SUST Journal of Natural and Medical Sciences (JNMS) vol. 20 (1) June 2019
ISSN (Print): 1858-6805 e-ISSN (Online): 1858-6813

SUST
Journal of Natural and Medical Sciences
Journal home page:
http://Scientific-journal.sustech.edu/

An Alternative Strategy for Non-response Weighting Adjustment in Longitudinal Surveys

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Received: December 2018 **Accepted: April 2019**

Abstract.
Longitudinal survey organizations can offer data for analysis from many subsets of data that are related to the longitudinal population at the latest wave, from a large number of wave-combinations. However, only one set of non-response weights (which is often based on respondents from all waves up to the latest) is often offered to be used with any of the wave-combinations. This use of non-response weights is a single weighting strategy. Weights are derived based on information from one subset of waves but used for analysis with other subsets of waves. In this paper, the limitations of the single weighting strategy was illustrate. Creating subsets of weights for all the possible combinations of waves is impractical. However, weights are more useful for some combinations than others. a criterion of designing subsets of weights based on considering wave-combinations that are concerned with the same module of questions was evaluated . Data from the British Household Panel Survey (wave 1 to 8) were used to conduct the investigation. I found that the use of a single weighting strategy may lead to an unnecessary loss of respondents and hence less precision and bias on some, but not all, of the survey estimates.

Keywords: Non-response error, Bias, Precision, Weighting.

Introduction

In longitudinal surveys, a central role for the survey organization is to prepare weights to adjust for non-response and include them in public use data files (Lynn and Kaminska, 2010). Designing non-response weights from cross-sectional data is straightforward in comparison with longitudinal data. This is because in cross-sectional surveys observations are recorded at a single point in time so that the response process can be defined by a binary variable (non-response=0 and response=1). Moreover, it is known that the developed weights will compensate for non-respondents at the defined single time when the data were collected. In contrast, in longitudinal studies data are collected at multiple occasions, so respondents have many records in the data set, each referring to a different data collection point. Thus, the variable representing the response process can have a large number of categories, each category identifies response outcome in a certain combination of data collection points. This complexity implies changing the weights as time goes on. Furthermore, it permits designing different sets of non-response weights from different combinations of subsets of data. Moreover, if a set of weights is derived from a particular subset of data which is linked to certain data collection times, it cannot be asserted that it can compensate for non-respondents from a different subset of data that is connected to different data collection times. This is because the set of respondents in the two subsets of data can be different. For example, in a survey with a limited number of waves, say 15, the set of non-response weights at wave 15 is designed by reference to responding in all waves up to wave 15. Hence, this set of weights can be used to correct for non-response in any analysis that requires a sample of respondents who responded at all of the 15 waves. However, supposing that the analysis was to be carried out using data only from the last five waves, the sample used in the analysis in this case may be different than the sample used for the analysis on data from all 15 waves (likely to be larger as it consists of sample members who responded in wave 11, 12, 13, 14 and 15 regardless of whether they also responded at any other wave). Thus, the set of non-response weights at wave 15 would then be suboptimal in this case, since it rules out all sample members who did not respond in all of the 15 waves by assigning a weight of zero to them, even if they have responded in the required last five waves. Furthermore, the covariates used to specify the weighting model were not selected specially to predict the response pattern in wave 11, 12, 13, 14 and 15. Clearly, this is an unnecessary loss of information which could be avoided if a set of weights was designed specifically for respondents in wave 11, 12, 13, 14 and 15.

Therefore, there are two dimensions need to be thought of when creating non-response weights for longitudinal data. First, non-response weights are not fixed over time i.e. any set of weights that is created at a certain wave needs to be updated when the next wave is conducted as the set of responding units will be updated as well. Second, the multi-wave feature in longitudinal surveys allows for data to be drawn for analysis from different combinations of waves. However, the set of responding units can differ across wave-combinations offering potentially different subsamples for every possible combination. Thus, weights may be required for a number of combinations of waves too, as one set of weights might not be sufficient in handling non-response error in all subsets of data.

However, in the major longitudinal surveys in the world, weighting for non-response is often a single weighting strategy overlooking the fact that different wave-combinations can potentially provide different sets of respondents. For instance, in the British Household Panel Survey (BHPS), longitudinal weights at any wave ‘w’ are only available for a balanced panel from all waves up to wave ‘*w*’ (Taylor *et al*, 2010). Likewise, longitudinal weights in a current wave in the Swiss Household Panel (SHP) are designed to extrapolate to the population living in Switzerland at that wave using respondents from all waves up to the current (Plaza and Graf, 2008). This is also the case in the German Socio Economic Panel (GSOEP) and the Panel Study of Income Dynamics (PSID), where no particular combination of waves are provided with specially designed longitudinal weights; instead, weights in the latest wave are available for the set of respondents from all waves including the latest (Kroh, 2009; Gouskova, 2001).

This single non-response weighting strategy, which is used in almost every survey, could be helpful and practical in reducing non-response bias, but may be suboptimal in respect to the subsample being used for analysis.

In theory, the way out of this problem is to design a subset of non-response weights for every possible combination of waves. However, providing weights for all possible combinations of waves might not be achievable in practice sometimes. For example, after k waves are conducted, there is a (2^k-1) possible combination of waves to provide weights for. Moreover, this number increases rapidly when more waves are added, and it could even outnumber the number of variables in the survey in a long term panel. However, in practice, not every possible combination of waves is of use for researchers. Therefore, only desirable subsets of weights should be produced. Nevertheless, it is a challenging task to identify combinations of waves that will be of interest for data users. But the possibility that a single weighting strategy might not be sufficient generates interest in the development of more subsets of weights. Hence, the investigation of this is an important aspect of weighting panel data.

In this paper, data from the British Household Panel Survey (BHPS) are used to conduct empirical evaluation of considering wave-combination with the same module of question as a choice to design optimum subsets of non-response weights. The investigation reveals the sub optimality of the single weighting strategy in handling non-response error in a subset of waves, by comparing results from its weights and weights that are designed specifically for the selected subset of waves.

Materials and methods

The data for this study are from the BHPS: exclusively, data from wave 1 to 15 with a specific focus on the combination of waves 5, 10 and 15.

The choice of wave-combination

Although all BHPS waves generally provide data to be used for analysis in many of the social science disciplines, some waves are designed to cover certain components extensively (Lynn, 2006). For instance, wave 11 and 16 provide data on ageing, retirement, family support, health and quality of life whilst data about wealth, assets and debt is available in wave 5, 10 and 15. Therefore, data from such subsets of waves might be required for analysis frequently. However, BHPS does not provide subsets of weights that are designed especially for the analysis of these combinations of waves. For example, if a researcher wanted to do analysis on wealth, assets and debt, which involves using data from wave 5, 10 and 15, the weights available for this would be the longitudinal weights based on the respondents at all waves up to wave 15.

This research used data from wave 5, 10 and 15 from the BHPS and designed a subset of non-response weights specifically for this combination. To evaluate the efficiency of this set of weights, another set of non-response weights was designed based on respondents at all waves up to wave 15 (the usual weights from a single weighting strategy). To allow for a fair comparison, the two sets of weights were created using the same variables and the same method. Thus, any potential difference between the two sets of weights will be due to differences in the two wave-combinations in terms of the responding sample as other factors were held constant. Analysis was carried out on savings and debts data using the two sets of weights. The issue of interest here is to compare estimation results produced from the use of the two sets of weights and conclude on which set of weights is better based on these.

Construction of longitudinal weights

Both sets of weights were created using a model based method. The analysis was restricted to respondents aged 16 or above and alive during the course of the 15 waves.

For both sets of respondents, logistic regression was used to estimate the response propensity in each case. Two indicators R_{1i} and R_{2i} represented the independent variables in each model. R_{1i} and R_{2i} take the following values:

$$R_{1i} = \begin{cases} 1, & if\ unit\ i\ responded\ in\ wave\ 1,5,10\ and\ 15 \\ 0, & otherwise \end{cases} \tag{1}$$

$$R_{2i} = \begin{cases} 1, & if\ unit\ i\ responded\ in\ all\ waves\ up\ to\ wave\ 15 \\ 0, & otherwise \end{cases} \tag{2}$$

The relationship between the response propensity in our two wave-combinations and the weighting variables may vary from a wave to another and between wave-combinations too. This can be because the values of some variables can change overtime for the same respondent (time-varying variables) allowing for a different probability of responding. For example, considering the combination of waves 1, 5, 10 and 15, some respondents may be unemployed at wave 1 in which they are easier to make contact with. But, they may become employed at wave 15 which makes it more difficult to contact them and hence this may result in non-response. Thus, one way of creating weights for this wave-combination might involve modeling the response in wave 5 conditional on responding in wave 1, modeling the response in wave 10 conditional on responding in wave 5, and modeling the response in wave 15 conditional on responding in wave 10. Each model can be estimated using variables from the previous waves in that combination in order to take into account the potential effect of the time-varying variables on responding. An overall non-response weight can then be calculated by multiplying weights produced from the three models. Another way is to ignore the effect that time-varying variables may introduce in the process of responding and use variables from one wave (usually wave 1) to create the weights. The latter approach can produce a more parsimonious model which has the advantage of avoiding the risk of inflating the variance due to weighting. In this paper, a large mixture of continuous and categorical variables from wave 1 was used to model the response propensity in the two wave-combinations. Namely, these variables are: sex, age, ethnic group, region, health status, household size, presence of children in household, housing tenure, income, number of people aged 75+ in the household, type of household, number in employment in household, education, employment status, savings, debt, type of accommodation, financial situation, socioeconomic group, number of weekly working hours, number of weekly overtime hours, work location, smoking status, car ownership, number of own children in the household, presence of others during interview, interviewer sex and length of interview. These variables were chosen from three categories of variables that are thought to affect the response propensity. These are: interview and interviewer characteristics (e.g. interviewer's sex and length of interview), household characteristics (e.g. household size and household type) and individual characteristics (e.g. age, sex and savings).

A number[1] of respondents joined the BHPS after the first wave; those have been ruled out as there are no available data for them at wave 1. Two logit models were estimated to explain the variation in the response propensity in wave 5, 10 and 15 and in all

[1] This is a small number of those who resulted in non-contact at wave 1, but they were contacted at wave 2.

ISSN (Print): 1858-6805 e-ISSN (Online): 1858-6813

the waves up to wave 15 conditional on responding at wave 1.

$$\text{Logit}\ (R_{1i}) = f\ (\sum_j \beta_{1j} I_j + \sum_t \gamma_{1t} H_t + \sum_l \delta_{1l} D_l + \varepsilon_{1i}) \tag{3}$$

$$\text{Logit}\ (R_{2i}) = f\ (\sum_j \beta_{2j} I_j + \sum_t \gamma_{2t} H_t + \sum_l \delta_{2l} D_l + \varepsilon_{2i}) \tag{4}$$

Where:
R_{1i} ≡ Responding Status at wave 1, 5, 10 and 15.
R_{2i} ≡ Responding Status at all waves up to wave 15.
I_j ≡ Interview and Interviewer characteristics.
H_t ≡ Household characteristics.
D_l ≡ Individual characteristics.
ε_i ≡ Error term.

The non-response weights for the two sets of respondents were then calculated as the inverse of the predicted value from the fitted model as shown in equations (5) and (6).

$$w_{NR1i} = \begin{cases} \frac{1}{r_{1i}} & if\ unit\ i\ responded\ in\ wave\ 1, 5, 10\ and\ 15 \\ 0, & otherwise \end{cases} \tag{5}$$

$$w_{NR2i} = \begin{cases} \frac{1}{r_{2i}} & if\ unit\ i\ responded\ in\ all\ waves\ up\ to\ 15 \\ 0, & otherwise \end{cases} \tag{6}$$

Where:
w_{NR1i} ≡ Case i non-response weight based on respondents in wave 1, 5, 10 and 15.
w_{NR2i} ≡ Case i non-response weight based on respondents in all waves up wave 15.
r_{1i} ≡ Predicted value from the first model.
r_{2i} ≡ Predicted value from the second model.

In order to check if the two sets of weights lead to different results, w_{NR1i} and w_{NR2i} were incorporated in modelling the change in two variables: Savings and Debts from wave 5, 10 and 15. The process of modelling each variable is explained in the next section. However, before applying the non-response weights on the data, w_{NR1i} and w_{NR2i} were multiplied by wave 1 non-response weights. This set of weights was provided by BHPS. In BHPS wave 1 non-response weight is a product of two weight components. The first is a weight to adjust for the variation in the inclusion probabilities. The second weight component is to compensate for non-response at wave 1. Thus, any of the final two sets of weights corrects for the differences in the selection probabilities and non-response in wave 1 and non-response in its wave-combination simultaneously. The final two sets of weights can be written as:

$$w_{1i} = w_{Di} * w_{NR1i} \tag{7}$$

$$w_{2i} = w_{Di} * w_{NR2i} \tag{8}$$

Where:
w_{1i} ≡ Case i final weight based on respondents in wave 1, 5, 10 and 15.
w_{2i} ≡ Case i final weight based on respondents in all waves up to 15.
w_{Di} ≡ Case i wave 1 weight.

Modelling savings and debts using the longitudinal weights

The British Household Panel Survey provides detailed information on savings and debts at the individual level for the years 1995, 2000 and 2005, representing waves 5, 10 and 15 respectively. In each of these waves, respondents were asked if they have money in savings and whether they owe money. If respondents have money in savings and/or owe money, they are then asked to state the amount held in these. This setting permits two main sets of dependent variables which were used in the analysis: (a) Dichotomous: these are two variables, one indicates whether an individual has savings or not and the other indicates if the individual is in debt; (b) Continuous: these are two variables reflecting the amount of money held in savings and debts.

Across the three waves, the proportion of missing values among the first category of the dependent variables is negligible (less than 1%). However, the second category of the dependent variables shows a large number of missing values across the three waves. Therefore, an imputation process was carried out to reduce any inefficiency or bias that might be brought in due to missing values. The values were imputed using Hot Deck procedure. The steps involved categorizing the respondents in the sample into similar subgroups based on the variables sex, age group, ethnic group, household size and household income. Missing data for respondents in any subgroup were then randomly replaced with comparable data from respondents in the same subgroup. The values were only imputed for those who reported having savings or are in debts. The imputation was done separately for 1995, 2000 and 2005 before aggregating data from the three waves into one data set.

The main independent variables used in the analysis are annual income, marital status, employment status, presence of children aged 16 or under, housing tenure, financial status and household size, as these variables are important in predicting both the existence and level of wealth (see for example Kan and Laurie, 2010). Also, other variables such as sex and year of data collection (wave) are included for control. Each variable in the data was observed at three time points (1995, 2000 and 2005). Using a long format type of data set in STATA 11, the analysis was done at the individual level. Before estimating the models, the data was introduced as a panel data set so that the multiple observations per person are linked to one case rather than being treated as different cases. Also, in order to take account of the effects of weighting, clustering and stratification, the commands '*svyset*' were used in STATA to specify that the sample is not a simple random sample (clustered and stratified) and that weights are incorporated in the analysis.

Two random effects logistic regression models were used to estimate the determinants of having money in savings or being in debts respectively. However, each model was estimated twice using the two different longitudinal sets of weights. Similarly, to model the amounts of savings and debts, two random effects OLS regression models were estimated in which every model was estimated two times using the two sets of longitudinal weights.

With two different sets of longitudinal weights (one based on the respondents at waves 1, 5, 10 and 15 and the other based on the respondents at all waves up to wave 15), eight models were estimated as each set of weights is used to estimate the main four models.

The main idea is to assess the change on the regression coefficients when varying weight adjustments procedures. In particular, the point of interest is to spot the influence of creating non-response longitudinal weights based on the consideration of combination of waves with the same module of questions.

Results and Discussion

Descriptive findings

Table 1 shows the number of respondents, number of non-respondents, response rates and non-response rates in waves 5, 10 and 15 and in all waves up to wave 15 respectively. The response rate in the subset of waves (50.08%) is 4.67% greater than the response rate in all the 15 waves (45.41%). This difference in response rates is caused by 478 (9.3%) respondents who took part in waves 5, 10 and 15 but failed to respond in at least one other wave between 1 and 15. This result indicates that if a weighting adjustment that is based on respondents from all waves up to wave 15 is used for analysis of data from waves 5, 10 and 15 it will assign a weight of zero to 478 respondents. Consequently, this approach, which corresponds to use of the BHPS wave 15 longitudinal weight, the only weight on the public use data file that could be used for this analysis, results in a loss of 9.3% of the sample that could be used for analysis from waves 5, 10 and 15.

Table 1: Number of respondents and non-respondents at wave 5, 10 and 15 and in all waves up to 15

	Respondents	Non-respondents	Total
Wave 5, 10 and 15	5,132(50.08%)	5,116(49.92%)	10,248
All waves up to 15	4,654(45.41%)	5,594(54.59%)	10,248
Difference	478		

Analysis findings

The models in tables 2 and 3 investigate the factors associated with the possession of savings and debt and the amount held in these in the years 1995, 2000 and 2005 respectively. Each model is estimated twice using our two sets of weights. The issue of interest here is to examine whether the two sets of weights lead to different results, whereby weights based solely on sample members in wave 5, 10 and 15 would then prove optimal.

Possession of savings and debts

As seen in table 2, regardless of the set of weights used in analysis, the possession of savings and/or debts is significantly associated with gender, age, financial situation, housing tenure, work status, and income. For example, women are more likely than men to have savings and debts ($\hat{b}_1$ = 0.208, $p < 0.01$; $\hat{b}_2$= 0.201, $p < 0.01$; $\hat{b}_3$ = 0.134, $p < 0.05$; $\hat{b}_4$= 0.147, $p < 0.05$), meanwhile, those who are out of the labour force are less likely to have savings and debts ($\hat{b}_1$ = -1.129, $p < 0.01$; $\hat{b}_2$= -1.121, $p < 0.01$; $\hat{b}_3$ = -0.963, $p < 0.01$; $\hat{b}_4$= -0.992, $p < 0.01$).

Focusing on the difference between the coefficients arrived at via the two sets of weights, there is much to be learnt from the comparison. For instance, in models concerned with savings, having a second job and being unemployed are significant in the first but not the second model ($\hat{b}_1$ = -0.246, $p < 0.01$, $\hat{b}_2$= -0.089, $p > 0.10$; $\hat{b}_1$ = -0.116, $p < 0.10$, $\hat{b}_2$= -0.152, $p > 0.10$). This is clearly showing the effect of the increase in the sample size used to estimate the first model on these particular variables (recall that the sample size used to estimate the first model is bigger by 478 respondents). In other words, using a weights adjustment method based on respondents in all waves which is associated with the loss of 478 respondents in the sample, results in underestimating the importance of having a second job and being unemployed. Moreover, although living with a partner is not significant in any of the two models, the signs of the coefficients in the two models are different ($\hat{b}_1$ = 0.001, p > 0.10, $\hat{b}_2$= -0.012, p > 0.10).

As for debts, the coefficients of having a second job are highly significant in both models; however, they are different in magnitude ($\hat{b}_3$ = -0.466, p < 0.01; $\hat{b}_4$= -0.242, p < 0.01; $\hat{b}_3$- $\hat{b}_4$= -0.224). Also, having a dependent child is significant once weights based on waves 1, 5, 10 and 15 are used to estimate the model ($\hat{b}_3$ = 0.121, p < 0.10; $\hat{b}_4$= 0.105, p > 0.10).

Table 2: Logistic regression models of possession of savings and debts

	Having Savings		Having Debts	
	Using weights based on waves 1, 5, 10, and 15	Using weights based on all waves up to wave 15	Using weights based on waves 1, 5, 10, and 15	Using weights based on all waves up to wave 15
Year 2000	0.057	0.080	0.037	0.060
Year 2005	0.025	0.039	0.130**	0.116**
Female	0.208***	0.201***	0.134**	0.147**
Age	-0.007***	-0.008***	-0.040***	-0.041***
Financially okay	-0.841***	-0.832***	0.436***	0.468***
Having financial deficits	-2.384***	-2.439***	1.400***	1.401***
Mortgage payer	-0.117*	-0.122*	1.025***	0.995***
Council tenant	-0.416***	-0.422***	0.961***	0.948***
Private renter	-0.477***	-0.509***	0.922***	0.886***
Having a second job	-0.246***	-0.089	-0.466***	-0.242***
Having a dependent child	-0.302***	-0.297***	0.121*	0.105
Living with partner	0.001	-0.012	0.024	0.062
Member of a large household	-0.473**	-0.478**	-0.282	-0.247
Unemployed	-0.116*	-0.152	-0.234***	-0.270***
Out of the labour force	-1.129***	-1.121***	-0.963***	-0.992***
Annual income/1000	0.018***	0.019***	0.004*	0.004*
Constant	0.894***	0.933***	0.172	0.183
lnsig2u	0.594***	0.621***	0.748***	0.770***
N	5132	4654	5132	4654

Note: The entries are odd ratios. The reference categories of the dependent variables are having no savings and having no debts respectively. The reference categories of the categorical independent variables in the models are year 1995, male, having a good financial situation, outright owner, has no second job, has no dependent child, not living with a partner, having a small household and employed respectively. * p < 0.10, ** p < 0.05, *** p < 0.01.

Amount of savings and debts

Table 3 shows that the amounts of savings and debts significantly depend on gender, age, financial situation, housing tenure, work status and income. For instance, mortgage payers have lower level of savings and debts than outright house owners ($\hat{b}_1$ = -0.096, p < 0.01; $\hat{b}_2$= -0.105; $\hat{b}_3$ = -0.124, p < 0.01; $\hat{b}_4$= -0.109). Also, income is positively correlated with the amounts held in savings and debts ($\hat{b}_1$ = 0.009, p < 0.01; $\hat{b}_2$= 0.009; $\hat{b}_3$ = 0.009, p < 0.01; $\hat{b}_4$= 0.008).

Turning to the differences amongst coefficients, regarding the amount of savings, having a second job is yet again significant in the first model but not in the second model ($\hat{b}_1$ = 0.038, p < 0.05; $\hat{b}_2$= 0.011, p > 0.10). Once more, the explanation for this is that the first model uses extra respondents and hence gains more precision for its estimates.

Considering the level of debts, once weights based on waves 1, 5, 10 and 15 are used to estimate the model, being financially okay, having financial deficits, and being unemployed are seem to be more significant ($\hat{b}_3$ = -0.040, $p < 0.05$, $\hat{b}_4$= -0.043, $p < 0.10$; $\hat{b}_3$ = -0.074, $p < 0.05$, $\hat{b}_4$= -0.102, $p < 0.10$; $\hat{b}_3$ = -0.092, $p < 0.01$, $\hat{b}_4$= -0.074, $p < 0.05$). Additionally, having a second job does not appear to be significant if estimated using weights based on all waves up to wave 15 ($\hat{b}_3$ = 0.071, $p < 0.05$; $\hat{b}_4$= 0.024, $p > 0.10$)

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Table 3: Random effects models of the amount of savings and debts

	Savings		Debts	
	Using weights based on waves 1, 5, 10, and 15	Using weights based on all waves up to wave 15	Using weights based on waves 1, 5, 10, and 15	Using weights based on all waves up to wave 15
Year 2000	0.008	0.007	-0.002	-0.008
Year 2005	-0.007	-0.013	-0.026	-0.020
Female	-0.045***	-0.040***	-0.226***	-0.224***
Age	-0.001**	-0.001**	0.006***	0.006***
Financially okay	-0.107***	-0.104***	-0.040**	-0.043*
Having financial deficits	0.035	0.039	-0.074**	-0.102*
Mortgage payer	-0.096***	-0.105***	-0.124***	-0.109***
Council tenant	-0.094***	-0.100***	-0.380***	-0.383***
Private renter	-0.048*	-0.062**	-0.183***	-0.185***
Having a second job	0.038**	0.011	0.071**	0.024
Having a dependent child	-0.018	-0.017	-0.014	-0.007
Living with partner	0.046***	0.047***	-0.010	-0.027
Having a large household	0.046	0.047	0.070	0.044
Unemployed	-0.006	0.005	-0.092***	-0.074**
Out of the labour force	0.058***	0.057***	0.027	0.032
Annual income/1000	0.009***	0.009***	0.009***	0.008***
Constant	-1.980***	-1.985***	0.836***	0.842***
N	5132	4654	5132	4654

Note: The dependent variables in all the models are transformed to the natural logarithm. The reference categories of the categorical independent variables in the models are year 1995, male, having a good financial situation, outright owner has no second job, has no dependent child, not living with a partner, having a small household and employed respectively. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In sum, the two models lead to similar results in showing no big differences between the coefficients in the two models. Thus it can be concluded that weight adjustments based on the respondents in waves 1, 5, 10 and 15, lead to similar results as weight adjustments based on the respondents at all waves up to wave 15, when analysing wealth data from waves 5, 10 and 15 from BHPS. However, the latter set of weights results in less accurate results for some of the estimates. This inaccuracy takes one of two forms:

(1) An independent variable is less significant or not significant at all due to the loss of some respondents in the sample (less precision).
(2) False magnitude of a regression coefficient (bias).

Conclusion

A longitudinal type of survey is the best design for a thorough understanding of the change in dynamic populations. However, like all surveys, a longitudinal survey must undergo a level of non-response that may annihilate its excellent reward. In recent decades, rates of non-response have risen in most survey research. Perhaps this is why survey researchers have become more wary about non-response and more convinced regarding the use of statistical weights to adjust for its negative consequences in terms of bias. In longitudinal surveys non-response is not a one-off event (Watson and Wooden, 2009) it is rather dynamic and can take different patterns among different sub-periods of time during the life of the panel. Therefore, non-response error can vary not just between survey estimates but also within and between sub-periods of times for the same estimate in the same survey. Consequently, different combinations of data collection points might suffer from different sizes of non-response error. This variation might be due to changes in the sample size and/or the sample composition among different combinations of waves. It might also be due to other factors associated with unobserved individual heterogeneity. Since it is impossible to take the latter into account when designing weight adjustments, the former should be borne in mind in order to tackle non-response more accurately. Thus, an ordinary weighting strategy, which does not take into account the changes in the responding sample between waves combinations, can only deal with the fixed part of non-response error. Instead, a subset of weights that takes into account the change in the responding sample can tackle the fixed as well as the variable part of non-response error.

The substantive comparison between the models in this paper shows that using ordinary longitudinal non-response weights - equivalent to the ones provided to BHPS users- to analyse wealth data from waves 5, 10 and 15 from the BHPS does not take into account 478 respondents who are present in this combination of waves. Compared to a weighting strategy that is designed specifically to consider these 478 respondents, the ordinary weighting strategy provides different results.

Weights from a single weighting strategy do take care of a part of non-response error on several estimates, but clearly fail in tackling the error introduced in other estimates due to the loss of information. Creating a set of weights for respondents in every possible combination of waves is not practical and may be unachievable sometimes, in particular if too many waves are conducted. But a limited number of subsets of weights could be produced for significant wave-combinations. The choice of these wave-combinations should be guided by a rule that takes into account two issues:

(a) The subsample drawn for analysis from any chosen combination of waves should be considerably different from the subsample in other wave-combinations.
(b) The selected combination of waves should be usable for analysis that achieves the objectives of the survey.

Otherwise the created subset of weights will not be of use because:

(a) It does not add information to the subsample used for analysis.
(b) It uses a subsample that is not of interest for analysts to construct an estimate from.

Designing weights specifically for a combination of waves of analytical interest evidently showed an impact on estimates.

Hence, this can be considered as a more adequate strategy. However, other features of longitudinal surveys may push for different types of considerations to be taken into account too. For example, to enhance the accuracy of survey estimates, survey organisations sometimes add extra information to the original sample. For instance, two samples (from Scotland & Wales) were added to BHPS in wave 9. Also, an additional sample (from Ireland) is added at wave 11. Thus, for BHPS, providing subsets of weights for waves 9 onwards and 11 onwards might be of interest.

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