitudinal analyses, one can expect the impact of imputation to be even more relevant because INR may be an issue in at least one of the waves under consideration. For matter of simplification in this application, we just use a series of two-wave balanced panels (pooled across all available waves in each survey), i.e., the effects shown below would be even more pronounced in any multi-wave analyses (see lower panel of Table 2).

Above and beyond the general finding of inequality being understated among the "observed cases", clearly more distinct and statistically significant differences can be found for labor income mobility. Depending on the mobility measure applied as well as depending on the population share affected by imputation, the results between "observed" and "all" cases deviate in case of the BHPS by as much as 26% to 39%. In the SOEP the corresponding shares are 10% to 31% and in HILDA “only” 8% to 13%.

Focusing only on “complete cases” would yield an even higher loss in efficiency due to the massive reduction in the number of observations. The last row in Table 2 indicates that the (weighted) population share containing imputed data in at least one of the two waves considered is as high as 16% in HILDA, 31% in SOEP, 37% in BHPS and even 43% in SOEP’s young sub-sample F.

4.2 Imputation and wage regressions

Obviously, there is convincing evidence for selectivity in INR on labor income questions in all three considered panel datasets. Concluding from this, it stands to reason that coefficients derived from (simple) wage regressions will be biased as well. Potential ways of dealing with such phenomena could be given by estimating a Heckman selection model where the selection function would focus on the INR and the wage regression would be based only on the “observed” values. Even if this would allow for a perfect correction, there remains the problem of a loss in efficiency (caused by the loss in observations).

Following we will try to shed some light on this issue by comparing the results of fixed effects wage regressions based on the “observed” cases (column 1 in Table 3) to those based on the entire population including the imputed ones (columns 2). Finally, in column 3 we add a dummy-variable identifying the imputed observations. Table 3 gives those results separately for the three panels controlling for usual covariates relating to human capital, socio-demographics, regional agglomeration, health status and labor market participation over the last year. We refrain from including covariates focusing on the current employment situation in order to be able to include individuals currently not employed (e.g., those who recently retired or who are unemployed).

In general, the findings based on “observed cases” are widely consistent for SOEP and BHPS with respect to direction and significance of most parameter estimates as well as with respect to the overall degree of explained variance (about 50%). While not significant in the case of the German data, becoming disabled in Britain is positively related to earnings and becoming retired has a negative effect as expected. Contrary results are given in case of the unemployment experience in the previous year, which is found to be significantly positive in the BHPS and significantly negative in SOEP.[9]

[9] Results for the young SOEP-subsample F are, by and large, in line with those of the entire SOEP sample.

For HILDA, however, the specified model performs rather poor with an exceptionally low R-squared (approx. 20%) for such kind of an analysis.[10] Nevertheless, the estimated coefficients show into the expected direction, although often lacking statistical significance.

More important for the sake our paper, however, is the effect of the additional consideration of imputed observations (see columns 2): In all three panels, this yields a pronounced reduction in the degree of explained variance: This decline is most prominent for HILDA with a reduction in R-Squared by about 28% to only 0.1439. Obviously, this effect is driven by the consideration of a group of less homogenous individuals following the above mentioned selectivity of INR. This may be exemplified by the fact, that "all" observations (see column 2) include 10%, 22% and 29% more self-employed in SOEP, HILDA, and BHPS, respectively. Other striking differences are given in case of the BHPS by under-representing individuals who retired (-4%), in SOEP and HILDA by those who experienced at least one month of unemployment in the previous year (-5% and –8%, respectively). Observations from the first waves of BHPS and HILDA are also underreported among the observed cases, while this is not the case in the more mature panel population in SOEP.[11]

In addition, it is worthwhile considering whether the size of a given estimated coefficient varies once we include observations with imputed earnings. Bearing in mind a 95% confidence interval around the estimators, we find the effect of self-employment to significantly deviate in the two estimations (columns 1 and 2, respectively) in HILDA and BHPS, while the strong effect of number of months in employment is even different in all three panels.

Finally, column 3 contains the repetition of the estimation in column 2, however, controlling for imputation status. The corresponding effect indicates that individuals with imputed incomes, ceteris paribus, earn significantly above average in SOEP and HILDA (about 6% more), while they earn 3% less in BHPS-data. Noteworthy appears the consistent increase in the respective R-Squared, indicating that the imputation dummy proxies information not contained in any of the other controls which remain unchanged.[12]

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[10] However, this finding is confirmed by Watson 2005.

[11] These figures are not reported in a table, however, these are available from the authors on request.

[12] Separately for each panel, we estimated quantile regressions (at the 25th, 50th and the 75th percentile) controlling for potential regression-to-the-mean effects emerging from the imputation process across the earnings distribution (see appendix Table A-2). In line for all estimations, the results for the imputation dummy in the lowest quartile is smallest, of intermediate size at the median, and finally, strongest at the 75th percentile. Using an appropriate F-test confirms this effect to be statistically different between the 25th and the 75th percentile. We interpret these findings as indication that the applied imputation techniques did not produce a relevant regression-to-the-mean effect.

Table 3: Results from fixed-effects Wage Regression; Dependent variable: log annual labor income

	Germany (SOEP)			Australia (HILDA)			UK (BHPS)			Germany (SOEP) – Sample F		
	(1) Population: observed cases	(2) Population: all cases	(3) Population: all cases	(1) Population: observed cases	(2) Population: all cases	(3) Population: all cases	(1) Population: observed cases	(2) Population: all cases	(3) Population: all cases	(1) Population: observed cases	(2) Population: all cases	(3) Population: all cases
Age	0.050**	0.050**	0.049**	0.126**	0.194**	0.196**	0.063**	0.068**	0.068**	0.097**	0.084**	0.084**
	(0.002)	(0.002)	(0.002)	(0.018)	(0.018)	(0.018)	(0.009)	(0.009)	(0.009)	(0.010)	(0.009)	(0.009)
Age squared	-0.000**	-0.000**	-0.000**	-0.002**	-0.002**	-0.002**	-0.001**	-0.001**	-0.001**	-0.001**	-0.001**	-0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female with kid(s)*	-0.162**	-0.159**	-0.159**	-0.208**	-0.180**	-0.179**	-0.313**	-0.324**	-0.324**	-0.054*	-0.057**	-0.056**
	(0.007)	(0.007)	(0.007)	(0.033)	(0.034)	(0.034)	(0.009)	(0.010)	(0.010)	(0.022)	(0.021)	(0.021)
Male with kid(s) *	0.030**	0.028**	0.028**	-0.036	-0.031	-0.030	0.018*	0.015	0.015	0.008	0.002	0.002
	(0.006)	(0.006)	(0.006)	(0.030)	(0.030)	(0.030)	(0.009)	(0.010)	(0.010)	(0.022)	(0.020)	(0.020)
Married*	-0.006	-0.013*	-0.013*	0.019	0.000	0.002	-0.019*	-0.020*	-0.020*	-0.011	-0.016	-0.017
	(0.006)	(0.006)	(0.006)	(0.023)	(0.024)	(0.024)	(0.009)	(0.009)	(0.009)	(0.034)	(0.031)	(0.031)
Disability Status *	-0.018	-0.012	-0.013	0.009	0.014	0.014	0.024**	0.030**	0.030**	0.004	-0.017	-0.017
	(0.011)	(0.011)	(0.011)	(0.016)	(0.016)	(0.016)	(0.008)	(0.008)	(0.008)	(0.024)	(0.022)	(0.022)
Metrop. area *	0.031**	0.036**	0.036**	0.069	0.051	0.051	0.096**	0.109**	0.108**	-0.030	-0.003	-0.001
	(0.011)	(0.011)	(0.011)	(0.044)	(0.045)	(0.045)	(0.019)	(0.020)	(0.020)	(0.044)	(0.044)	(0.044)
Remote area*	-0.001	0.000	0.000	0.128	0.106	0.106	0.028	0.036	0.036	0.018	0.029	0.028
	(0.007)	(0.007)	(0.007)	(0.091)	(0.093)	(0.093)	(0.023)	(0.025)	(0.025)	(0.028)	(0.026)	(0.026)
Intermed. education*	-0.020*	-0.016*	-0.016*	0.132+	0.023	0.023	-0.078**	-0.079**	-0.079**	0.039	0.009	0.007
	(0.008)	(0.008)	(0.008)	(0.070)	(0.068)	(0.067)	(0.017)	(0.018)	(0.018)	(0.047)	(0.045)	(0.045)
Upper education*	0.013	0.010	0.008	0.435**	0.317**	0.318**	-0.016	-0.006	-0.006	0.076	0.068	0.065
	(0.011)	(0.011)	(0.011)	(0.086)	(0.086)	(0.086)	(0.017)	(0.017)	(0.017)	(0.062)	(0.059)	(0.059)
Highest educ. level*	0.307**	0.289**	0.287**	0.448**	0.312**	0.311**	0.168**	0.167**	0.168**	0.405**	0.357**	0.354**
	(0.014)	(0.013)	(0.013)	(0.106)	(0.108)	(0.108)	(0.036)	(0.039)	(0.039)	(0.065)	(0.062)	(0.062)
East Germany*	-0.101**	-0.088**	-0.088**	---	---	---	---	---	---	-0.144*	-0.148**	-0.146**
	(0.017)	(0.017)	(0.017)	---	---	---	---	---	---	(0.058)	(0.054)	(0.054)
Self employed*	-0.019*	-0.007	-0.010	0.007	0.125**	0.112**	-0.282**	-0.230**	-0.224**	-0.139**	-0.067**	-0.070**
	(0.009)	(0.008)	(0.008)	(0.024)	(0.021)	(0.021)	(0.011)	(0.010)	(0.010)	(0.027)	(0.024)	(0.024)
Became retired*	-0.020	-0.008	-0.010	0.005	-0.006	-0.002	-0.254**	-0.263**	-0.262**	0.020	0.074+	0.073+
	(0.014)	(0.013)	(0.013)	(0.050)	(0.049)	(0.049)	(0.015)	(0.016)	(0.016)	(0.049)	(0.043)	(0.043)
Left education *	-0.065**	-0.056**	-0.055**	-0.001	-0.001	-0.001	-0.254**	-0.267**	-0.268**	-0.057*	-0.066**	-0.066**
	(0.007)	(0.007)	(0.007)	(0.015)	(0.016)	(0.016)	(0.019)	(0.020)	(0.020)	(0.022)	(0.021)	(0.021)

... contd. …

... contd. … Table 3

Unempl. (last year) *	-0.068**	-0.065**	-0.065**	-0.034**	-0.037**	-0.037**	0.109**	0.091**	0.091**	-0.070**	-0.069**	-0.069**
	(0.001)	(0.001)	(0.001)	(0.005)	(0.005)	(0.005)	(0.010)	(0.010)	(0.010)	(0.003)	(0.003)	(0.003)
Months FT (last year)	0.118**	0.113**	0.113**	0.109**	0.090**	0.090**	0.179**	0.169**	0.169**	0.108**	0.102**	0.102**
	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Months PT (last year)	0.066**	0.064**	0.065**	---	---	---	---	---	---	0.066**	0.064**	0.064**
	(0.001)	(0.001)	(0.001)	---	---	---	---	---	---	(0.002)	(0.002)	(0.002)
Imputed Labor Y*	**---**	**---**	**0.064****	**---**	**---**	**0.061****	**---**	**---**	**-0.031****	**---**	**---**	**0.042****
	---	---	(0.005)	---	---	(0.018)	---	---	(0.007)	---	---	(0.010)
Constant	7.515**	7.543**	7.533**	6.610**	4.344**	4.303**	6.103**	6.122**	6.133**	6.291**	6.614**	6.605**
	(0.042)	(0.042)	(0.042)	(0.429)	(0.450)	(0.450)	(0.290)	(0.297)	(0.297)	(0.202)	(0.191)	(0.191)
Observations	119030	134337	134337	21416	23491	23491	54117	63494	63494	20355	24392	24392
N (Persons)	24183	25487	25487	9658	10142	10142	9903	10642	10642	6797	7448	7448
R-squared	**0.4869**	**0.4474**	**0.4484**	**0.1989**	**0.1439**	**0.1447**	**0.5004**	**0.4239**	**0.4241**	**0.3849**	**0.3393**	**0.3400**

* indicates dummy variables.
Population: working age: 20-60 (Germany), 20-65 (Australia and UK)
Note: Time effects controlled, but not reported. Standard errors in parentheses; Significance level: + significant at 10%; * significant at 5%; ** significant at 1%.
Source: SOEP survey years 1992-2004; HILDA survey years 2001-2003; BHPS survey years 1991-2002.

5 Conclusion

This study deals with item-non-response (INR) on labor income questions and imputation as a specific type of measurement error in three large panel surveys (the German SOEP, the British BHPS and the Australian HILDA). We provide empirical evidence for considerable cross-country variation with respect to incidence and selectivity of INR. Longitudinal imputation is the preferred way to handle INR in all three panels, with HILDA and SOEP using in principle the same strategy, and the BHPS making use of a hot-deck regression approach.[13]

The selectivity of item-non-response and hence, the imputation of such missing observations, appears to have a significant impact on both, the distribution of earnings and earnings mobility. Results on *inequality* suggest that using observed values only, i.e. “case-wise deletion”, produces downward biased estimates. Likewise, analyses of earnings *mobility* based only on cases with observed information clearly understate income variability over time. Additionally, our analyses provide evidence for a positive inter-temporal correlation between item-non-response and any kind of subsequent (item- and unit-) non-response, including permanent refusals.

Estimating wage regressions based on observed vs. all cases and controlling for imputation status, indicates that individuals with imputed incomes, ceteris paribus, earn significantly above average in SOEP and HILDA, while this relationship is negative using BHPS data. Furthermore, selected estimated coefficients are subject to change when considering the entire population instead of the more homogenous population with observed income data.

Last but not least, the cross-national variation found in these analyses with respect to scope and selectivity of INR, as well as with respect to imputation strategies and its consequences on prototypical analyses around wage income strongly argues for future harmonization of the handling of missing (income) data in (panel) survey data. Given the need to know about the eventual assumptions embedded in the imputation process, it is most important that providers of survey data document their imputation strategy as well as flag the imputed values in micro data in order to differentiate them from truly observed information. This supports sensitivity tests with respect to the impact of imputation which may be even more important in case of cross-national analyses as shown in this paper.

[13] The single imputation techniques currently applied in all three panels probably underestimate the true variance, and as such there may be demand for more complex variance estimation methods (e.g. jackknife estimators). However, the L&S imputation technique used in case of SOEP and HILDA may also be extended to a multiple imputation procedure by matching any non-respondent to more than one neighboring case (see Little & Su 1989: 415).

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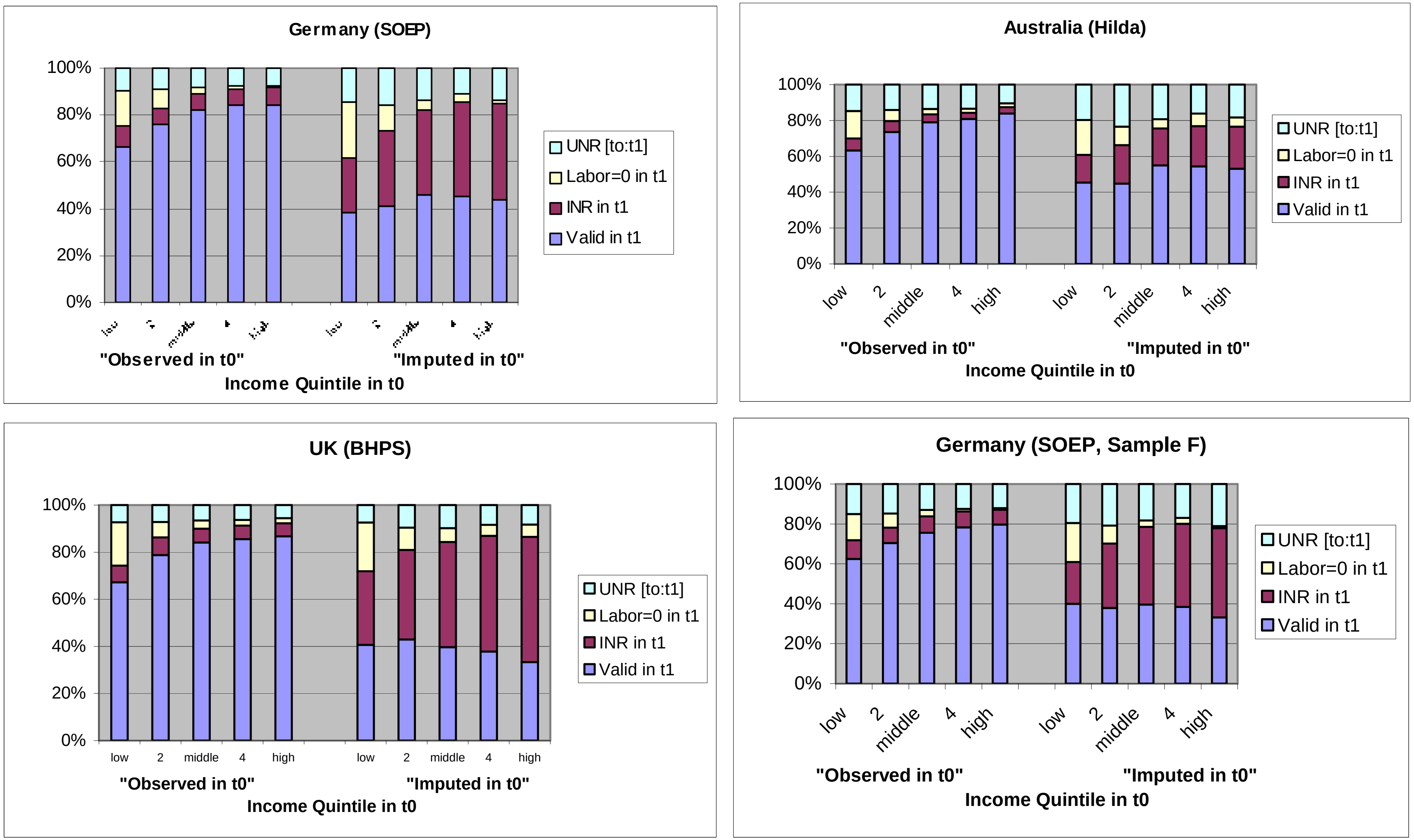
Appendix:

Figure A-1a-d: Item-Non-Response in a longitudinal Perspective: The Case of individual labor earnings



Source: SOEP survey years 1992-2004; HILDA survey years 2001-2003; BHPS survey years 1991-2002.

Table A-1: Time series on Labor Income Inequality in Germany, Australia, and in the UK (based on valid observations, only)

	1991	**1992**	**1993**	**1994**	**1995**	**1996**	**1997**	**1998**	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**
SOEP														
Gini		0,374	0,384	0,386	0,388	0,393	0,401	0,397	0,403	0,415	0,424	0,431	0,430	0,432
Theil 1		0,245	0,261	0,262	0,263	0,276	0,284	0,276	0,282	0,302	0,318	0,320	0,321	0,324
Theil 0		0,317	0,342	0,348	0,356	0,371	0,388	0,394	0,395	0,423	0,447	0,453	0,454	0,453
HalfSCV		0,286	0,322	0,305	0,297	0,340	0,331	0,304	0,305	0,344	0,378	0,351	0,357	0,364
HILDA														
Gini											0,421	0,425	0,421	
Theil 1											0,326	0,337	0,325	
Theil 0											0,436	0,452	0,443	
HalfSCV											0,455	0,487	0,451	
BHPS														
Gini	0,429	0,416	0,423	0,427	0,431	0,424	0,435	0,429	0,417	0,406	0,411	0,401		
Theil 1	0,324	0,300	0,307	0,314	0,330	0,314	0,337	0,343	0,311	0,300	0,312	0,281		
Theil 0	0,425	0,395	0,406	0,414	0,423	0,411	0,436	0,422	0,395	0,369	0,376	0,356		
HalfSCV	0,404	0,355	0,352	0,366	0,450	0,387	0,445	0,574	0,443	0,461	0,502	0,343		
SOEP-F														
Gini										0,418	0,423	0,437	0,433	0,443
Theil 1										0,305	0,313	0,330	0,324	0,340
Theil 0										0,421	0,441	0,462	0,445	0,469
HalfSCV										0,344	0,351	0,367	0,369	0,396

Source: SOEP survey years 1992-2004; HILDA survey years 2001-2003; BHPS survey years 1991-2002.

Table A-2: Results from quantile wage regressions; Dependent variable: log annual labor income (normalized)

	Germany (SOEP)			Australia (HILDA)			UK (BHPS)			Germany (SOEP) – Sample F		
	p25	**p50**	**p75**	**p25**	**p50**	**p75**	**p25**	**p50**	**p75**	**p25**	**p50**	**p75**
Age	0.0333**	0.034**	0.0324**	0.1160**	0.0846**	0.0755**	0.078**	0.071**	0.075**	0.035**	0.039**	0.043**
	(0.0012)	(0.0013)	(0.0013)	(0.0037)	(0.0025)	(0.0036)	(0.003)	(0.002)	(0.002)	(0.004)	(0.003)	(0.002)
Age squared	-0.0003**	-0.000**	-0.0002**	-0.0014**	-0.0009**	-0.0008**	-0.001**	-0.001**	-0.001**	-0.000**	-0.000**	-0.000**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female with kid(s)	-0.1754**	-0.152**	-0.1181**	-0.6782**	-0.4750**	-0.3631**	-0.855**	-0.613**	-0.404**	-0.192**	-0.192**	-0.140**
	(0.0086)	(0.0058)	(0.0047)	(0.0222)	(0.0158)	(0.0134)	(0.016)	(0.008)	(0.010)	(0.019)	(0.011)	(0.013)
Male with kid(s)	0.1377**	0.122**	0.1286**	0.1556**	0.1420**	0.1612**	0.108**	0.082**	0.089**	0.160**	0.142**	0.136**
	(0.0026)	(0.0030)	(0.0031)	(0.0109)	(0.0080)	(0.0117)	(0.008)	(0.006)	(0.008)	(0.010)	(0.009)	(0.008)
Married	-0.0080	-0.009	-0.0225**	-0.1833**	-0.0972**	-0.0810**	-0.177**	-0.146**	-0.125**	-0.019	0.011	-0.013
	(0.0074)	(0.0059)	(0.0054)	(0.0262)	(0.0160)	(0.0153)	(0.014)	(0.009)	(0.006)	(0.021)	(0.021)	(0.016)
Disability Status	0.0025	0.074*	0.0085**	0.0800**	0.0489**	0.0652**	0.330**	0.271**	0.222**	0.010	0.020*	0.022*
	(0.0024)	(0.0032)	(0.0026)	(0.0124)	(0.0076)	(0.0106)	(0.009)	(0.004)	(0.005)	(0.011)	(0.008)	(0.010)
Metrop. area	0.0505**	0.043**	0.0548**	0.1320**	0.1179**	0.1136**	0.139**	0.143**	0.147**	0.040*	0.036**	0.042**
	(0.0066)	(0.0041)	(0.0046)	(0.0121)	(0.0103)	(0.0102)	(0.008)	(0.005)	(0.005)	(0.016)	(0.011)	(0.011)
Remote area	-0.0325**	-0.029**	-0.0202**	0.0241	-0.010	-0.0051	-0.034*	-0.036**	-0.053**	-0.039**	-0.033**	-0.020+
	(0.0027)	(0.0028)	(0.0033)	(0.0291)	(0.0233)	(0.0326)	(0.014)	(0.008)	(0.007)	(0.008)	(0.007)	(0.010)
Educational level	0.1573**	0.174**	0.1878**	0.1949**	0.1948**	0.1875**	0.230**	0.236**	0.235**	0.170**	0.187**	0.199**
	(0.0030)	(0.0014)	(0.0014)	(0.0075)	(0.0041)	(0.0045)	(0.006)	(0.003)	(0.002)	(0.005)	(0.003)	(0.003)
East Germany	-0.3443**	-0.331**	-0.3342**	---	---	---	---	---	---	-0.308**	-0.306**	-0.286**
	(0.0045)	(0.0032)	(0.0038)	---	---	---	---	---	---	(0.009)	(0.008)	(0.011)
Self employed	-0.2093**	-0.017*	0.1905**	-0.3344**	-0.0736**	0.0677**	-0.390**	-0.200**	-0.007	-0.196**	0.001	0.183**
	(0.0119)	(0.0069)	(0.0109)	(0.0319)	(0.0206)	(0.0205)	(0.019)	(0.017)	(0.013)	(0.027)	(0.017)	(0.020)
Became retired	-0.1925**	-0.132**	-0.0612**	-0.0448	0.0660	0.0419	-0.121**	-0.085**	-0.024	-0.442**	-0.602**	-0.190**
	(0.0143)	(0.0175)	(0.0114)	(0.0814)	(0.1067)	(0.0729)	(0.033)	(0.019)	(0.023)	(0.064)	(0.080)	(0.058)
Left education	-0.0960**	-0.102**	-0.0871**	-0.0606**	-0.0439**	-0.0531**	-0.257**	-0.238**	-0.307**	-0.156**	-0.190**	-0.156**
	(0.0125)	(0.0102)	(0.0088)	(0.0202)	(0.0155)	(0.0167)	(0.044)	(0.030)	(0.027)	(0.034)	(0.032)	(0.017)
Months UE (last year)	-0.0525**	-0.081**	-0.0917**	-0.0478**	-0.0317*	-0.0434**	0.097**	0.055**	-0.070**	-0.063**	-0.098**	-0.112**
	(0.0017)	(0.0012)	(0.0013)	(0.0103)	(0.0133)	(0.0097)	(0.020)	(0.020)	(0.013)	(0.004)	(0.004)	(0.004)
Months FT (last year)	0.1721**	0.120**	0.0915**	0.2159**	0.1667***	0.0972**	0.222**	0.194**	0.149**	0.175**	0.117**	0.084**
	(0.0015)	(0.0012)	(0.0007)	(0.0074)	(0.0058)	(0.0048)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)
Months PT (last year)	0.0374**	0.039**	0.0288**	---	---	---	---	---	---	0.039**	0.032**	0.019**
	(0.0016)	(0.0012)	(0.0008)	---	---	---	---	---	---	(0.002)	(0.003)	(0.002)
Imputed Labor Income	**-0.0274****	**0.004**	**0.0457****	**-0.1714****	**-0.0247+**	**0.0686****	**-0.111****	**-0.065****	**-0.030****	**-0.016**	**0.013+**	**0.052****
	(0.0068)	(0.0054)	(0.0041)	(0.0361)	(0.0144)	(0.0210)	(0.012)	(0.006)	(0.006)	(0.012)	(0.008)	(0.009)
Constant	1.4541**	2.155**	2.6652**	-0.9733**	0.4510**	1.6732**	0.174**	0.846**	1.531**	1.239**	1.996**	2.447**
	(0.0327)	(0.0274)	(0.0284)	(0.1239)	(0.0795)	(0.0706)	(0.056)	(0.045)	(0.038)	(0.084)	(0.053)	(0.045)
Observations	139351			23491			63494			25634		
R-squared	0.477	0.395	0.349	0.259	0.203	0.164	0.332	0.275	0.232	0.470	0.396	0.345

contd. … Table A-2

Test on significant differences of imputation effect between the 25th and 75th percentile:				
	F(1,139321) = 94.41 Prob > F = 0.0000	F(1, 23473) = 24.93 Prob > F = 0.0000	F(1, 63467) = 35.89 Prob > F = 0.0000	F(1, 25612) = 27.19 Prob > F = 0.0000

Population of working age: 20-60 (Germany), 20-65 (Australia and UK)
Note: Time effects controlled, but not reported. Standard errors in parentheses; Significance level: + significant at 10%; * significant at 5%; ** significant at 1%.
Source: SOEP survey years 1992-2004; HILDA survey years 2001-2003; BHPS survey years 1991-2002.

Appendix B: Exact wording on earnings related questions in original survey instruments

BHPS:

The last time you were paid, what was your gross pay - that is including any overtime, bonuses, commission, tips or tax refund, but before any deductions for tax, national insurance or pension contributions, union dues and so on?

IF `DON'T KNOW / CAN'T REMEMBER' PROBE: `Can you give me an approximate amount?'
ENTER TO NEAREST £: ASK E21 ***IPAYGL***
Don't know................ 8 **GO TO E22**
Refused .... 9 **GO TO E31** **(page 43)**

RESPONDENT TO CHECK PAY SLIP IF POSSIBLE

HILDA:

F19 ***Last financial year*****, what was your total wage and salary income from** ***all*** **jobs** ***before*** **tax or anything else was deducted?**
Do not include income from businesses. This should be gathered at F24, rather than here.
Enter **annual** amount
(whole $) $____ → **F22**
Don't know..................................999999 → F20

F22 During the last financial year did you, at any time:
work in your own business or farm; or were a silent partner in a partnership; or were a beneficiary of a trust (excluding those that are used just for investment purposes)?
Yes...1
No.. 2 → F28a

F24 Excluding dividends, in the last financial year, what was ***your*** **total income from wages and salary from these incorporated businesses** ***before*** **income tax was deducted? Please exclude wages and salary already reported.**
This includes trusts from F22
Enter amount (whole $) $
Recorded elsewhere.................................9999998
Don't know..9999999

F26a In the last financial year, did you have any unincorporated businesses?
Yes...1
No.. 2 → F28a

Note: respondents cannot answer NO to both F26a and F23.
If they do, query.

F26b What was your total share of profit or loss from your unincorporated businesses or farms before income tax but after deducting business expenses in the last financial year?

Enter amount (whole $) ……. → F27
Don't know 9999999→ F28a

SOEP:

Q76. We have already asked for your current income. In addition, please state what sources of income you received in the past calendar year 2001, independent of whether the income was received all year or only in certain months. Look over the list of income sources and check all that apply. For all sources that apply please indicate how many months you received this income in 2001 and how much this was on average per month.
(Please state the gross amount which means not including deductions for taxes or social security).

	Source of income in 2001	**Received Months in 2001**	**Gross amount per month EURO**
Wages or salary as employee (including wages for training, "Vorruhestand", wages for sick time ("Lohnfortzahlung")			
Income from self-employment, free-lance work			
Additional employment			
Pay for compulsory military service, community service in place of military service ("Zivildienst")			

Q77. Did you receive any of the following additional payments from your employer last year (2001)? If yes, please state the gross amount.
13th month salary .... in total EURO
14th month salary .... in total EURO
Additional Christmas bonus .... in total EURO
Vacation pay .... in total EURO
Profit-sharing, premiums, bonuses .... in total EURO
Other .... in total EURO
No, I received none of these ....