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Non-response Subgroup-tailored Weighting: The Choice of Variables and the Set of Respondents Used to Estimate the Weighting Model

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Non-technical summary

Sample surveys are useful in studying large populations. The sample members are usually selected at random and in a way that they reflect all the important sub-groups in the population. This way, information obtained from the sample can be generalised to the population. However, most of the time, some of the selected sample members do not participate in the survey of which they are chosen to be part of. As this non-participation can negatively affect the results of the survey, survey researchers sometimes make some adjustments to the data provided by the participating sample members. The way the adjustment is made involves using factors, such as the gender and age of sample members, which are thought to influence whether they participate in the survey. The aim of the adjustment is to compensate for those who did not participate to improve the quality of the survey results.

This research looks into the current method applied in longitudinal surveys to make the non-participation adjustment. The current method uses all sample members together and looks at general factors that may cause them to participate or not participate. However, factors that influence participation/non-participation may be different for different types of sample members. For example, previous research has shown that, in general, white sample members are more cooperative with surveys than non-white. However, this might not be the case in a sub-group of highly educated sample members. In turn, other factors may only be influential to the group of highly educated persons. Thus, in this research I suggest an alternative approach to make the non-participation adjustment. My approach is based upon dividing the sample members into a number of sub-groups and looking for factors that influence members of each sub-group to participate/not participate independently. Accordingly, the adjustment is then made for each of the sub-groups separately. I find that this way of making the adjustment to compensate for non-participation leads to differences in some of the survey results compared to the currently used approach.

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Abstract

The use of the logistic regression model to predict the probability of response and create non-response weights is classic. In most cases, the model is estimated using socio-demographic variables and all units in the selected sample. However, substantive analyses are often restricted to a sub-group of the sample. This paper investigates whether weights are more effective if they are designed using variables correlated with the response propensity in the sub-group in question and sample units in the selected sub-group using data from the British Household Panel Survey (BHPS). The findings demonstrate that, for some estimates, the tailored weights results in significantly different results than the usual weights.

Key words

Non-response bias, Weighting variables, Well-being, Life satisfaction.

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1. Introduction

In recent decades, non-response has become a major concern amongst survey researchers since most surveys in the world have experienced a decrease in their response rate (Watson and Wooden, 2009; Särndal and Lundstrom 2005; Groves and Couper 1998). In longitudinal surveys, the worrying issue is that any increasing pattern of survey non-response may increase the difference between respondents and non-respondents to a sufficient extent that it can cause bias in survey-based estimates. There are two types of non-response. The first is *wave non-response* which refers to absence from the survey for at least one wave; the second is *attrition* which describes permanent drop out from the survey after participating in earlier wave(s) (Sadig, 2011; Chang, 2010).

Weighting is a means to tackle unit non-response problem at the analysis stage. In sample surveys, non-response weights are calculated using one of two approaches. The first is direct weighting classes. In this approach, the sample is divided into non-overlapping classes by using a few main variables, calculating the response rate in each class and then constructing the weight for each cell as the inverse of the response rate of the cell (Sadig, 2011; Biemer and Christ, 2008; Lynn, 2005). This weight will then be assigned to each sample unit in the class. The second approach involves estimating a logistic regression model to predict the probability of response and calculating the weights as the inverse of the model-estimated probabilities (Sadig, 2011; Biemer and Christ, 2008; Lynn, 2005; Grau *et al* 2006). In this paper, the discussion is limited to the modelling approach (i.e. the second).

In most cases, the model used to create non-response weights is estimated using a set of weighting variables (also known as Correlates of non-response) that is available for both respondents and non-respondents. It is necessary to use variables that are highly correlated with the survey target variables in order to produce a set of weights that is successful in reducing non-response bias. However, the extent to which the bias is reduced is also based on good specification of the model in terms of using variables that significantly explain the variation in the response propensity in all sub-groups in the sample. Otherwise, weights will not reduce non-response bias in estimates related to sub-groups where variation in response propensity either is not, or is poorly, accounted for by the weighting variables. Moreover, weights will only reduce non-response bias to the maximum possible extent if they are applied in an analysis that uses the set of respondents that provided the data to create the weights.

In longitudinal surveys, there are at least two ways of estimating the weighting model to create weights. Although both approaches aim at producing weights to reduce the bias that is potentially introduced by non-response, each has a different methodology. The first approach estimates a marginal weighting model at every wave. This model is defined based on the response status in the current wave conditional on response at the previous wave. The overall response propensity is then estimated as the product of the predicted values from each of the wave specific models. The second approach involves estimating one weighting model based on response in all the conducted waves (i.e. response= responding at all waves; non-response= not responding in at least one wave). Thus, both approaches define response as responding at all waves together up to the last one conditional on responding at wave 1. Both use the same set of sample members as the base (those who responded at wave 1) and the same set of respondents are defined as responding. The differences lie in the form of the model and the set of weighting variables. The first approach models non-response as a series of steps, while the second approach treats non-response as a single process. The first approach can use variables from the previous wave as covariates in each model, while the second approach can only use variables from wave 1. Both approaches create a set of weights that aims at reducing non-response bias in all estimates related to the relevant population. In other words, a single multi-purpose set of weights is produced. In this paper, any of these methodologies of weighting will be referred to as the 'standard weighting approach'.

However, non-response is known to be different in some sub-groups than others both in terms of its rate and reason. For example, when considering a survey that collects data from individuals belonging to different social classes, for a particular social class, say a social class that is formed of teachers and lectures, assumed that there is a rate of non-response amongst this group. This rate might be low compared to non-response rates in other sub-groups belonging to other social classes in the sample. This is because, individuals within academia may feel obligated to cooperate with the survey out of their academic scene of duty. In any case, in this example, it is likely that the factors responsible for non-response in the sub-group of teachers and lectures are rather different than the usual non-response predictors (such as age, race, sex and education), which could be more responsible for non-response in other sub-groups in the sample. Meanwhile, with teachers and lectures, variables such as age, race, sex and education might not explain much of the variation in the response propensity.

In the light of this scenario, consider a case in which a researcher would like to construct an estimate using only the set of teachers and lectures in the sample. However, because of non-response problem the researcher decides to use non-response weights to reduce any potential bias in the estimate in question. Thus, a model that is correctly specified to predict response probability in general which is based upon all sample units, using variables that may be strongly correlated with the response propensity in many sub-groups in the sample but weakly correlated with the response propensity in the sub-group of teachers and lectures, might result in producing weights that successfully reduce non-response bias in many survey estimates but not necessarily in estimates which are constructed using the set of teachers and lectures in the sample. With respect to any analysis that is restricted to this sub-group in the sample, weights would be more effective if the weighting model is:

a) Estimated to deliberately account for the variance in the response probability in the sub-group of teachers and lectures by using variables that strongly affect their response propensity regardless of whether or not they also affect the response propensity in other sub-groups in the sample.
b) Estimated using the set of teachers and lectures in the sample.

It can prove impossible in practice to fit one model to predict response propensity and be able to account for the variation in all sub-groups in the sample while using a particular sub-group of respondents to fit the model, especially if the weighting variables need to be associated with a number of the survey key variables. However, a number of weighting models can be estimated with an intention to: explain a larger amount of variance in response propensity in certain sub-groups in the sample (perhaps the main sub-groups in the sample which are more likely to be used for analysis); use a particular set of variables (rather than generic) which account for variation in the response probability in the sub-group under investigation; and use the same set of respondents that is intended to be used to construct estimates of interest. This way the weights can be more powerful in dealing with non-response bias in the sub-group under investigation. Moreover, if the created subsets of weights put together to form a general set of weights for all of the sample, the new weighting may also reduce non-response bias in estimates constructed based on the whole sample (total sample estimates). Applied research to date has not yet examined whether this approach of weighting can benefit analysis conducted on certain sub-groups or analysis based on the whole sample.

This paper investigates whether there is evidence to show that designing weights specifically for a given sub-group in the sample can significantly affect survey-based estimates to the extent that they become different from the estimates produced through the standard weighting approach. In this paper, the introduced method of weighting will be referred to as 'subgroup-tailored weighting' and weights produced from this method will be called 'tailored weights'.

The subgroup-tailored weighting will be done by taking into account two issues:

a) Designing the weights using variables that are thought to be associated with the response propensity in the sub-group under investigation regardless of whether or not these variables are also used in the standard weighting approach.
b) Designing the weights using the set of respondents that is used to construct the estimates in question.

Two sub-groups in the sample are selected to carry out this investigation. The investigation is based on conducting analysis using the tailored weights and then repeating the same type of analysis using weights from the standard weighting approach. Holding the analysis method constant and varying the weighting approaches will allow a comparison between the estimates resulting from the two weighting methods and therefore will enable one to refer to differences between the two methods of weighting.

2. The choice of sub-groups

The data used in this paper were from the first eight waves of the British Household Panel Survey (BHPS)[1]. The data cover the period 1991 to 1998. The analysis was restricted to those aged 16 or older at wave 1 and are not known to be ineligible at any stage before wave 8. The data were used at the individual-level. The analysis was carried out using STATA. Weights were designed to deliberately target non-response bias in estimates related to two sub-groups of respondents:

1) Those who retired in the year 1991 or before.
2) Those who were born in the year 1965 or after.

The first sub-group refers to the group of retired respondents. These are respondents who started the survey as retired individuals. Therefore, this sub-group does not include respondents who retired at a later wave (i.e. in any year from 1992 to 1998). The complement sub-group to this is respondents who were not retired at the start of the survey.

Since the analysis is restricted to respondents aged 16 or older, the second sub-group identifies respondents who were within the age group 16 to 26 at the start of the survey. Thus, the complement sub-group to this consists of respondents aged over 26 at the first wave of the survey.

Thus, this setting splits the sample into three non-overlapping sub-groups: 1) retired respondents; 2) respondents who were born in 1965 or after; and 3) non-retired respondents who were born before 1965 (i.e. the rest of the sample).

Based on the three non-overlapping sub-groups, three sub-sets of weight were designed. However, the tailored weighting focuses on retired respondents and those who were born in 1965 or after. Thus, two sub-sets of tailored weights were designed specifically for these two sub-groups. Each of these was designed using just its corresponding sub-group

[1] The BHPS has 18 waves. This paper uses data only from the first 8 waves since some of the variables used in the analysis are not available across all waves.

of respondents and a specific choice of weighting variables. As for the third sub-group (non-retired respondents who were born before 1965), a sub-set of weights was also designed. However, the creation of this used the same weighting variables as the standard weighting since the focus on tailored weighting is only on retired respondents and those who were born in 1965 or after. These three sub-sets of weights were combined together to construct an overall set of tailored weights. Section 3 explains the weights' construction process in details.

The methodology of the analysis in this paper involves using the set of overall tailored weights against the set of standard weights to analyse data from the selected sub-groups and data from the whole sample, and compare the resulting estimates. The investigation is based on the assumption that both the set of variables and the set of respondents used to create the tailored weights distinguish response from non-response in the relevant subgroup better than the variables and the set of respondents used in the standard weighting. The more this assumption applies to the data, tailored weights will tend to deal with non-response bias better than the standard weights.

One of the main problems in the analysis of non-response is that data on those who do not participate are unlikely to be available. This limits the choice of non-response predictors when analysing non-response in the sample or creating its weights. This paper only considers non-response conditional on responding at wave 1. In other words, those who did not participate in the first wave of the survey were ignored when estimating the weighting models. This allows the usage of the first wave as the base line for the investigation. Thus, a large number of variables would be available for every participant at wave 1.

3. Weights creation

3.1 Weights from standard weighting approach

Using a model-based method, standard non-response weights were created based on the responding status in all of the 8 waves together conditional on responding at wave 1. The response propensity was modelled using logistic regression. The dependent variable was a categorical variable with two categories indicating whether a respondent participated in all of the 8 waves or not. In other words, the paper uses the second approach of the standard weighting explained in section 1. This method guarantees the availability of information, from wave 1, for both respondents and non-respondents in the 8 waves, which is essential in modelling the response propensity. A number of continuous and categorical variables from wave 1 were used to estimate the model. These variables[2] were selected from three categories of variables: interview/interviewer condition/characteristics (e.g. interviewer's sex), household characteristics (e.g. household size and household type) and individual characteristics (e.g. age, sex and savings). These variables can be considered to be standard non-response weighting variables and are commonly used to predict response propensity in longitudinal surveys (Sadig, 2011; Uhrig, 2008; Nicoletti and Peracchi, 2005).

$$\text{Logit } (R_i) = f\ (\textstyle\sum_k I_k + \sum_{jk} H_{jk} + \sum_{ijk} D_{ijk} + \varepsilon_i) \tag{1}$$

Where:

$R_i \equiv$ Responding Status at the 8 waves.

$$R_i = \begin{cases} 1, & \mathit{if\ unit\ i\ responded\ in\ all\ of\ the\ 8\ waves} \\ 0, & \mathit{otherwise} \end{cases} \tag{2}$$

$I_k \equiv$ Interview/Interviewer condition/characteristics.

$H_{jk} \equiv$ Household characteristics.

$D_{ijk} \equiv$ Individual characteristics.

$\varepsilon_i \equiv$ Error term.

Table 1 shows the results of modelling the response propensity in the 8 waves through the logistic regression model. The table presents the odds ratios.

The results show that most variables have a significant effect on response propensity. For example, females are more likely to respond than males ($\hat{b}$ = 1.290, p < 0.001). In addition, respondents of a white ethnic origin tend to participate more than respondents of other ethnic origins ($\hat{b}$ = 1.917, p < 0.001). Bad health however, appears to be negatively correlated with the response propensity ($\hat{b}$ = 0.849, p < 0.001), indicating that individuals

[2] The variables are sex, age, ethnic group, region, health status, household size, presence of children in household, housing tenure, income, type of household, number in employment in household, education, employment, type of accommodation, presence of others during interview and the sex of the interviewer.

with better health have a greater tendency to respond. Also, homeowners are more likely to respond than non-homeowners ($\hat{b}$ = 1.231, $p < 0.001$), while an increase in age is negatively associated with survey participation ($\hat{b}$ = 0.993, $p < 0.05$). As for single-person households, this is negatively correlated with the response propensity ($\hat{b}$= 0.735, $p <$ 0.001).

These findings are in line with non-response theory. Studies have shown that survey participation is higher amongst women, respondents from white ethnic groups, homeowners and those with higher incomes; meanwhile response propensity is known to be low among respondents with bad health, single-person households and also among old people (Uhrig, 2008; Nicoletti and Peracchi, 2005; Nicoletti and Buck, 2004; Watson, 2003; Lepkowski and Couper, 2002; Fitzgerald *et al.*, 1998; Gray *et al.*, 1996; Becketti *et al*., 1988).

Table 1 Logistic regression model of the response propensity in the first 8 waves of BHPS.

	Model of response propensity for standard weighting
Female	1.290***
White	1.917***
Bad health	0.849***
Household size	0.959
Household with children dependent	1.294
Home owner	1.231***
Age	0.993*
Personal annual income/1000	1.100**
Number in employment in household	1.027**
Single person household	0.735***
Has GCE qualification or above	1.335**
Employed	1.021***
Having a second job	0.727***
Has no savings	0.0876**
Living in a flat	0.769***
Based in business premises	0.599
Living in a bedsit	0.168
Living in other housing type	0.839
Interviewed by a female	1.208**
Others not present when interviewed	0.862
Lives in South-East	1.002
Lives in South-West	1.070*
Lives in East Anglia	1.456*
Lives in the Midlands	1.088
Lives in the North	1.192
Lives in Wales	1.024
Lives in Scotland	0.792
N	10248
Pseudo R^2	0.074

Note: The entries are odd ratios. The reference categories of the categorical independent variables in the model are male, non-white, good health, household with no children, not a home owner, multi-person household, does not have a GCE or higher degree, unemployed, has no second job, has savings, living in a house, interviewed by a male, others present when interviewed and lives in London respectively. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Standard non-response weights were calculated as the inverse of the predicted probabilities from the model for each case in the sample.

$$w_{SWi} = 1/r_i \quad (3)$$

Where:

w_{SWi} ≡ Case i standard non-response weight.

r_i ≡ Predicted probability of response for the response propensity of case i from the model.

3.2 Weights for sub-groups

In this research, there are three non-overlapping sub-groups. These are: 1) retired respondents; 2) respondents who were born in 1965 or after; and 3) the remaining sample (RS) which consists of non-retired respondents born before 1965. The aim is to construct a sub-set of tailored weights for each sub-group and put together an overall set of tailored weights for the whole sample based on these three sub-sets of weights. The focus is on the sub-groups of retired respondents and respondents who were born in 1965 or after. The sets of variables used to create sub-sets of weights for these are somewhat different from each other and from the set of variables used in the standard weighting.

In other words, letting X_{SW} be the vector of weighting variables used in the standard weighting approach, and X_{RR}, X_{1965} and X_{RS} are the three vectors of weighting variables used to create subsets of weights for retired respondents, respondents born in 1965 or after and the remaining sample members (i.e. respondents who are non-retired or born before 1965) respectively. While X_{SW} and X_{RS} are identical, X_{RR} and X_{1965} are rather different from each other and from X_{SW}. Variables were included in X_{RR} and X_{1965} on the assumption that they are good predictors of non-response in the corresponding sub-group.

Suppose N_{RR}, N_{1965} and N_{RS} are the sets of respondents at wave 1, R_{RR}, R_{1965} and R_{RS} are the response outcomes and w_{RR}, w_{1965} and w_{RS} are the sub-sets of non-response weights in the sub-groups of retired respondents, those who were born in 1965 or after and the remaining sample respectively. The response outcomes for units in each sub-group can be identified as follows:

$$R_{RRi} = \begin{cases} 1, & if\ unit\ i\ in\ the\ sub-group\ of\ retired\ respondents\ responds\ to\ all\ of\ the\ first\ 8\ waves \\ 0, & otherwise \end{cases} \quad (4)$$

$$R_{1965i} = \begin{cases} 1, & if\ unit\ i\ in\ the\ sub-group\ of\ those\ born\ in\ 1965\ or\ after\ responds\ to\ all\ of\ the\ first\ 8\ waves \\ 0, & otherwise \end{cases} \quad (5)$$

$$R_{RSi} = \begin{cases} 1, & if\ unit\ i\ in\ the\ sub-group\ of\ the\ remaining\ sample\ responds\ to\ all\ of\ the\ first\ 8\ waves \\ 0, & otherwise \end{cases} \quad (6)$$

The aim is to use each of N_{RR}, N_{1965} and N_{RS} with X_{RR}, X_{1965} and X_{RS} to estimate each of R_{RR}, R_{1965} and R_{RS} and produce w_{RR}, w_{1965} and w_{RS} respectively.

The following three sections discuss the practical sides and results of implementing N_{RR}, N_{1965} and N_{RS} with X_{RR}, X_{1965} and X_{RS} to create the tailored sub-set of weights for each sub-group.

3.2.1 Retired respondents

A number of variables were used to fit the weighting model for retired respondents. Some of the variables that were used in the standard weighting model were dropped in this model; new variables were also added. This modification makes the set of variables used to estimate the weighting model for retired respondents similar to, but somewhat different from the set of weighting variables used in the standard weighting. Moreover, the weighting model was estimated using only the set of retired respondents. Thus, the weights for retired respondents are expected to be different from those from the standard weighting approach because both the model specification and the set of respondents (and hence the non-response process) used to estimate the model are different.

The results of the weighting model of the retired respondents are presented in table 2. The table presents odds ratios.

Dropped variables

1- Employment status: employment status is an important factor that predicts response propensity in the analysis of non-response because it is a good predictor of the probability of contact. Normally, those who are in full-time employment are more difficult to contact since they are less likely to be at home (Groves and Couper, 1998). However, employment status was dropped from the model in this case as all of the respondents used to estimate the model are retired.

2- Whether respondent has a second job: having a second job is associated with a low chance of contact. Those who have a second job usually spend limited time at home and this can negatively affect the contact attempts with the respondents (Uhrig, 2008). However, and similar to employment status, this variable was dropped from the weighting model of retired respondents.

3- Number in employment in household: in any survey that contacts sample members at their home, a successful contact attempt with any household depends on whether some (or at least one) of the household members are (is) actually at home to respond to the contact attempt. Thus, in this context, the number of household members in employment can be negatively associated with successful contact attempts. However, dealing with retired respondents guarantees that at least one household member is not in a full-time employment and hence the chance of a successful contact attempt is higher. Based on this guarantee, this variable was excluded from the weighting model of retired respondents.

Added variables

1- Religion: having a religion is considered as a form of social participation. While some research suggests that social participation can negatively affect the contact attempt –by affecting the at-home pattern- (Lepkowski and Couper, 2002), other research supports the idea that social participation is an indication of higher human interaction levels and therefore a person who is socially interactive is more likely to cooperate and provide data for the survey (Groves and Couper, 1998). As for the BHPS sample, Uhrig (2008) found that those who have religious beliefs are significantly more likely to respond than those who do not have religious beliefs. However, he found that this significant effect disappeared once organisational participation such as joining sport clubs and professional organisations is included in the model. This is because organisational participation is also an indicator of higher human interaction levels and hence survey cooperation. However, some of the organisational participations are more common among working-age respondents than retirees especially if they require a high load of physical activities and/or someone within the labour force. In this research, it was assumed that organisational participation such as joining sport clubs and professional organisations is more common amongst working-age respondents than their retired counterparts and hence it can only affect the significance of religion beliefs in the weighting models of working-age respondents. As for the retired respondents, religion can then be considered as a good predictor of non-response.

Religion was included in the model as a categorical variable with two categories: has a religion and does not have a religion (reference category).

Table 2 shows that those who have a religion are more likely to respond than those who do not have a religion ($\hat{b} = 1.193$, $p < 0.05$).

2- Respondent's energy compared to average at their age: the effect of this variable on response propensity can be viewed in two different ways. On the one hand, those who are more energetic than average at their age can be more mobile and are less likely to stay at home than those who have less energy. Thus, for surveys that make contact with respondents at their homes, it is more likely to find less energetic people at home than those with more energy. On the other hand, having less energy than average at their age may be associated with bad health conditions implying a lower level of cooperation or even refusal due to health conditions. Prior research on non-response suggests that refusal for health reasons is common amongst elderly respondents (Uhrig, 2008). For the sub-group of retired respondents (relatively old sample members), energy compared to average at the same age can be seen as an important indicator for both at-home pattern and health condition. Thus, whether or not this variable affects response propensity in the sub-group of retired respondents is worth investigation.

Accordingly, this variable was included in the weighting model of retired respondents as a dummy variable with three categories: has more energy compared to the average at the same age (reference category), has the average amount of energy for their age and has less energy compared to the average at their age.

As it can be seen from table 2, both those who have the same or less amount of energy compared to the average at their age are less likely to respond than those who have more energy compared to the average at their age ($\hat{b} = 0.782$, $p < 0.05$ and $\hat{b} = 0.698$, $p < 0.05$ respectively).

3- Whether respondent supports a political party: there is little research that has used political views and opinions to predict non-response since it is not clear that there is a direct relationship between the two factors. However, prior research on the nature and cause of non-response in the BHPS sample showed that those who do not support a political party are more likely to not respond to the survey (Uhrig, 2008). Furthermore, Groves and Couper (1998) implicitly indicate that those who have political views such as supporting a political party maybe more aware of the government's role in the society and therefore may feel more obligated to provide data for the survey. Some of the literature on political engagement suggests that it is less amongst working-age persons. One reason for this is that working-age respondents often do not have the time to engage with politics (Brandon, 2012). On the other hand, retirees do not often face time problems; instead, they have the time to participate in politics. In fact, retirees may feel the need to be socially interactive and therefore may participate in politics. Moreover, retirees could support and vote for a political party for reasons such as protecting the valuable benefits they receive from the government. Thus, based on the assumption that supporting a political party can influence response propensity and it is more frequent amongst retired respondents, this variable was included in the weighting model for retired respondents.

This variable was included in the model as a categorical variable with two categories: supports a political party and does not support a political party (reference category).

Table 2 shows that those who support a political party are more likely to respond than those who do not ($\hat{b} = 1.088$, $p < 0.05$).

4- Subjective financial situation: research on non-response has established the positive relationship between wealth/financial position and response propensity (Groves and Couper, 1998; Fitzgerald *et al.*, 1998; Lepkowski and Couper, 2002). That is to say, those who are in better financial positions are more likely to respond than those who are less well off. However, for the BHPS sample, the evidence for subjective financial situation is in contradiction with the general financial findings. Previous research on subjective financial position on BHPS has found that those who subjectively report themselves as being in better financial positions are less likely to respond than those who report themselves as being in worse financial positions (Uhrig, 2008). Nonetheless, the effect of subjective financial situation might change and confirm evidence from the general non-response literature once some sub-groups in the sample are controlled for (i.e. when the investigation is only done on retirees for example). For this reason, subjective financial situation was included in the weighting model of retired respondents.

BHPS measure the subjective financial situation by asking respondents this question "how well would you say you yourself are managing financially these days?" In turn, respondents have to report their financial situation by selecting one of these options: living comfortably, doing alright, just about getting by, finding it quite difficult and finding it very difficult. Rearranging these options by combining the second option with the third, and the fourth option with the fifth, subjective financial situation was included in the model as a categorical variable with three categories: having a good financial situation (reference category), financially okay and having financial deficits.

As expected, table 2 shows that, for retired respondents, those who have a good financial situation and those who are financially okay are more likely to respond than those who are having financial deficits. With those having good financial situation as the reference group, this result is presented in the table as: there is no difference in the response propensity between those who are in the reference category and those who are financially okay ($\hat{b}$ = 1.098, $p > 0.10$) while those who have financial deficits are less likely to respond than those with a good financial situation ($\hat{b}$ = 0.912, $p < 0.05$).

5- Having access to a car: having access to a car for personal use is considered –to an extent- as an indication of wealth and a good financial situation. In the BHPS, having access to a car was found to be predictive of maintaining survey response (Uhrig, 2008). As for retired respondents, having access to a car may also be thought of –to some extent- as an indicator of a good health (since driving a car require performing a set of physical acts that may not be possible to conduct with a bad health condition). Thus, this variable was included in the model under the assumption that it is indicative of good health status and good financial situation.

Having access to a car was included in the model as a categorical variable with two categories: has a car and has no car (reference category).

The results in table 2 show that retired respondents who have access to a car are more likely to maintain response than those who do not have access to a car ($\hat{b}$ = 1.046, $p < 0.10$).

Finally, table 2 also shows that the number of respondents used to estimate the weighting model for retired respondents is 1763. In the standard weighting approach the number of respondents used to estimate the model is 10248 (shown in table 1). This shows that the set of respondents used to estimate the weighting model for retired respondents differs from the one in the standard weighting approach both in terms of size and composition.

3.2.2 Those who were born in 1965 or after

Similar to estimating the weighting model for retired respondents, the weighting model for the sub-group of respondents who were born in 1965 or after was estimated by changing some of the weighting variables and by using the set of respondents who were born in 1965 or later. The results of the weighting model of those who were born in 1965 or after are also displayed in table 2.

Dropped variables

1- Age: age is an important factor in predicting non-response. The literature indicates that, in general, elderly people are more likely to refuse to participate in the survey than younger respondents (Groves and Couper, 1998; Lepkowski and Couper, 2002). However, other research suggests that the youngest respondents in the sample are more difficult to locate as they have a higher tendency to move house, and even if they are located, they are still difficult to contact because they are less likely to be at home (Stoop, 2005). This pattern is very common among the vast majority of younger sample members. In this research, respondents who were born in 1965 or after fell into the age group 16-26 by the time the first wave of BHPS was conducted. This age group forms the youngest age group in the sample. Preliminary analysis for this age group showed that age is not an important factor to predicting non-response in this age group. Thus, the weighting model for those who were born in 1965 or after was estimated without including the variable age.

2- Whether children in household: this variable was used to estimate the weighting model of the standard weights. It indicates that if there are children within the household. Regardless of whether these children are the respondent's own children (i.e. could be nephews, nieces, etc…), the presence of children in the household is associated with high levels of response. This is because the presence of children in the household indicates more social integration (e.g. taking the kids to school or nursery) and hence it is easier to locate and contact households with children than single-person households or households with no children (Groves and Couper, 1998; Uhrig, 2008). However, the weighting model of those who were born in 1965 or after includes a variable that measures the respondent's own children in the household. This variable somewhat substitutes for the presence of children in the household and therefore the latter was excluded from the weighting model of those who were born in 1965 or after.

Added variables

1- Liking the neighbourhood: this, in a way, expresses whether one is attached to one's current neighbourhood. The feelings of respondents about their settlement in a neighbourhood are indicative of whether they will continue to live in that neighbourhood, and hence of the likelihood of locating and contacting them successfully. In theory, younger respondents are more likely to move house (Uhrig, 2008). Thus, this variable was assumed to have a distinctive effect on the response propensity for those who were born in 1965 or after (younger respondents) compared to their other counterparts' sub-groups. Thus, this variable was added to the weighting model of this sub-group.

Liking the neighbourhood was included in the model as a categorical variable with two categories: likes living in neighbourhood and does not like living in neighbourhood (reference category).

As shown in table 2, those who like living in their neighbourhood are more likely to respond than those who do not like living in their neighbourhood ($\hat{b}$ = 1.321, $p < 0.05$).

2- School leaving age: it is well known that in the United Kingdom (UK) most people leave school at the age of 15 or 16. However, there are some exceptions where people may leave school at different ages, either aged less than 15 or more than 16. This may occur for example, due to coming to the UK at the age of six and having to start school a year or two later than the average starting age (five years old). Circumstances in which one has to leave school at a different age than the average person may affect one's tendency to participate in the survey. Regardless of the nature of these circumstances, their existence can be expressed through their school leaving age. In this paper, it is assumed that the effect of the circumstances associated with the school leaving age on survey participation fades over time. In other words, the effect is stronger at a younger age than at an older age. This is because living longer enables one to experience more life-events that may deactivate any influence on survey cooperation due to the reasons why they left school at a different age than the average person. Thus, the relationship between school leaving age and non-response maybe of more interest for those who were born in 1965 or after than for those who were born before 1965.

To measure this variable, BHPS sample members were asked the following question:

"how old were you when you left school"

In return, if not still at school, respondents reported the age at which they left school. The reported ages range between 9 and 22. These answers were categorised into three categories: left school aged 14 or below, left school aged 15 or 16 (reference category) and left school aged 17 or above. Additionally, those who are still in school form a fourth category of this variable "still in school". At the first wave of the BHPS, respondents who were born in 1965 or after are in the age group 16-26. Thus, those who fall in the category of "still in school" were aged 16+.

In table 2, it is shown that those who left school aged 14 or below are not significantly different in terms of survey response from those who left school age 15 or 16 ($\hat{b}$ = 0.874, $p > 0.10$). However, those who left school aged 17 or above and those who are still in school appear to respond less than those who left school aged 15 or 16 ($\hat{b}$ = 0.761, $p < 0.05$) and ($\hat{b}$ = 0.709, $p < 0.05$) respectively.

3- Having children: this measures whether the respondent has his or her own children within the household. Non-response theory suggests that the presence of children in the household is positively associated with survey response (Groves and Couper, 1998; Lepkowski and Couper, 2002; Uhrig, 2008). This is regardless of whether or not these children are the respondent's own children. Because, households with children are more settled and less likely to move house, and even if they move house, they are easier to relocate and contact since there are children in the household. This is especially important for younger respondents who are more mobile and less settled. Therefore, an item that measures if the respondent has their own children within the household for those who were born in 1965 or after (younger respondents) can be considered as a good weighting variable in the weighting model of this sub-group. This is because of its distinctive effect on the response process of those who were born in 1965 or after. Thus, in the weighting model of those who were born in 1965 or after, the general presence of children in the household was replaced with this variable.

In the BHPS data set there is a variable that refers to the number of the respondent's own children in the household. The value of this variable ranges from between 0 and 9. This variable was used to indicate whether the respondent has children or not. It was categorised into two categories: has their own children in household (by combining the numbers from 1 to 9 in one category) and does not have their own children in household (reference category).

Table 2 shows that those who have their own children within the household are more likely to respond than those who do not have children in the household ($\hat{b}$ = 1.340, $p < 0.05$).

4- Subjective financial situation: in the sub-group of retired respondents it was mentioned that the evidence for subjective financial situation in the BHPS is in contradiction with the general financial findings (in the BHPS those in better financial positions are less likely to respond than those in worse financial positions). However, testing this in the sub-group of retired respondents, gave evidence that is in line with the general financial findings. Thus, it is worth retesting the effect of subjective financial situation on the response propensity of those who were born in 1965 or after too. This might change and confirm evidence from the general non-response literature since other sub-groups in the sample are controlled for.

Thus, subjective financial situation was included in the weighting model of those who were born in 1965 or after.

Subjective financial situation was included in the model as a categorical variable with three categories: having a good financial situation (reference category), financially okay and having financial deficits.

Table 2 shows that there is no difference in the response probability of those who are financially okay and those with a good financial situation ($\hat{b}$ = 1.145, $p > 0.10$). However, those who have financial deficits are less likely to respond than those with a good financial situation ($\hat{b}$ = 0.899, $p < 0.01$). These results are similar to those of retired respondents indicating no difference in the response process of those who were born in 1965 or later and those who are retired with regard to the variable subjective financial situation.

5- Having access to car: aside from being indicative of wealth, having access to a car may have a distinctive effect on younger survey participants. It can be argued that having access to a car may affect the contractibility of younger respondents. Therefore, this was included in the weighting model of those who were born in 1965 or after.

Having access to a car was included in the model as a categorical variable with two categories: has a car and has no car (reference category).

The results in table 2 show that, for those who were born in 1965 or after, respondents who have access to a car are more likely to maintain a response than those who do not have access to a car ($\hat{b}$ = 1.105, $p < 0.05$). This result is also similar to the result from the model for retired respondents. However, the effect of this variable in this model is stronger ($\hat{b}_{1965}$= 1.105> $\hat{b}_{retired}$= 1.064).

Table 2 shows that the number of respondents used to estimate the weighting model for those who were born in 1965 or after is 1997 Note the number of respondents used to estimate the standard weighting model as shown in table 1 is 10248. Yet again, this reflects another difference between the standard weighting model and the weighting model of those who were born in 1965 or after, in terms of the set of respondents used to estimate the model.

3.2.3 The remaining sample (non-retired and born before 1965)

The set of weighting variables used to estimate the weighting model for the set of remaining sample units is the same as the weighting variables used in the standard weighting. However the model is only restricted to those who are non-retired and were born before 1965. Table 3 shows the results of modelling the response propensity in the 8 waves for the non-retired who were born before 1965. The results are similar to the ones from the standard weighting approach with regard to the variables affecting the response propensity. As can be seen from table 3 the number of non-retired respondents who were born before 1965 is 6488. This indicates a difference of 3760 from the set of respondents used to estimate the weighting model in the standard weighting approach.

Table 2 Logistic regression models of the response propensity for sub-groups in the first 8 waves of BHPS.

	Model of response propensity for retired respondents	Model of response propensity for those who were born 1965 or after
Female	1.013***	1.309***
White	1.511***	1.229***
Bad health	0.609***	0.876***
Household size	1.017	1.234
Household with children	1.510	-
Home owner	1.411***	1.290***
Age	0.909*	-
Annual income/1000	1.031**	1.033**
Number in employment in household	-	0.912**
Likes living in neighbourhood	-	1.321**
Single person household	0.783**	-
Has a religion	1.193**	-
Has GCE qualification or above	1.450*	1.072**
Employed	-	1.023**
Has same energy as people at the same age	0.782**	-
Has less energy than people at same age	0.698**	-
Left school aged 14 or below	-	0.874
Left school aged 17 or above	-	0.761**
Still in school	-	0.709**
Financially okay	1.098	1.145
Having financial deficits	0.912**	0.899***
Has their own children in household	-	1.340**
Supports political party	1.088**	-
Has no savings	0.820*	0.739**
Having a second job	-	0.844*
Has a car	1.046*	1.105**
Living in a flat	0.817***	0.799***
Based in business premises	0.912	0.933
Living in a bedsit	0.911	0.871
Living in other housing type	0.877	0.649

Note: The table is continued in the next page.

Table 2 (continued) Logistic regression models of the response propensity for sub-groups in the first 8 waves of BHPS.

	Model of response propensity for retired	**Model of response propensity for those who were born 1965 or after**
Interviewed by a female	1.120**	1.209**
Others not present when interviewed	0.845	0.790
Lives in South-East	1.040	1.072*
Lives in South-West	1.110	1.324**
Lives in East Anglia	1.208*	1.311***
Lives in the Midlands	1.087	1.082
Lives in the North	1.035	1.156*
Lives in Wales	1.340	1.202
Lives in Scotland	0.934	0.891
N	1763	1997
Pseudo R^2	0.078	0.079

Note: The entries are odd ratios. The reference categories of the categorical independent variables in the two models are male, non-white, good health, household with no children, not a home owner, does not like living in neighbourhood, multi-person household, has no religion, does not have a GCE or higher degree, unemployed, has more energy compare to people at the same age, left school aged 15 or 16, having a good financial situation, does not have their own children in household, does not support a political party, has savings, has no second job, does not have a car, living in a house, interviewed by a male, others present when interviewed and lives in London respectively. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3 Logistic regression model of the response propensity in the first 8 waves of BHPS for non-retired respondents who were born before 1965.

	Model of response propensity for non-retired respondents who were born before 1965
Female	1.370***
White	1.713***
Bad health	0.803***
Household size	0.932
Household with children dependent	1.486
Home owner	1.371***
Age	0.861*
Personal annual income/1000	1.070**
Number in employment in household	1.176**
Single person household	0.871***
Has GCE qualification or above	1.102**
Employed	1.091***
Having a second job	0.629***
Has no savings	0.751**
Living in a flat	0.609***
Based in business premises	0.830
Living in a bedsit	0.154
Living in other housing type	0.629
Interviewed by a female	1.520**
Others not present when interviewed	0.498
Lives in South-East	1.276
Lives in South-West	1.135*
Lives in East Anglia	1.097*
Lives in the Midlands	1.003
Lives in the North	1.041
Lives in Wales	1.087
Lives in Scotland	0.962
N	6488
Pseudo R^2	0.064

Note: The entries are odd ratios. The reference categories of the categorical independent variables in the model are male, non-white, good health, household with no children, not a home owner, multi-person household, does not have a GCE or higher degree, unemployed, has no second job, has savings, living in a house, interviewed by a male, others present when interviewed and lives in London respectively. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

The sub-sets of weights for the sub-groups in the analysis were then created as follows:

$$w_{RRi} = 1/r_{RRi} \quad (7)$$

$$w_{1965i} = 1/r_{1965i} \quad (8)$$

$$w_{RSi} = 1/r_{RSi} \quad (9)$$

Where

$w_{RRi} \equiv$ Tailored non-response weight of case i in the sub-group of retired respondents.

$w_{1965i} \equiv$ Tailored non-response weight of case i in the sub-group of respondents who were born in 1965 or after.

$w_{RSi} \equiv$ Tailored non-response weight of case i in the sub-group of non-retired respondents who were born before1965 (remaining sample).

And

$r_{RRi} \equiv$ Predicted value of the response probability of case i from the weighting model of retired respondents.

$r_{1965i} \equiv$ Predicted value of the response probability of case i from the weighting model of those who were born in 1965 or after.

$r_{RSi} \equiv$ Predicted value of the response probability of case i from the weighting model of the remaining sample.

Accordingly, an overall set of tailored weights (w_{TW}) for the whole sample was put together from the three sub-sets of tailored weights.

$$w_{TW} = w_{RR} \cup w_{1965} \cup w_{RS} \quad (10)$$

At this stage, there are two main different sets of weights. These are: 1) w_{SW} (standard weights); and 2) w_{TW} (tailored weights).

The analysis in this paper focuses on whether w_{TW} affects estimates produced from the sub-groups used to create this set of weights (retired respondents and those who were born in 1965 or before) and estimates based on the whole sample differently than w_{SW}. As mentioned earlier, assuming that the set of variables and the set of respondents used in the tailored weighting capture more variability in the response propensity, in the relevant subgroup, than the variables and respondents used to create the standard weights, w_{TW} would result in less biased estimates in comparison with w_{SW}. The analysis will be carried out to investigate the determinants of psychological well-being (for retired respondents and for the whole sample separately) and life satisfaction (for those who were born in 1965 or after and for the whole sample separately).

Accordingly, one is able to explore differences between the standard weighting and the proposed method of weighting by:

- estimating the models of psychological well-being with standard weights (w_{SW}) and then with tailored weights (w_{TW}) and compare the results from standard and tailored weighting.
- estimating the models of life satisfaction with standard weights (w_{SW}) and then with tailored weights (w_{TW}) and compare the results from the standard and tailored weighting.

Therefore, the analysis in this paper has eight models: four of these concern the investigation of the determinants of psychological well-being, while the other four investigate the determinants of life satisfaction.

Letting M_P and M_L denote the models for psychological well-being and life satisfaction respectively, the eight analysis models can be identified as follows:

psychological well-being

M_{PRSW} is estimated using retired respondents and standard weights (w_{SW}).

M_{PRTW} is estimated using retired respondents and tailored weights (w_{TW}).

M_{PHSW} is estimated using the whole sample and standard weights (w_{SW}).

M_{PHTW} is estimated using the whole sample and tailored weights (w_{TW}).

life satisfaction

$M_{L1965SW}$ is estimated using respondents born in 1965 or after and standard weights (w_{SW}).

$M_{L1965TW}$ is estimated using respondents born in 1965 or after and tailored weights (w_{TW}).

M_{LHSW} is estimated using the whole sample and weights from the standard weighting (w_{SW}).

M_{LHTW} is estimated using the whole sample and tailored weights (w_{TW}).

Comparisons between M_{PRSW} and M_{PRTW} (or $M_{L1965SW}$ and $M_{L1965TW}$) can reveal whether the tailored weighting results in different estimates based only on information from a sub-group; while comparisons between M_{PHSW} and M_{PHTW} (or M_{LHSW} and M_{LHTW}) disclose if tailored weighting also results in different estimates based on data from the whole sample.

Note that the BHPS provides a set of weights (w_D) for the sample to adjust for the differences in the selection probabilities and compensate for wave 1 non-response. This set of weights is considered as the set of design weights (or base weights). Thus, including w_D in the analysis will reduce bias that is due to unequal probabilities of selection and also wave 1 non-response. Accordingly, w_{SW} and w_{TW} were multiplied by w_D before using any of them in the analysis.

4. Analysis and results

4.1 Psychological well-being

Measure of psychological well-being

There is a range of variables that measures psychological well-being in the BHPS. But, the most appropriate variables are probably the ones that are available within the General Health Questionnaire (GHQ). This is because the GHQ variables are reliable measures of psychological well-being (Taylor, Jenkins and Sacker, 2011). These are 12 items and they are obtained by asking the following questions:

- Have you recently been able to concentrate on whatever you're doing?

- Have you recently lost much sleep over worry? *

- Have you recently felt that you were playing a useful part in things?

- Have you recently felt capable of making decisions about things?

- Have you recently felt constantly under strain? *

- Have you recently felt you couldn't overcome your difficulties? *

- Have you recently been able to enjoy your normal day-to-day activities?

- Have you recently been able to face up to problems?

- Have you recently been feeling unhappy or depressed? *

- Have you recently been losing confidence in yourself? *

- Have you recently been thinking of yourself as a worthless person? *

- Have you recently been feeling reasonably happy, all things considered?

Respondents are asked to rate each item on a four-point scale: better than usual, same as usual, less than usual and much less than usual. The codes assigned to each answer are 0, 1, 2 and 3 respectively. Questions marked as * are coded in reverse. The GHQ items are added together to construct a general score which measures the mental distress of the cases in the sample. This score is known as the likert score (or likert scale). The likert score ranges from 0 to 36. Low scores indicate high feelings of well-being; meanwhile, high scores indicate high stress. The likert score was used in this study as a measure of psychological well-being (dependent variable). The likert score was then categorised into two categories. It was assumed that scores from 0 to 18 refer to good psychological health while scores from 19 to 36 indicate bad psychological health. Accordingly, the likert score was turned into a categorical variable with two categories:

$$Likert=\begin{cases} 1, & if\ the\ score\ is\ between\ 0\ and\ 18\ this\ indicates\ good\ psychological\ health. \\ 0, & if\ the\ score\ between\ 19\ and\ 36\ this\ indicates\ bad\ psychological\ health. \end{cases} \quad (11)$$

Modelling psychological well-being

A random effects logistic regression model was used to investigate the determinants of psychological well-being for retired respondents and the whole sample separately. Psychological well-being is known to be associated with measures of wealth (such as income and financial situation), health (such as energy compared to others at the same age), cohabitation (such as whether living with a partner) and social interaction (such as supporting a political party and having a religion) (Taylor, Jenkins and Sacker, 2011; Kohler, Behrman and Skytthe, 2005; Ryan and Frederic, 2006). The variables used to model psychological well-being were selected to correspond to these measures. Some of these variables were used to create the weights for retired respondents. These are financial situation, energy compared to others at the same age, religion, supporting a political party and having a car. Additionally, other variables such as time, gender and age were also included in the model for control.

Taking the standard weights and the tailored non-response weights into account, in total there are four models of the determinants of psychological well-being. These are:

M_{PRSW}: this was estimated using the set of retired respondents and w_{SW}.

M_{PRTW}: this was estimated using the set of retired respondents and w_{TW}.

M_{PHSW}: this was estimated using the whole sample and w_{SW}.

M_{PHTW}: this was estimated using the whole sample and w_{TW}.

Table 4 and table 5 present the results from modelling psychological well-being for retired respondents and the whole sample respectively. Both tables present odds ratios. 95% Confidence Intervals (CI) are presented for coefficients constructed through w_{SW}. CI will be used as a yardstick to check whether or not w_{TW} produces different results than w_{SW}. For example, if a coefficient constructed through w_{TW} does not fall in the CI of the same coefficient constructed through w_{SW}, it can be argued that, for the relevant variable, w_{TW} leads to a significantly different coefficient. Thus, it can be concluded that using tailored weights instead of standard weights in the analysis can result in different estimates.

As can be seen from tables 4 and 5, across the four models, the majority of the variables have a significant effect on psychological well-being. For example, across the four models, those who have money in savings tend to have higher feelings of psychological well-being than those who do not have savings ($\hat{b}_{RSW}$ = 1.691, $p < 0.01$; $\hat{b}_{RTW}$= 1.533, $p < 0.01$; $\hat{b}_{HSW}$ = 1.915, $p < 0.01$; $\hat{b}_{HTW}$= 1.934, $p < 0.01$). However, those who have financial deficits show less feelings of psychological well-being than those with a good financial situation ($\hat{b}_{RSW}$ = 0.689, $p < 0.05$; $\hat{b}_{RTW}$= 0.618, $p < 0.05$; $\hat{b}_{HSW}$ = 0.727, $p < 0.05$; $\hat{b}_{HTW}$= 0.769, $p < 0.05$).

Turning to the comparison between the models and focussing on the models for retired respondents in table 4 first (M_{PRSW} and M_{PRTW}), two differences between the same estimates in M_{PRSW} and M_{PRTW} were found. These are:

Age: the coefficient on age in M_{PRTW} ($\hat{b}_{RTW}$ = 0.910, $p < 0.10$) falls out of the CI (0.687 – 0.905) of the equivalent coefficient in M_{PRSW} ($\hat{b}_{RSW}$= 0.749, $p < 0.10$) meaning that, for age, w_{SW} and w_{TW} result in two different coefficients. This result indicates that using tailored weights in the analysis of the sub-group of retired respondents rather than standard weights resulted in a significantly different estimate with respect to the variable age.

Living with a partner: in both M_{PRSW} and M_{PRTW} living with a partner is associated with higher feelings of psychological well-being than not living with a partner. However, using CI as a yardstick to compare the coefficients shows that the two coefficients are different. The coefficient in M_{PRTW} ($\hat{b}_{RTW}$= 1.932, $p < 0.05$) is bigger than the upper boundary of the CI calculated in M_{PRSW} (1.403 – 1.904). Yet again this results indicates that tailored weighting may significantly affect the magnitude of some of the estimates.

Focussing on the models for the whole sample in table 5 second (M_{PHSW} and M_{PHTW}), two differences were also found here. These are:

Has the same amount of energy as average at their age: similar to the case in the retired respondents sub-group, this variable shows a different coefficient in M_{PHSW} than in M_{PHTW}. The coefficient in M_{PHTW} ($\hat{b}_{HTW}$= 0.893, p < 0.05) is bigger than the upper boundary of the CI in M_{PHSW} (0.693 – 0.885).

Living with a partner: as expected, for both models, living with a partner is positively associated with psychological well-being. Nonetheless, it shows different coefficient with standard weights than with tailored weights as the coefficient in M_{PHTW} ($\hat{b}_{HTW}$= 2.207, p < 0.05) is out of the range of the CI in M_{PHSW} (1.606 – 2.180).

In sum, analysis using tailored weights produces similar estimates as standard weights. However, on some estimates tailored weights produce significantly different results. These results demonstrate that changes in the set of variables and the set of respondents upon which the weighting model is based in order to customise weights' construction, may have notable effect on the set of weights produced from the model. As a result, the tailored weights may significantly affect some of the coefficients by leading them to fall out of the boundaries of CI calculated based on the standard weighting. Furthermore, the tailored weights have an impact on estimates constructed both from the sub-groups used to create the tailored weights and from the whole sample.

Table 4 Random effects logistic regression models of the determinants of psychological well-being for retired respondents.

	M_{PRSW}	95% *Confidence Interval*		M_{PRTW}
Years 1995 to 1998	1.032	0.944	1.120	1.011
Female	0.814**	0.597	1.030	0.863**
Age	0.796*	0.687	0.905	0.910*[a]
Financially okay	1.582**	0.699	2.464	1.438**
Having financial deficits	0.572**	0.239	0.904	0.618**
Home owner	1.797**	1.057	2.536	1.327**
Has same energy as average at their age	0.865**	0.775	0.954	0.921**
Has less energy as average at their age	0.803**	0.371	1.234	0.742**
Living with a partner	1.654**	1.403	1.904	1.932**[a]
Has a religion	1.087*	0.851	1.323	1.046*
Supports a political party	1.012**	0.910	1.113	1.077**
Annual income/1000	1.492**	0.984	2.000	1.238**
Has a car	1.391**	0.730	2.051	1.119**
Has savings	1.395***	0.781	2.008	1.533***
N	1463	-		1463

Note: The entries are odds ratios. [a] indicates if a coefficient in M_{PRTW} falls out of the boundaries of the confidence interval calculated in M_{PRSW}. The reference categories of the categorical independent variables in the models are years 1991 to 1994, male, having a good financial situation, not a home owner, has more energy than the average at their age, not living with a partner, has no religion, does not support a political party, has no car and has no savings respectively. * $P < 0.10$, ** $P < 0.05$, *** $p < 0.01$.

Table 5 Random effects logistic regression models of the determinants of psychological well-being for the whole sample.

	M_{PHSW}	95% *Confidence Interval*		M_{PHTW}
Years 1995 to 1998	1.034	0.934	1.134	1.101
Female	0.962**	0.880	1.044	0.922**
Age	0.792**	0.433	1.151	0.752**
Financially okay	1.227**	0.937	1.516	1.251**
Having financial deficits	0.748**	0.569	0.926	0.769**
Home owner	1.028**	0.896	1.159	1.027**
Has same energy as average at their age	0.789**	0.693	0.885	0.893**[a]
Has less energy as average at their age	0.716**	0.324	1.108	0.579**
Living with a partner	1.893**	1.606	2.180	2.207**[a]
Has a religion	1.072*	0.885	1.259	1.044*
Supports a political party	1.054**	0.899	1.208	1.031**
Annual income/1000	1.609**	0.925	2.293	1.611**
Has a car	1.166**	0.878	1.453	1.102**
Has savings	1.915***	1.516	2.314	1.934***
N	6753	-		6753

Note: The entries are odds ratios. [a] indicates if a coefficient in M_{PHTW} falls out of the boundaries of the confidence interval calculated in M_{PHSW}. The reference categories of the categorical independent variables in the models are years 1991 to 1994, male, having a good financial situation, not a home owner, has more energy than the average at their age, not living with a partner, has no religion, does not support a political party, has no car and has no savings respectively. * $P < 0.10$, ** $P < 0.05$, *** $p < 0.01$.

4.2 Life satisfaction

Measuring life satisfaction

In the BHPS, respondents are asked to report a general level of life satisfaction on a seven-point scale starting from *not satisfied at all* to *completely satisfied*. However, this item is only available in waves 6, 7, 8, 9, 10, 12 … 17 and 18 (note: it is also not available in wave 11). The analysis in this section uses the BHPS longitudinal data (wave 1 to 8) to investigate the determinants of life satisfaction for those who were born in 1965 or after. Thus, to be able to achieve this, one should use a measure of life satisfaction that is available in all of the first 8 waves of the BHPS. Since this is not available, a measure of life satisfaction was constructed specifically for the purpose of this analysis.

The literature on life satisfaction identifies a number of life domains that contribute hugely to general life satisfaction. These are: financial position, health, job, family, social relationships and well-being (Kapteyn, Smith and Soetst, 2009). The BHPS has a number of variables spread over the period 1991 to 1998 (the first 8 waves) that can represent at least most of these domains. To produce a measure of life satisfaction, four main variables were used as they are thought to reflect the different domains of the variable of interest appropriately. These are: financial situation, health status, number of own children and the measures of well-being from the GHQ. The first two variables are self-reported and their levels are measured on a 5-point scale. Respondents are asked to rank their financial situation and health status using one of the following categories:

For financial situation: living comfortably, doing alright, just about getting by, finding it quite difficult and finding it very difficult.

For health status: excellent, good, fair, poor and very poor.

The codes assigned to these categories are 1, 2, 3, 4 and 5 respectively for both variables. This means that, for both variables, a low rank indicates a better financial situation and health status while a high rank suggests a worse financial situation and health status.

As for the number of own children, this is a continuous variable. It ranges from 0 (the minimum) to 9 (the maximum). Thus, this variable was categorized into five categories. These are: has no children, has a maximum of two children, has three or four children, has five or six children and has more than six children[3]. The codes assigned to these categories are 5, 4, 3, 2 and 1 respectively (note: they are coded in reverse). Lower codes indicate a large number of children while higher codes denote a small number of children. It is assumed that having children is associated with good feelings of life satisfaction. Thus, having more children contributes to an overall level of life satisfaction.

As for the fourth variable, the likert score from the GHQ was used as a measure of well-being. Low likert scores reflect good psychological health while high likert scores indicate bad psychological health.

Accordingly, it was assumed that good financial situation, good health status, a large number of children and a high feeling of well-being is associated with a high level of life satisfaction.

[3] The assumption here is that, with all other factors being held constant, the feelings of life satisfaction for those who have a similar number of children are the same but the feelings are different from those who have a different number of children. For example, those who have one child have the same feelings of life satisfaction of those who have two children; however, their feelings are different from those who do not have children at all.

To create a measure of life satisfaction from the four items, Principal Component Analysis (PCA) was carried out.

PCA is originally designed for interval data and it works better if the variables used to produce the components are approximately normally distributed (Hair *et al*, 1992). However, PCA can also be conducted on categorical data (Cornish, 2007). Also, PCA can be applied to data that are not normally distributed as it is robust to the assumption of normality.

Table 6 shows the result from the PCA. Results are displayed for the first three components.

The eigen values in the table represent the variances of the components and are ordered from the largest to the smallest. As can be seen from the table, the first component has a variance of 1.55 explaining 39.44% of the total variance. The second and third components have the variances of 0.98 and 0.84 explaining 24.94% and 21.37% of the total variance respectively. The first three components together explain about 85.75%of the total variance.

Table 6 also shows the loadings on each component. Looking at the loadings on the variables for the first component, excluding the variable number of children, the first component has similar size positive loadings. Thus, the first component distinguishes happiness and life satisfaction for number of children versus financial situation, health status and well-being feeling. The second component has positive loadings on all variables but with different loading sizes. This can be interpreted as overall life satisfaction. As for the third component, it has positive loadings on the number of children and financial situation and negative loadings on health status and well-being. Thus, it distinguishes between happiness and life satisfaction for the number of children with financial situation and health status with well-being.

Based on these results, the first three components were used to create the measure of life satisfaction since a large amount (85.75%) of the total variance is explained in this case.

$$LS_1 = 0.56*FS + 0.53*HS - 0.20*NC + 0.61*WB \quad (12)$$

$$LS_2 = 0.97*FS + 0.33*HS + 0.18*NC + 0.28*WB \quad (13)$$

LS_3 = 0.11*FS -0.71*HS +0.41*NC -0.16* WB (14)

Where

LS_1 ≡ Life satisfaction measure from the first principal component.

LS_2 ≡ Life satisfaction measure from the second principal component.

LS_3 ≡ Life satisfaction measure from the third principal component.

FS ≡ Financial situation.

HS ≡ Health status.

NC ≡ Number of children (categorised).

WB ≡ Well-being.

An overall measure of life satisfaction was constructed as the mean value of the measures of life satisfaction from the three components as follows:

$$LS = (LS_1 + LS_2 + LS_3)/3 \quad (15)$$

Where

LS ≡ Overall measure of life satisfaction.

Based on equation 15, LS is a continuous variable and it ranges from 0.73 to 15.53. Smaller values of LS indicate high levels of life satisfaction while its larger values reflect low levels of life satisfaction. However, for the purpose of the analysis in this paper LS was categorised into two categories. The first category was assigned the value LS_i= 1. It includes the values of LS from 0.73 to 8.13 (the median), and it indicates higher levels of satisfaction with life. The second category was assigned the value 0. It includes values greater than 8.13 indicating lower levels of satisfaction with life. Thus, the categorised LS can be identified as follows:

$$LS_i = \begin{cases} 1, & if\ respondent\ i\ is\ (relatively)\ satisfied\ in\ life. \\ 0, & otherwise. \end{cases} \quad (16)$$

The categorised version of LS was used as the dependent variable in this analysis.

Table 6 Variance explained by the first three principal components and their loadings.

	Component 1	**Component 2**	**Component 3**
Eigen value	1.55	0.98	0.84
Proportion of explained variance	39.44%	24.94%	21.37%
Cumulative proportion of explained variance	39.44%	64.38%	85.75%
Variables			
Financial situation	0.56	0.97	0.11
Health status	0.53	0.33	-0.71
Number of children	-0.20	0.18	0.41
Well-being	0.61	0.28	-0.16

Modelling life satisfaction

Similar to modelling psychological well-being, random effects logistic regression model was used to investigate the determinants of life satisfaction. The model was estimated for those who were born in 1965 or after and for the whole sample separately. The variables used to estimate the model were gender, home ownership, subjective financial situation, savings, education, having children, having a car, attachment to living neighbourhood, cohabitation status, school leaving age employment and income. Most of these variables were used to explain life satisfaction in prior research on global life satisfaction (Kapteyn, Smith and Soetst, 2009).

Taking the standard weights and the tailored non-response weights into account, in total there are four models of the determinants of life satisfaction. These are:

$M_{L1965SW}$: this was estimated using respondents who were born in 1965 or after and w_{SW}.

$M_{L1965TW}$: this was estimated using respondents who were born in 1965 or after and w_{TW}.

M_{LHSW}: this was estimated using the whole sample and w_{SW}.

M_{LHTW}: this was estimated using the whole sample and w_{TW}.

The results from modelling life satisfaction are displayed in table 7 for those who were born in 1965 or after and in table 8 for the whole sample. Both tables present odds ratios. As it was done in the analysis of psychological well-being, CI will be used to test whether or not coefficients arrived at via standard weighting and tailored weighting are actually different. CIs are presented only for estimates arrived at through standard weighting.

As can be seen from tables 7 and 8, across the four models, most variables predict life satisfaction significantly. For example, across the four models, women are less satisfied than men ($\hat{b}_{1965SW}$ = 0.791, $p < 0.05$; $\hat{b}_{1965TW}$= 0.821, $p < 0.05$; $\hat{b}_{HSW}$ = 0.708, $p < 0.05$; $\hat{b}_{HTW}$= 0.687, $p < 0.05$). However, those who are employed tend to have higher levels of life satisfaction than those who are not employed ($\hat{b}_{1965SW}$ = 1.024, $p < 0.05$; $\hat{b}_{1965TW}$= 1.115, $p < 0.05$; $\hat{b}_{HSW}$ = 1.321, $p < 0.01$; $\hat{b}_{HTW}$= 1.445, $p < 0.01$).

Regarding the comparison between the models and starting with the models for those who were born in 1965 or after ($M_{L1965SW}$ and $M_{L1965TW}$) which are presented in table 3.7, differences were also found. Based on confidence intervals, two coefficients in $M_{L1965TW}$ were out of the boundaries of the CI of the equivalent coefficients in $M_{L1965SW}$. These are: the coefficient on *"has children"* ($\hat{b}_{1965TW}$ = 1.627 $\notin$ CI= [0.995 – 1.580]); and the coefficient on *"likes living in neighbourhood"* ($\hat{b}_{1965TW}$ = 1.442 $\notin$ CI= [0.884 – 1.430]). These results are in line with the results from modelling psychological well-being confirming that tailored weights may produce different results than the standard weights.

Turning to models concerning the whole sample (M_{LHSW} and M_{LHTW}) which are presented in table 8, w_{TW} produced two coefficients that are different than the results arrived at through w_{SW}. These are: the coefficient on "*has children"* differs in M_{LHSW} than in M_{LHTW} in terms of magnitude. In M_{LHTW}, the coefficient is smaller ($\hat{b}_{HTW}$ = 0.982, $p < 0.05$) than the lower boundary of the calculated CI (0.996 – 1.580) in M_{LHSW}; and the coefficient on "*likes living in neighbourhood"* in M_{LHTW} ($\hat{b}_{HTW}$ = 1.511, $p < 0.05$) falls out of the boundaries of its CI in M_{LHSW} (1.090 – 1.482) indicating that w_{TW} resulted in a different estimates than w_{SW} for the same variable. Thus, these results suggest that tailored weights may also affect total sample estimates.

To sum up, using w_{SW} against w_{TW} to model both psychological well-being and life satisfaction suggests that the two sets of weights are similar in their overall effect on estimates. However, w_{TW} has a different impact on some estimates. Based on CI, these differences were proved to be significant since the relevant estimates constructed through w_{TW} fell out of the CI of the equivalent estimates that are constructed based on w_{SW}. Since the analysis method was held constant, such differences can only result because the values of the weights in w_{TW} are different than in w_{SW}. Therefore, this suggests that the steps introduced in this paper to create the tailored weights have produced a different set of non-response weights than the standard weighting approach. Assuming that the changes adopted in the tailored weighting (different sets of weighting variables and respondents) explain more variability in the response propensity than in the weighting model in the standard weighting, estimates resulted from w_{TW} are less biased than estimates produced from w_{SW}. Moreover, the tailored weighting has an impact on estimates constructed from a sub-group of the sample (the sub-groups used to create the tailored weights) as well as estimates based on the whole sample.

Table 7 Random effects logistic regression models of the determinants of life satisfaction for those who were born in 1965 or after.

	$M_{L1965SW}$	95% Confidence Interval		$M_{L1965TW}$
Years 1995 to 1998	0.825	0.459	1.190	1.090
Female	0.785**	0.532	1.038	0.821**
Home owner	1.134	0.867	1.401	1.097
Financially okay	0.870**	0.708	1.032	0.866**
Having financial deficits	0.720**	0.429	1.011	0.699**
Has savings	1.250**	0.719	1.781	1.210**
Has a GCE qualification or above	1.428	0.631	2.225	1.209
Has children	1.288**	0.995	1.580	1.627**[a]
Has a car	1.136*	0.626	1.645	1.176*
Likes living in neighbourhood	1.157**	0.884	1.430	1.442**[a]
Living with partner	1.446**	0.876	2.015	1.019**
Left school aged 14 or below	0.965*	0.636	1.293	0.939*
Left school aged 17 or over	0.816**	0.415	1.217	0.772**
Still in school	0.917*	0.655	1.178	0.866*
Employed	1.201**	0.574	1.828	1.115**
Annual income/1000	1.307**	0.603	2.011	1.211**
N	1615	-		1615

Note: The entries are odds ratios. [a] indicates if a coefficient in $M_{L1965TW}$ falls out of the boundaries of the confidence interval calculated in $M_{L1965SW}$. The reference categories of the categorical independent variables in the models are years 1991 to 1994, male, not a home owner, having a good financial situation, has no savings, does not have a GCE qualification or above, has no children, has no car, does not like living in neighbourhood, not living with a partner, left school aged 15 or 16 and unemployed respectively. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8 Random effects logistic regression models of the determinants of life satisfaction for the whole sample.

	$M_{L1965SW}$	*95% Confidence Interval*		$M_{L1965TW}$
Years 195 to 1998	1.074	0.827	1.321	1.103
Female	0.768**	0.588	0.947	0.687**
Home owner	0.837	0.693	0.980	0.877
Financially okay	0.836***	0.647	1.024	0.789***
Having financial deficits	0.679***	0.476	0.882	0.733***
Has savings	1.778**	0.947	2.608	1.642**
Has a GCE qualification or above	1.302	1.059	1.544	1.290
Has children	1.288**	0.996	1.580	0.982**[a]
Has a car	1.234***	0.821	1.646	1.121***
Likes living in neighbourhood	1.286**	1.090	1.482	1.511** [a]
Living with partner	1.136***	0.903	1.369	1.081***
Left school aged 14 or below	0.957**	0.674	1.240	0.818**
Left school aged 17 or over	0.854**	0.601	1.107	0.880**
Still in school	0.861**	0.623	1.099	0.787**
Employed	1.444***	0.981	1.906	1.413***
Annual income/1000	1.448***	1.003	1.892	1.445***
N	6753	-		6753

Note: The entries are odds ratios. [a] indicates if a coefficient in M_{LHTW} falls out of the boundaries of the confidence interval calculated in M_{LHSW}. The reference categories of the categorical independent variables in the models are years 1991 to 1994, male, not a home owner, having a good financial situation, has no savings, does not have a GCE qualification or above, has no children, has no car, does not like living in neighbourhood, not living with a partner, left school aged 15 or 16 and unemployed respectively. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5. Conclusion

In this paper an alternative procedure (subgroup-tailored weighting) to create non-response weights in longitudinal studies was investigated. Tailored weighting is based upon selecting certain sub-group(s) of respondents from the sample and designing weights particularly for this sub-group(s). In this procedure, weights are created using: a set of weighting variables that affect the response probability in the selected sub-group(s) whether or not it also affect the response probability in the rest of the sample; and just respondents from the sub-group(s) in question.

The findings in this paper can be summarised in three main points:

1. In the application presented here, the effect of tailored weighting on estimates is generally similar to that of standard weighting.
2. On some estimates, tailored weighting produces different results than standard weighting.
3. Tailored weighting affects estimates both from the selected sub-group and from the whole sample.

These findings suggest that the set of tailored weights is somewhat different than the set of standard weights. The difference emerged as a result of the different methodology that was followed to create the tailored weights. Changing the standard non-response covariates and restricting the weighting model to the sub-group for which the tailored weights are created resulted in a set of tailored weights that has different weight values than the standard weights. As a result, the tailored weights drove some estimates to differ from their equivalents in the models of standard weights. If both the changes in the non-response covariates and the set of respondents in the tailored weighting reflect the non-response process in the sub-group in question better than the standard weighting, the set of tailored weights can be said to handle non-response better than standard weights in the sub-group under investigation. Assuming this, based on the analysis here, seems to be reasonable.

Thus, estimating a model that best represents the non-response process in most sub-groups in the sample (by using the best set of covariates that explains most of the variation in the response probability) is the key to a successful weighting. However, and particular in longitudinal surveys where samples are larger and complex, a single weighting model may not always explain the non-response process well in all sub-groups and this is precisely why sub-group tailored weighting may be a good alternative.

The availability of a large number of auxiliaries in longitudinal surveys (possibly from wave 1) is advantageous. However, the whole process of non-response weighting, in our opinion, depends on an independent profound understanding of the non-response process in the major sub-groups in the sample rather than the number of variables included in a single weighting model. Even in the same survey sample, the cause of non-response may differ vastly across some sub-groups suggesting different sets of auxiliaries (both in terms of scale and type) for weighting. Thus, looking at the non-response reasons in the sample as a whole may lead to ignoring variables that may appear insignificant in general while they are in fact important to explain non-response in some sub-groups. The findings in this paper have demonstrated this.

For example, it is known that factors like ‘age’ are powerful weighting variable while factors such as ‘religion’ are weak predictors of non-response; though, the results in this paper showed the exact opposite. At first glance, it is hard to understand how a –well known- powerful auxiliary as ‘age’ could not be important in predicting response while a variable such as ‘religion’ is more significant. However, once the cause of non-response is understood at a sub-group level, it can all be explained. Thus, if this methodology of weighting applied in other studies, it is likely that similar findings can be arrived at.

With its possibility to estimate a number of weighting models, tailored weighting provides a unique opportunity for survey researchers to use the set of variables that best explains the variation in response in the equivalent sub-group, and hence improve the construction of non-response weights.

Therefore, in sample surveys, the issue of tailored weighting may need to be considered. However, in large longitudinal surveys this might be tricky. On the one hand, it is beneficial to customise weights’ production and produce a set of tailored weights based on a number of sub-groups. On the other hand, it is –to some extent- challenging for survey organisations that create and release weights for public use. This is because identifying the number of sub-groups that the tailored weighting should be based on maybe a subjective matter especially in large longitudinal survey samples where sub-groups maybe identified in a number of dimensions. However, it should be pointed out that the more sub-groups used to create tailored weights (bearing in mind that the relevant sample sizes should be large enough to estimate non-response well) the stronger the effect of the overall tailored set of weights will be. This way, each created tailored sub-set of weights will be responsible of adequately handling the bias in the relevant sub-group. In return, this requires more time and additional effort to create the extra sets of weights.

However, and more importantly, even if the number of the required sub-groups is accurately identified, survey organisations will face the problem of identifying “which specific sub-groups should be used for tailored weighting?” as this maybe a subjective matter too.

Sub-groups can be non-overlapping (e.g. the sub-groups used in the analysis of this paper). In this case, the sub-sets of tailored weights can be put together to form an Overall Set of Tailored Weights (OSTW). Therefore, the OSTW can be beneficial in analyses that target the whole sample or analyses restricted to sub-groups. However, the sub-groups selected for tailored weighting maybe overlapping (e.g. sub-groups of males, disabled and white respondents). In this case, producing a OSTW is not possible and hence the survey organisation may need to include a number of sets of tailored weights in the public data files. The number of these sets of weights depends on the number of the overlapping sub-groups. Thus, a future research may investigate a procedure that decides on:

- The number of sub-groups required for an effective overall set of tailored weights.
- Whether sub-groups should or should not be overlapped.
- Which specific sub-group should be selected for tailored weighting.

In any case, for survey organisations, subgroup-tailored weighting should be considered.

Finally, sub-sets of tailored weights are created using different sets of weighting variables than the variables usually used in the standard weighting approach (which uses general weighting variables that are correlated with the main variables in the survey). In return, researchers who are deciding between tailored weights and standard weights may want to pay attention to the set of variables used to create the tailored weights. This is because weights are also powerful in dealing with non-response bias if they are created using a set of variables that is strongly correlated with the main variable in the analysis (the dependent variable). Therefore, standard weights may also be a good choice if its weighting variables are more correlated with the dependent variable in the analysis. In this case it is a trade off between the known reward of the tailored weights and the relationship between the dependent variable and the weighting variables used to create the standard weights. Thus, if tailored weighting is considered, survey organisation may still want to keep standard weights in the public data files. Moreover, if a set of tailored weights is included in data set files, survey organisation should properly document the process of weights creation as well as clearly stating the variables used to create the weights.

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