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Methodological Lessons from the Pilot Longitudinal Survey on Debt Advice

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Non-Technical Summary

A large new survey has been suggested, to study how people manage debts, how these influence their lives, and to what extent formal advice is helpful. The survey would collect data from a sample of people at intervals over a period of months and years – a “longitudinal survey”. The survey would be challenging in several ways. Some of the major challenges would include how to recruit people to take part in the survey, how to persuade people to continue to take part once they have been recruited, how large the sample would need to be, and how best to identify the effect of advice.

To help understand how best to deal with these challenges, a pilot study was carried out. The pilot study was designed to help identify the best procedures to use on the new survey and to provide estimates of the sample size that would be needed. This paper presents methodological findings from the pilot study. Specifically:

- We estimate what proportion of the general population appear to be over-indebted and how this proportion varies between population subgroups (age groups, gender, regions of the country, working status, etc). This will help to determine the sample size needed for the new survey and how the sample should be designed.
- We investigate whether the proportion who are over-indebted depends on the method used to recruit the sample and if so, how. This will help to determine the most appropriate recruitment method for the new survey.
- We analyse “attrition rates” – the proportion of sample members who take part in the survey initially but do not continue to participate on future occasions. This will help to determine how much large the initial sample will need to be in order to provide enough people taking part on each occasion.
- We investigate whether the people who continue participating at each stage of the survey are systematically different from those who drop out. If they are, this could introduce bias to the survey estimates and some special measures may be needed to reduce the possible impact of this bias.
- In order to enable the effect of advice to be identified, a random proportion of over-indebted sample members were encouraged to seek advice. We investigate whether this randomised treatment had an effect on subsequent participation in the survey. Any effect could undermine the survey objectives, and statistical adjustment would be needed.

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Abstract

Relatively little is known about the micro-level dynamics of over-indebtedness and associated social, health and other outcomes, and the role of formal debt advice in this process. To rectify this, a large-scale longitudinal survey has been proposed. However, such a survey would face several challenges, notably in sample recruitment and retention and in statistical identification of the effects of debt advice. A medium-scale pilot survey was carried out in order to test survey procedures and obtain estimates of key parameters that would determine the sample size and design of the main survey. This paper reports the findings of the pilot.

Keywords: causality, encouragement design, indebtedness, response rates, sample recruitment, survey modes

JEL Classifications: C81, C83

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1. Introduction

In 2016, the Money Advice Service (MAS; now part of the Money and Pensions Service (MaPS)) commissioned a pilot longitudinal survey on debt advice (PLSDA). The purpose of the PLSDA was to establish the feasibility of a large-scale longitudinal survey of indebtedness, which would focus particularly on the role of formal debt advice in shaping long-term outcomes and identifying variation in outcomes by demographic groups, debt circumstances and channel of delivery of debt advice. The PLSDA was to inform the design of the envisaged main survey by assessing the suitability of the randomised encouragement design to provide a basis for causal analysis and estimating key parameters necessary to design the main survey and provide a basis to predict the required budget.

The survey was carried out under contract by a commercial survey agency with survey design and scientific guidance from the University of Essex and involved a large recruitment exercise (wave 1) carried out between October 2016 and February 2017, a randomised intervention in early 2017, and two further survey waves (waves 2 and 3) in autumn 2017 (September to December) and autumn 2018 (November 2018 to January 2019). The first wave (recruitment wave) used two survey modes; online omnibuses and face-to-face (F2F) omnibuses. The samples identified as eligible for wave 2 (i.e. screened in on the basis of wave 1 data as "over-indebted") were split in two groups; control and treatment. The treatment group received encouragement (in early 2017) to seek debt advice from formally recognised advice agencies. The encouragement took the form of letters and subsequent phone calls from advice professionals. The control group received no such encouragement.

The specific methodological questions addressed in this report are:

- What eligibility rates can be expected through asking screening questions of a general population sample? How might these vary by sample source and by demographic characteristics?
- What response rates can be expected at waves 2 and 3? How might these vary between treatment and control groups, by type and severity of debt, by sample source and by other sample characteristics?
- For any given starting sample size, what sample sizes of analytically-important subgroups are likely to be achieved? What proportion of a sample recruited in this way is likely subsequently to report various debt-related experiences and behaviours?

2. Methodological Background

This report examines the methodological implications of a longitudinal survey design. This type of survey combines both cross-sectional and time series dimensions, containing time series observations of a given number of units (Hsiao, 2007). In general, the same sample of units is interviewed at different points of time (waves), which provides repeated observations of the same measures. Therefore, with panel data we can observe dynamic and cross-sectional aspects of a problem (Frees, 2004). For instance, we can explore both the proportion of individuals over-indebted at different points of time as well as whether poor health follows periods of over-indebtedness or vice versa. Longitudinal data has some well documented benefits: it allows 1) controlling for time-invariant heterogeneity (Hsiao, 2007), i.e. omitted variables; 2) studying dynamics, i.e. understanding why individuals transition between different states (Longhi and Nandi, 2017); 3) establishing causality, since it allows to control from omitted variables and understand the order of the phenomena (Toon, 2000); 4) improving the efficiency of estimates (Hsiao et al., 1995), by having more variance (across time and individuals), etc.

Apart from the previously mentioned benefits of using panel data instead of repeated cross-sectional data, there are some potential drawbacks that must be considered. The sample structure of panel data is more complex, with multiple points of selection (nonresponse), resulting in a risk of changing selection bias. Individual panel members can drop out from the study (attrition), eroding the sample. If this attrition is not random for those variables and attributes that concern the survey estimates, these will be biased (Lynn, 2009). For instance, imagine that people that lose their jobs have a higher probability of moving and, with this, a higher probability of not being contacted for subsequent waves, e.g. because they do not communicate the new address. If losing a job is associated with being at risk of over-indebtedness, our sample will be biased: a lower proportion of our sample will be at risk compared to the target population of inference.

2.1. The study

For the first wave the objective was to select a representative sample of people over-indebted in the UK. Once this sample had been selected and some key information collected, the objective was to implement an experiment to encourage taking up debt advice. The project uses a randomised encouragement methodology. With this design, a group of people is identified who are facing debt problems, half of whom are selected at random and encouraged to contact a debt advice service, while the other half is not encouraged to do so. The outcomes of both groups are then tracked using subsequent waves of survey data collection. Three different fieldwork approaches were used to identify and recruit individuals for the study during the first wave:

- Kantar's face to face omnibus survey;
- Kantar's online omnibus survey;
- An ad hoc online survey recruited using Kantar's online panel provider (Lightspeed).

The inclusion of both face-to-face and online omnibus surveys was planned to allow testing of the relative viability and effectiveness of each of these data collection modes for the mainstage. The later addition of an online ad-hoc survey was not originally envisaged and was driven by the need to boost sample numbers in a relatively short space of time due to a problem in obtaining permission to access contact details from the online omnibus. Such permission was needed in order to be able to follow-up the recruited sample members for the intervention and subsequent survey waves. It was only after the completion of the online omnibus that it was discovered that the research team would not be given access to contact details held by the panel provider. The inclusion of the third fieldwork vehicle did, however, present an opportunity to collect further data on recruitment methods for the mainstage and assess the feasibility of another recruitment source for the mainstage. It also caused the wave one data collection to last longer than planned.

Furthermore, for wave 3 the survey agency changed from Kantar Public to BMG Research and participants had to agree to share their contact details with the new agency. Out of 1,081 respondents at wave 2, 298 were unwilling to share their details, making it impossible to re-contact them for wave 3. It is important to note some fundamental differences between online and face-to-face recruitment. Both the online omnibus and ad-hoc survey used sample from an online panel provider (Lightspeed). This is a panel made up of respondents who have agreed to take part in surveys in return for rewards. As the sample drawn is not randomly selected, quotas are put in place to ensure that the overall profile of the interviewed sample closely matches the GB national population. In contrast, face-to-face omnibus uses random location sampling conducted in-home using computer-assisted personal interviewing (CAPI) methodology. Each wave, an interviewer is allocated an area (typically a census output area) and asked to achieve a set number of interviews. Additional quotas are also used to ensure that the achieved sample is representative of the British population.

Eligible individuals completed a ten minute questionnaire which formed the wave 1 baseline for the study. The questionnaire collected a brief snapshot of their finances and use of debt advice agencies in the past. At wave 1 respondents were recruited to the study if they met the following criteria:

- They were classified as over-indebted according to two screening questions which MAS uses to define this. These questions assess whether keeping up with bills is a heavy burden and/or whether they are missing payments;
- They had not sought any debt advice in the previous 6 months;
- They agreed to be re-contacted for a wave two survey

The eligible sample recruited to the study was 2,025. This was then reduced to 1,939 once duplicates (different unique IDs) and respondents recruited from a sister panel were excluded (due to a permissions disagreement). Once the sample for wave two was collated, the sample of respondents was systematically stratified and randomly allocated to either the treatment or control group. Respondents in the treatment group received encouragement to seek debt advice. This took the form of three mailings (using direct mail, emails and texts) alongside proactive calls from debt advice agencies for those who agreed to receive a call in the wave 1 interview.

Members of the control received no communication after the wave 1 interview. The recruitment was carried out between October 2016 and February 2017 and the encouragement between February 2017 and April 2017. The second survey wave took place between September 2017 and December 2017 and the third survey wave between November 2018 and January 2019.

2.2. Sample

After selecting the panellists to contact for further analysis, waves 2 and 3 were conducted. Table 1 presents descriptive statistics of the eligible panellists at wave 1 and the respondent panellists for wave 2 and 3, conditional on their answers at wave 1. The variables selected to describe the sample are the ones that we will use for most of the analyses. Appendix A presents the definitions of each variable, as well as the recodings used to create some variables.

Table 1. Sample statistics for wave 1, 2 and 3 respondents

	Wave 1	Wave 2	Wave 3
Gender			
Male	35.9	34.2	33.9
Age[a]			
16-17	0.4	0.2	0.2
18-24	9.0	4.6	3.4
25-34	24.8	20.6	20.6
35-44	24.1	27.9	27.7
45-54	24.4	28.2	31.2
55-64	11.8	12.2	11.1
65+	5.5	6.2	5.9
Working Status			
Working full-time	39.1	37.0	41.0
Working part-time	18.8	19.9	20.3
Not working	42.0	43.1	38.7
Income			
<10,000	26.0	24.6	21.2
10,000-19,999	31.8	32.5	32.2
20,000-29,999	20.1	21.5	23.8
30,000-39,999	9.7	9.0	10.1
40,000-49,999	5.8	6.7	6.8
50,000-59,999	2.9	2.6	2.7
>60,000	3.7	3.3	3.2
Region			
North East	4.3	4.4	3.6
North West	11.5	12.8	13.8
Yorkshire	7.9	7.2	7.1
East Midlands	7.5	9.1	9.3
West Midlands	9.1	8.2	9.7
East of England	10.3	10.2	10.3
London	13.2	12.1	10.5

South East	12.6	12.3	13.2
South West	9.5	9.9	9.7
Wales	5.2	5.2	5.3
Scotland	9.1	8.8	7.4
Children in household			
Yes	42.4	41.6	41.7
Level of debt			
No debt	22.0	20.0	15.2
Up to 2500	36.5	36.9	36.6
+2500	41.5	43.1	48.2
Length of debt[b]			
Up to one year	75.1	74.0	74.2
More than one year	24.9	26.0	25.8
Type of debt			
High burden	42.0	45.4	43.1
Missing payments	35.6	33.0	35.2
Both	22.4	21.6	21.7
N	1939	1081	659

a. For age there are 11 individuals eligible that, for some unknown reason, did not have a valid age value
b. Variable length of debt just applies to those that said that missed some payment.

2.3. Objectives

In this section we assess the sample design of the PLSDA. We first study the eligibility rates for different subsamples. Eligibility means that a person is a member of the target population. The first wave of this survey was conducted as the recruitment stage, at which respondents were screened in on the basis of wave 1 data as “over-indebted”, as described above. We are interested in understanding how the proportion of individuals classified as over-indebted in general and for each subpopulation varies, for example how does the proportion of over-indebted individuals vary across regions? Knowledge of the overall eligibility rate, and whether and how it differs between sample sources, allows estimation of the starting sample necessary to locate any given desired sample size of eligible persons for the main study. This in turn has a large influence on the budget needed to carry out the main study. Furthermore, knowledge of variation in eligibility rates provides understanding of how the population of interest is distributed across subgroups.

Second, we will focus on the response rates across waves and, therefore, how different subgroups attrite from the sample. We consider as respondents those participants who answer all or part of the wave in question. The response rates are computed as the division of those answering at wave 2 or 3 by those eligible to be contacted after wave 1 (the potential respondents for those waves). In addition, attrition means that an individual leaves the panel and, thus, we do not observe him or her anymore. Besides, we study which variables are related to leaving the panel.

Third, we investigate how attrition might affect the representativeness of subsequent waves. If attrition happens entirely at random, we will lose sample size but the sample composition will remain unaltered, not affecting the capacity to infer from our results about the target population. However, if the attrition is systematic, i.e. related to a statistic of interest, this will bias the survey estimates. Hence, changes in estimates might not necessarily reflect real within-individuals change (from over-indebted to not), but rather a change in the sample composition.

Finally, since an experiment was conducted in the context of this longitudinal survey, we study whether control and treatment groups are comparable across waves and, if not, which implications this might have for the analysis of its results. Control and treatment groups are created at random, therefore, their sample distributions should be the same (conditional on the probability of being allocated to the treatment group). If the treatment intervention not only affects the variable of interest but also the propensity to attrite for some subpopulations, this could make control and treatment groups no longer comparable, since differences could be attributed to the change in the sample composition instead of the effect of the treatment. Therefore, we will conduct several analyses to assess whether control and treatment groups are still comparable in subsequent waves.

3. Results

3.1. Eligibility rates

We first present the eligibility rate for different subgroups. Eligibility means that a case is part of the target population. In our case, to calculate the eligibility rate we consider eligible those that met certain constrained conditions e.g. being over-indebted. Different conditions are imposed to being considered eligible: 1) being over-indebted, 2) not having sought debt advice during the last six months, 3) being willing to participate in a next wave and 4) giving all the information for being re-contacted. Only those meeting the four conditions were contacted in the following wave. For having a better idea on how eligibility is constructed, in Table 1 we report the different eligibility rates depending on how many constraints we impose (cumulative). Eligible 1 defines all those who comply with the first condition (being over-indebted), Eligible 2 defines those complying with the two first conditions, Eligible 3 those complying with the three first conditions and the ones in the Final eligible group are those complying with all the conditions.

The eligibility rate is computed as the ratio of those eligible to the total sample multiplied by 100. For the questions used to determine whether an individual was over-indebted or not, there was the option to answer “don’t know” or “refuse”. Hence, the eligibility status of the participants answering these options is unknown. When calculating the rate these are excluded from the numerator following the proportional allocation or CASRO method[1], indeed the method used in AAPOR's on-line response rate calculator. This approach slightly overestimates eligibility rates because it assumes that the unknown cases have the same attributes as the

[1] The proportional allocation or CASRO method assumes that the ratio of eligible to not eligible cases among the known cases, in this case participants respondent questions 1 and 2, applies to the unknown cases, in this case participants answering do not know or refusing to answer questions 1 and/or 2.

known cases. Therefore, the eligibility rates can appear higher because of the use of this method. In our case, however, the inflation is minimal. Eligibility rates are presented in general and for different subpopulations as the sample source, gender, age, etc. Chi-square tests are conducted for each of the eligibility rates. These test whether two variables are related in the population. In our case, for instance, the Chi-square test establishes whether being eligible is independent of the variables of interest (e.g. mode of data collection at the recruitment wave, gender, age). Therefore, we are formally comparing the actual frequencies of our sample with the expected frequencies if no relationship would exist between variables (same eligibility rates across subgroups). If the Chi-square test is statistically significant it means that the association between our variables is not 0 with a 95% confidence. Table 2 presents the eligibility rates for various subgroups and a chi-square test of the differences between the subgroups.

Table 2 shows that overall, 4.30% of the total sample was eligible for the next waves. Exploring how this eligibility rate is composed, we can see that 14.17% of our sample was considered over-indebted, 10.62% over-indebted and did not seek debt advice in the previous 6 months and 8.74% were also willing to be re-contacted. Thus, it is probable that without the problems related to obtaining contact information the eligibility rate would be higher, at levels of Eligibility 3.

Table 2 shows that, overall, eligibility rates significantly differ between subgroups. Regarding sample source, F2F has a significantly lower eligibility rate than the two online sources. This difference is especially high for Eligibility 1, which means that for the F2F general sample there is a much lower rate of over-indebtedness identified than with online recruitment. This may be explained by a real difference in the sample composition (more indebted people complete online surveys) and/or by mode effects such as social desirability (people are less likely to admit indebtedness in a FTF interview than in an online survey). Comparing the online sources we can see similar patterns. However, the final eligibility rate for the online omnibus is lower than for the online ad-hoc because of the unwillingness to share contact details. Regarding the demographic variables, women have a significantly higher eligibility rate, though the magnitude of the difference in the rate of indebtedness is modest. Besides, the middle age cohorts (from 25 to 54) present the highest eligibility rates, with younger and older cohorts displaying significantly lower rates. Here, the differences in indebtedness rates are much larger. In addition, participants working-part time have a significantly higher eligibility rate as well as those with children. Besides, eligibility rates also significantly fluctuate across regions, meaning that the distribution of over-indebted and, consequently, eligible individuals is related to where they live. For instance, we can see that there is a higher proportion of over-indebted individuals in London than in South East England. These results for region are broadly similar to the ones presented in other research commissioned by MaPS[2]. The average deviation is of +/- 2.1 percentage points, with London presenting the lowest deviation (0.68 more percentage points of over-indebted individuals in our survey) and Yorkshire the highest (4.5 less percentage points of over-indebted individuals in our survey).

[2] "Levels of over-indebtedness in the UK", at https://www.moneyadviceservice.org.uk/en/corporate/a-picture-of-over-indebtedness-in-the-uk

Table 2. Eligibility rates for different subgroups.

	Eligible1	Eligible2	Eligible3	Final eligible	n
Total	14.17	10.62	8.74	4.30	45,118
Mode (E1 $\chi2(2)$ = 2.0e+03; p= .00. E2 $\chi2(2)$ =.1.3e+03; p= .00. E3 $\chi2(2)$ = 1.4e+03; p= .00; Final $\chi2(2)$ = 558.93; p=.00)					
F2F	5.1	4.3	2.6	2.6	18,044
Online omnibus	20.0	14.1	12.2	3.2	14,449
Online ad-hoc	20.4	15.8	13.5	7.9	10,046
Gender (E1 $\chi2(1)$ = 18.28; p= .00. E2 $\chi2(1)$ = 42.44; p= .00. E3 $\chi2(1)$ = 57.35; p= .00; Final $\chi2(1)$ = 67.88; p=.00)					
Male	13.4	9.6	7.6	3.4	20,295
Female	14.8	11.5	9.6	5.0	24,793
Age[a] (E1 $\chi2(7)$ = .1.9e+03; p= .00. E2 $\chi2(7)$ = 1.1e+03; p= .00. E3 $\chi2(7)$ = 1.1e+03; p= .00; Final $\chi2(7)$ = 471.61; p=.00)					
16-17	8.4	7.1	4.7	1.4	591
18-24	17.7	12.6	9.6	3.8	4,585
25-34	22.5	16.0	13.4	6.3	7,549
35-44	20.0	14.9	12.7	6.4	7,229
45-54	16.9	13.1	11.2	5.9	7,998
55-64	9.5	7.7	6.3	3.4	6,815
65+	3.1	2.7	2.0	1.0	10,161
Working Status (E1 $\chi2(2)$ = 296.83; p= .00. E2 $\chi2(2)$ = 115.50; p= .00. E3 $\chi2(2)$ = 115.19; p= .00; Final $\chi2(2)$ = 26.26; p=.00)					
Working full-time	16.8	11.6	9.7	4.5	16,923
Working part-time	16.8	13.1	10.9	5.2	7,001
Not working/Other	11.2	9.1	7.3	3.9	21,194
Region (E1 $\chi2(10)$ = 103.40; p= .00. E2 $\chi2(10)$ = 44.41; p= .00. E3 $\chi2(10)$ = 31.99; p= .00. Final $\chi2(20)$ = 13.54; p=.20)					
North East	14.1	10.1	8.7	4.0	2,062
North West	15.5	11.7	8.6	4.1	5,353
Yorkshire	12.4	10.0	9.5	3.9	3,976
East Midlands	13.9	10.1	8.7	4.1	3,513
West Midlands	14.5	10.5	8.5	4.3	4,076
East of England	13.2	10.0	8.9	4.6	4,353
London	17.9	12.6	8.4	4.8	5,334
South East	12.2	9.3	6.1	3.8	6,414
South West	13.6	10.7	7.4	4.5	4,145
Wales	14.1	10.5	8.5	4.5	2,236
Scotland	14.1	10.8	8.7	4.8	3,656
Children in household (E1 $\chi2(1)$ = 933.01; p= .00. E2 $\chi2(1)$ = 425.39; p= .00. E3 $\chi2(1)$ = 395.42; p= .00; Final $\chi2(1)$ = 222.77; p=.00)					
Yes	22.3	15.5	13.0	6.6	32,657
No	11.1	8.8	7.1	3.4	12,461

Ho: Eligibility and variable are not related in the population

Test: Chi-square test

a. There are 11 individuals who did not have a valid value of age recorded. The analysis sample size is therefore reduced slightly for the analysis by age groups and also for the regression analysis reported below.

3.2. Response rates and attrition

Next, we study the response rates at waves 2 and 3. We consider respondents those participants answering all or part of the wave in question. The response rates are computed as the ratio of those answering at wave 2 or 3 to those eligible to be contacted after wave 1 multiplied by 100. However, for wave 3 the survey agency changed and participants had to agree to share their contact details with the new agency. 298 respondents were unwilling to share their details, making it impossible to re-contact them for wave 3. Hence, although those participants did attrite from the panel, the reasons were different than for those that opted out or did not respond to wave 3. To estimate the response rates without taking into account these endogenous problems, we decided to exclude these respondents when computing the response rates for wave 3 (similar to the CASRO approach). Therefore, we are assuming that those dropping out of the panel because of an unwillingness to share their contact details have the same ratio of response and non-response than those that did not drop out.

Response rates are presented overall and for different subpopulations such as treatment group, sample source, gender, age, etc. Table 3 presents the different response rates for waves 2 and 3, conditional on participation at wave 1, for each subgroup and chi-square tests of differences between the subgroups.

Table 3. Response and non-response rates at waves 2 and 3 for different subgroups conditional on interview at wave 1

	Wave2			**Wave 3**		
	Response	**Non-response**	**Base**	**Response**	**Non-response**	**Base**
Total	55.8	44.3	*1,939*	40.2	59.8	*1,641*
Mode	W2 $\chi2(2)$ = 89.18; p= .00			W3 $\chi2(2)$ = 161.88; p= .00		
F2F	37.4	62.6	*476*	13.2	86.8	*387*
Online omnibus	65.0	35.0	*466*	54.3	45.7	*403*
Online ad-hoc	60.2	39.8	*997*	45.7	54.3	*851*
Name error F2F[d]	W2 $\chi2(1)$ = 17.00; p= .00			W2 $\chi2(1)$ = 4.89; p= .03		
Yes	28.0	72.0	*232*	9.5	90.5	*200*
No	46.3	53.7	*244*	17.1	82.9	*187*
Experimental group (*unweighted*)	W2 $\chi2(1)$ = 1.74; p= .19			W3 $\chi2(1)$ = .04; p= .832		
Control	57.2	42.8	*975*	40.4	39.9	*819*
Treatment	54.3	45.8	*964*	59.6	60.1	*822*
Gender	W2 $\chi2(1)$ = 3.18; p= .07			W3 $\chi2(1)$ = 1.70; p= .19		
Male	53.1	46.9	*695*	38.1	62.0	*586*
Female	57.3	42.7	*1,241*	41.4	58.7	*1,052*

Age[a]	W2 χ2(6) = 119.89; p= .00			W3 χ2(6) = 1.3e+03; p= .00		
16-17	25.0	75.0	*8*	14.3	85.7	*7*
18-24	28.9	71.1	*173*	13.8	86.2	*159*
25-34	46.4	53.6	*478*	32.3	67.7	*418*
35-44	64.9	35.1	*464*	47.2	52.9	*386*
45-54	64.5	35.5	*471*	51.5	48.5	*398*
55-64	57.9	42.1	*228*	40.1	59.9	*182*
65+	63.2	36.8	*106*	48.2	51.9	*81*
Working Status	W2 χ2(2) = 5.01; p= .08			W3 χ2(2) = 2.00; p= .37		
Working full-time	52.7	47.3	*759*	40.5	59.5	*666*
Working part-time	58.9	41.1	*365*	43.1	56.9	*311*
Not working	57.2	42.8	*815*	38.4	61.6	*664*
Income[b]	W2 χ2(6) = 10.78; p= .095			W2 χ2(6) = 17.17; p= .009		
<10,000	53.2	46.8	*464*	34.6	65.4	*387*
10,000-19,999	57.7	42.3	*567*	41.9	58.1	*484*
20,000-29,999	60.0	39.8	*359*	47.8	52.2	*314*
30,000-39,999	52.0	48.0	*173*	41.0	59.0	*156*
40,000-49,999	65.1	35.0	*103*	51.8	48.2	*84*
50,000-59,999	50.0	50.0	*52*	37.8	62.2	*45*
>60,000	50.0	50.0	*66*	36.4	63.6	*55*
Region	W2 χ2(10) = 19.24; p= .04			W3 χ2(16) = 99.11; p= .00		
North East	57.8	42.2	*83*	36.4	63.6	*66*
North West	62.2	37.8	*222*	48.7	51.3	*187*
Yorkshire	51.0	49.0	*153*	35.3	64.7	*133*
East Midlands	67.6	32.4	*145*	52.6	47.4	*116*
West Midlands	49.4	50.6	*176*	40.3	59.8	*159*
East of England	55.3	44.7	*199*	40.0	60.0	*170*
London	51.2	48.8	*256*	32.4	67.6	*213*
South East	54.5	45.5	*244*	40.7	59.4	*214*
South West	57.8	42.2	*185*	42.7	57.3	*150*
Wales	56.0	44.0	*100*	42.2	57.8	*83*
Scotland	54.0	46.0	*176*	32.7	67.3	*150*
Children in household	W2 χ2(1) = .67; p= .41			W3 χ2(1) = 1.23; p= .27		
Yes	54.7	45.3	*823*	38.6	61.4	*929*
No	56.5	43.5	*1,116*	41.3	58.7	*712*
Level of debt	W2 χ2(2) = 5.54; p= .06			W3 χ2(2) = 22.45; p= .00		
No debt	51.2	48.8	*389*	29.7	40.9	*135*
Up to 2500	56.9	43.1	*647*	40.9	59.1	*313*
+2500	58.4	41.6	*735*	45.7	54.3	*548*
Length of debt[c]	W2 χ2(1) = .83; p= .36			W3 χ2(1) = .48; p= .49		
Up to one year	51.9	48.1	*800*	37.6	62.4	*702*
More than one year	55.1	44.9	*265*	40.2	59.8	*356*
Type of debt	W2 χ2(2) = 12.23; p= .00			W3 χ2(2) = 4.30; p= .12		
High burden	60.3	39.7	*814*	43.2	56.8	*657*
Missing payments	51.7	48.3	*690*	38.0	62.0	*610*
Both	53.6	46.4	*435*	38.2	61.8	*374*

Type of incentive	W2 χ2(1) = .00; p= .95			W3 χ2(1) = .43; p= .51		
£10 conditional	55.7	44.3	*968*	40.9	59.1	*828*
£5+5	55.8	44.2	*971*	39.4	60.6	*813*
Mailing design	W2 χ2(1) = .27; p= .61			W3 χ2(1) = .66; p= .42		
Normal	55.2	44.8	*968*	39.2	60.8	*817*
Inkpact	56.3	43.7	*971*	41.1	58.9	*824*

Ho: Response and variable are not related in the population
Test: Chi-square test

a. For age there are 11 individuals eligible who did not have a valid age value
b. Lower sample size since there is not information for the full-sample (nonresponse)
c. Variable length of debt just applies to those who said they missed some payment.
d. Only for the subsample of Face to Face participants

Overall, the response rate at wave 2 conditional on interview at wave 1 was 55.8%. For wave 3 this rate dropped to 40.2%. Focusing on the subgroups of interest, we can see that the response rates for wave 2 and 3 do not significantly differ between control and treatment group. However, differences between sample sources are highly significant. The response rates for F2F for both waves are considerably lower than for both online sources. For instance, at wave 3 only 13.18% of the eligible participants at wave 1 answered, compared to the 54.34% answering from the online omnibus. When we only focus on the F2F respondents and compare those that were affected by the name errors, we can see that there is a significant effect of this problem on the response rates. Those individuals that were affected by the name error have a significantly higher nonresponse rates, reaching a 71.98% for Wave 2 and a 90.50% for Wave 3. This consequently inflates the nonresponse for the F2F group. However, the nonresponse rates of those on the F2F group not affected by this error remain higher than those of the online groups.

Focusing on the demographic variables, age and region present significant differences between subgroups for both waves. Younger cohorts present significantly lower response rates, especially those younger than 25. Age at wave 1 is associated with the propensity to participate at waves 2 and 3, with younger respondents presenting lower response rates than older respondents. Therefore, the panel has a problem with retaining young respondents, which attrite at a higher extent than older respondents. Furthermore, response rates significantly vary across regions. At both waves 2 and 3, London and Yorkshire & Humberside have a significantly higher nonresponse rate. Besides, individuals from North West, South West and East Midlands present lower nonresponse rates for both waves 2 and 3.

Moreover, the different types of debt significantly differ in terms of response rate for wave 2. Participants who identified their debt as a “high burden” in wave 1 present a significantly higher response rate. However, although this pattern can also be observed in wave 3, the difference is no longer significant. Hence, for wave 3 the type of over-indebtedness is no longer related with answering or not the survey. Besides, individuals with no declared debt at wave 1 present a significantly lower response rate at wave 3, though not at wave 2. The decrease in response rate from wave 2 to wave 3 is important, which can indicate that respondents with no debt at all are not as interested in the survey as those with debts. Finally, two experiments carried out with the type of incentive and the design of the mailing do not appear to have had any effect on attrition rates: rates are not significantly different between the treatment and control groups of either experiment.

Furthermore, it is informative to check the response pattern from wave 2 to 3, and how it differs between sample subgroups. Non-respondents from wave 2 to 3 can be divided in two groups: those who actively opted out in wave 2, answering that they did not want to participate in further waves, and those who accepted to participate in subsequent waves but then did not participate when contacted at wave 3. Table 4 presents the proportion responding, not-responding and opting out. For time variant variables (e.g. age) values are taken from wave 2, for time invariant variables (e.g. sample source), values are taken from wave 1. Length of debt is not included since this was not asked at wave 2.

Table 4. Response rates at wave 3 for different subgroups conditional on interview at wave 2

	Response	**Non-response**		**Base**
		Non-response	**Opt out**	
Total[a]	81.7	15.4	3.0	*807*
Mode W2 $\chi2(4) = 74.61$; p= .00				
F2F	51.5	38.4	10.1	*99*
Online omnibus	89.8	8.6	1.6	*244*
Online ad-hoc	83.8	14.0	2.2	*464*
F2F name error[a] W2 $\chi2(2) = 2.93$; p= .232				
Yes	55.9	41.2	2.9	*34*
No	49.2	36.9	13.9	*65*
Experimental group W2 $\chi2(2) = 3.23$; p= .199				
Control	79.4	17.0	3.6	*417*
Treatment	84.1	13.6	2.3	*390*
Gender W2 $\chi2(2) = 4.14$; p= .126				
Male	83.7	12.2	4.1	*270*
Female	80.9	16.7	2.4	*533*
Age[a]* W2 $\chi2(10) = .22.10$; p= .015				
16-17	NO	NO	NO	*NO*
18-24	57.1	40.0	2.9	*35*
25-34	81.0	15.3	3.7	*163*
35-44	80.1	16.7	3.2	*221*
45-54	85.9	12.1	2.0	*249*
55-64	81.1	14.4	4.4	*90*
65+	87.8	10.2	2.0	*49*

Working Status W2 $\chi 2(6) = 8.82$; p= .184				
Working full-time	85.8	11.8	2.4	*288*
Working part-time	84.7	13.0	2.3	*131*
Self-employed	80.0	17.8	2.2	*45*
Not working	77.3	19.0	3.8	*343*
Region* W2 $\chi 2(20) = .26.22$; p= .159				
North East	75.0	21.9	3.1	*32*
North West	86.7	11.4	2.9	*105*
Yorkshire	78.3	18.3	3.3	*60*
East Midlands	85.9	11.3	2.8	*71*
West Midlands	91.4	8.6	0.0	*70*
East of England	81.0	15.5	3.6	*84*
London	74.2	20.4	5.4	*93*
South East	80.6	14.8	4.6	*108*
South West	86.5	10.8	2.7	*74*
Wales	87.5	10.0	2.5	*40*
Scotland	70.0	28.6	1.4	*70*
Children in household W2 $\chi 2(2) = 2.87$; p= .238				
Yes	79.8	17.7	2.5	*357*
No	83.1	13.6	3.3	*450*
Level of debt W2 $\chi 2(4) = 18.19$; p= .001				
No debt	74.0	19.6	6.4	*173*
Up to 2500	78.9	17.9	3.1	*223*
+2500	86.4	12.2	1.5	*411*
Type of debt W2 $\chi 2(6) = 13.20$; p= .040				
High burden	88.2	10.6	1.2	*148*
Missing payments	85.4	13.9	0.8	*130*
Both	75.7	21.6	2.7	*161*
No longer in debt	80.1	15.6	4.4	*366*
Type of incentive W2 $\chi 2(2) = .63$; p= .728				
10 conditional	82.7	14.6	2.7	*410*
5+5	80.6	16.1	3.3	*397*
Mail W2 $\chi 2(2) = .22$; p= .895				
Normal	81.0	16.0	3.0	*395*
Inkpact	82.3	14.8	2.9	*412*

Ho: Response and variable are not related in the population
Test: Chi-square test
a. Only for the subsample of Face to Face participants

Overall, the response rate at wave 3 conditional on interview at wave 2 was of 81.7%. Of the participants not answering wave 3, 3.0% opted out and 15.4% did not answer the survey after being contacted. Focusing on the subgroups of interest, we can see that the conditional response rates for wave 3 do not significantly differ between encouragement control and treatment group. However, differences between sample sources are highly significant. The response rate for F2F is more than 30 percentage points lower than for the online sources. Besides, a significantly higher proportion of F2F respondents opted out at wave 2. However, the difference between those affected by the name error is not significant in this case, pointing out that the difference mainly occurred between wave 1 and 2.

Focusing on the demographic variables, only age presents significant differences in response rate between subgroups. Younger cohorts (18 to 24) present significantly lower response rates. Moreover, the different types of debt significantly differ in terms of response rate. Participants with higher amounts of debt (£2500 or more) present higher response rates than those with lower or no debt. Besides, those with no debt opted out in a much higher extent than those with some type of debt. Again, this seems to indicate that individuals without debt find this survey less interesting and have a higher propensity to abandon the panel. Finally, no difference can be seen between the treatment and control groups of the experiments on the type of incentives and mailing design.

3.2.1. Determinants of attrition

Next, focusing on the determinants of leaving the panel (nonresponse/attrition) and to control for the confounding effect of third variables, logistic regression models of attrition at waves 2 and 3 were fitted, each conditional on participation at wave 1. The same demographic and substantive variables used in table 2 are used as independent variables with the exception of the F2F name error variable, which would have forced the model to focus only on the panellists recruited by F2F. The dependent variable is a dichotomous variable indicating nonresponse (1=Nonresponse, 0= response). Besides, respondents unwilling to share contact details with the wave 3 survey agency have been excluded from the wave 3 regression, so the analysis focuses on attrition for other reasons.

Table 5. Determinants of attrition at waves 2 and 3 conditional on interview at wave 1

	Wave 2	**Wave 3**
Treatment	1.13	1.09
Re-contact phone	1.02	1.15
Mode		
F2F	-	-
Online omnibus	.34**	.21**
Online ad-hoc	.33**	.24**
Male	1.10	1.17
Age	.96**	.96**
Work status		
Working full-time	-	-
Working part-time	.84	.95
Not working	.85	.83

Income		
<10,000		
10,000-19,999	1.20	.99
20,000-29,999	1.04	.73
30,000-39,999	1.24	.81
40,000-49,999	1.17	.94
50,000-59,999	2.93*	.165
>60,000	1.34	1.23
Region		
North East	-	-
North West	.51	.39*
Yorkshire	1.32	.76
East Midlands	.48	.39
West Midlands	.97	.57
East of England	1.04	.75
London	1.04	1.02
South East	1.00	.66
South West	1.08	.91
Wales	.76	.64
Scotland	.96	.98
Children	.74	.80
Level debt		
No debt	-	-
Up to 2500	.90	.61
+2500	1.01	.62
Length debt		
Up to one year	-	-
More than one year	.83	.86
Type debt		
High burden	-	-
Missing payments	-	-
Both	1.25	1.33
Type of incentive		
5+5	.92	1.02
Type of mailing		
Inkpact	.94	.93
Constant	13.76**	60.43**
Negelkerke R2	.15	.20
N	946	831

Notes: cell entries are odds ratios from a logistic regression model. Thus, for example the entry of 1.09 for 'treatment' at wave 3 indicates that the log-odds of being a wave 3 nonrespondent are increased by a factor of 1.09 for the treatment group, relative to the control group, after control for all other independent variables in the model; * p_value<0.05; **p_value<0.01

Table 5 shows that the effect of being in the treatment group on the risk of leaving the panel is not significant in waves 2 and 3. The variables that seem to affect this risk most strongly are the mode of data collection at the recruitment wave, and respondent age. Both online modes reduce the probability to attrite compared to Face to Face recruitment. At both waves, the probability to attrite significantly reduces with increasing age. In addition, living in North East England (relative to the North West) reduces the probability to attrite in wave 3, while those earning between £50,000 and £59,000 have a significantly higher probability to attrite at wave 2 than those with an income of less than £10,000. It can be seen that the variables having a significant impact in the logistic model are practically the same that presented significant bivariate associations with nonresponse in Table 2, except for the level of debt which is no longer significant. Therefore, after controlling for confounding factors the conclusions from Table 2 still hold, with the exception of the finding that level of debt does not affect attrition.

3.3. Attrition bias

Descriptive sample statistics for waves 1, 2 and 3 were presented in table 1. Now, to check whether attrition has introduced bias to subsequent waves, tests of proportions are conducted to assess if the differences between waves are statistically significant. A test of proportions is a test (prtest in Stata) that tests the equality of two proportions. In other words, a significant difference between proportions in two samples means that we can be 95% confident that the true difference in the populations represented by the samples differs from 0. In our case the population proportions can be thought of as the average proportions over repeated hypothetical replications of the survey.

Table 6 presents the proportion of participants in each subcategory at each wave (e.g. 22.0% of the wave 1 sample have no debts). Sample members are classified based on their answers at wave 1. Proportions at waves 2 and 3 are compared with the equivalent proportion at wave 1, using a test of proportions. If significant differences exist, it will mean that the proportions have changed from wave 1 to wave 2 or from wave 1 to wave 3 and, consequently, the composition of the sample has changed over waves (e.g. at wave 3 the sample has a lower proportion of people with no debt). If this happens, changes on substantive conclusions are harder to extract since differences between waves can be provoked by a modification of the sample composition instead of by a change in attitudes and behaviours. Therefore, if significant and meaningful differences exist between wave 1 and wave 2 or between wave 1 and wave 3, this will mean that attrition has significantly altered the sample composition. The analysis is based on wave 1 respondents, hence the findings should be interpreted as indicating the extent of attrition bias conditional on being willing to participate in wave 1 (not relative to the total eligible population).

Table 6. Tests of differences in sample statistics between wave 1, 2 and 3 respondents

	Wave 1	Wave 2	Wave 3
Gender			
Male	35.9	34.2	33.9
Age[a]			
16-17	0.4	0.2	0.2
18-24	9.0	4.6	3.4

25-34	24.8	20.6**	20.6*
35-44	24.1	27.9*	27.7
45-54	24.4	28.2*	31.2**
55-64	11.8	12.2	11.1
65+	5.5	6.2	5.9
Working Status			
Working full-time	39.1	37.0	41.0
Working part-time	18.8	19.9	20.3
Not working	42.0	43.1	38.7
Income			
<10,000	26.0	24.6	21.2*
10,000-19,999	31.8	32.5	32.2
20,000-29,999	20.1	21.5	23.8
30,000-39,999	9.7	9.0	10.1
40,000-49,999	5.8	6.7	6.8
50,000-59,999	2.9	2.6	2.7
>60,000	3.7	3.3	3.2
Region			
North East	4.3	4.4	3.6
North West	11.5	12.8	13.8
Yorkshire	7.9	7.2	7.1
East Midlands	7.5	9.1	9.3
West Midlands	9.1	8.1	9.7
East of England	10.3	10.2	10.3
London	13.2	12.1	10.5
South East	12.6	12.3	13.2
South West	9.5	9.9	9.7
Wales	5.2	5.2	5.3
Scotland	9.1	8.8	7.4
Children in household			
Yes	42.4	41.6	41.7
Level of debt			
No debt	22.0	20.0	15.2**
Up to 2500	36.5	37.0	36.6
+2500	41.5	43.1	48.2**
Length of debt[b]			
Up to one year	75.1	74.0	74.2
More than one year	24.9	26.0	25.8
Type of debt			
High burden	42.0	45.4**	43.1
Missing payments	35.6	33.0	35.2
Both	22.4	21.6	21.7
N	1939	1081	659

Note: * p_value<0.05; **p_value<0.01
Ho: Proportions are the same for wave 1 and wave 2 and 3
Test: Test of proportions
a. For age there are 11 individuals eligible who did not have a valid age value
b. Variable length of debt just applies to those that said that missed some payment.

Table 6 shows that, overall, few significant differences appear. However, we can see some interesting differences for age, income and debt related variables. First, for age there is a tendency of having significantly fewer young respondents (16 to 34) and more middle age participants (35-54). Therefore, for waves 2 and 3 the sample is significantly older than for wave 1. Second, for wave 3 the proportion of participants with incomes lower than £10,000 is 4.8 percentage points lower than at wave 1 and the proportion with no debt is 6.8 percentage points lower than at wave 1. Besides, the proportion of participants that in wave 1 had more than £2,500 of debts is 6.7 percentage points higher at wave 3. Therefore, the sample for wave 3 is composed of individuals with deeper debt problems. We may speculate that those with less prone debt problems were less motivated and interested in the survey and, after wave 2, decided not to participate again at a higher extent than those with deeper debt problems. Finally, for wave 2 there is a significantly higher proportion of individuals that only chosen "high burden".

However, it should be considered that the sample for wave 3 has been affected by the unwillingness to share the contact details with another agency. We are, thus, assuming that the nonresponse distribution of those unwilling to share contact details would be the same as for the willing ones. If we make this assumption the results for wave 3 should not be affected by the sharing contact details issue. However, if the nonresponse distribution is different between willing and unwilling (e.g. for the unwilling group women are more prone to respond than for the willing) the attrition bias for a scenario without this issue would be different. The problem in this case is that we cannot know how the unwilling would have behaved. Hence, without this problem happening results could be different or not, we need to assume the uncertainty.

3.5. Endogenous attrition for treatment and control

It is informative to study whether attrition is an endogenous phenomenon that differs between control and treatment groups. To study this, we must look at different things: 1) whether the attrition is different between treatment and control groups for the different subgroups. This would imply that, for some reason, people from a given subgroup (e.g. male) attrite at a higher extent when on the treatment or control group. 2) whether being in the treatment or the control group is associated with attrition. This would imply that the fact of being in the treatment group increases or decreases the probability to attrite. 3) whether the determinants of attrition and their impact vary between control and treatment group. If this happens it would imply that, for some reason, some participants' characteristics impact differently the propensity to attrite depending on whether the participant is in the control or the treatment group. 4) finally, if the sample compositions of the treatment and the control group statistically differ. If attrition does not affect differently treatment and control groups, this will be reflected in the fact that subgroup distributions are the same for control and treatment groups in all the waves. However, if this is requirement is not met, it will imply that because of attrition control and treatment groups are no longer comparable. In addition, for all analysis in this section we will consider the whole attrition, including those leaving the panel because of their unwillingness to share contact details.

3.5.1. Attrition differences between treatment and control

To check if attrition differs between control and treatment group, table 7 presents the attrition rates for control and treatment at both waves 2 and 3, overall and by different subgroups. The attrition rate for wave 3 is cumulative (all that have left the panel until that moment). Besides, since we are interested in the potential endogeneity introduced by the attrition in this study, we include those participants that left because of unwillingness to share contacted details with another agency. Several demographic and substantive variables are compared, all observed at wave 1. Tests of proportions have been used to assess the significance of the difference between treatment and control groups.

Table 7. Attrition rate at waves 2 and 3 for treatment and control group

		Wave 2		Wave 3		
		Control	**Treatment**	**Control**	**Treatment**	***n***
General		42.8	45.8	66.1	66.0	*1,939*
Mode						
	F2F	62.3	62.9	92.4*	86.3	*476*
	Online omnibus	33.3	36.6	51.7	54.3	*466*
	Online ad-hoc	38.0	41.7	60.0	61.6	*997*
Male						
	Male	45.2	48.7	65.8	70.1	*695*
	Female	41.3	44.1	66.1	66.1	*1,241*
Age[a]						
	16-17	100.0	100.0	100.0	100.0	*6*
	18-24	69.6	74.7	89.1	87.3	*171*
	25-34	52.6	57.6	70.1	73.2	*465*
	35-44	34.5	36.3	64.6	58.6	*460*
	45-54	33.9	36.1	55.1	55.2	*477*
	55-64	39.5	41.2	68.6	70.2	*238*
	65+	33.3	35.2	56.7	68.5	*141*
Work status						
	Working full-time	46.2	48.5	63.7	65.2	*759*
	Working part-time	40.7	41.5	63.8	62.8	*365*
	Not working	40.4	45.3	69.3	68.1	*815*

Income					
<10,000	43.9	49.2	70.8	71.4	464
10,000-19,999	41.2	43.5	66.6	61.6	567
20,000-29,999	36.5	43.5	55.6	61.2	359
30,000-39,999	47.6	48.3	60.7	65.2	173
40,000-49,999	35.2	34.7	55.6	61.2	103
50,000-59,999	55.2	43.5	72.4	60.9	52
>60,000	53.3	47.2	73.3	66.7	66
Region					
North East	33.3	52.6	73.3	68.4	*83*
North West	39.2	36.1	59.2	58.8	*222*
Yorkshire	46.8	51.4	73.4	64.9	*153*
East Midlands	32.8	32.1	58.2	57.7	*145*
West Midlands	51.7	49.4	65.2	62.1	*176*
East of England	40.7	47.8	64.0	67.3	*199*
London	51.9	45.7	77.5	68.5	*256*
South East	40.0	51.3	56.8**	72.3	*244*
South West	39.1	45.2	65.2	65.6	*185*
Wales	45.7	42.6	63.0	66.7	*100*
Scotland	42.4	50.0	72.8	71.4	*176*
Children					
Yes	45.5	45.2	68.4	64.7	*823*
No	40.8	46.2	64.3	66.9	*1,116*
Level debt					
No debt	47.6	50.3	76.2	76.0	*389*
Up to 2500	42.8	43.5	64.8	66.0	*647*
2500.0	39.2	44.1	59.2	60.5	*735*
Length debt[b]					
Up to one year	47.2	49.0	66.6	67.4	*800*
More than one year	43.2	46.4	66.4	67.4	*265*
Type of debt					
High burden	38.1	41.5	65.0	65.3	*814*
Missing payments	47.1	49.4	67.1	65.7	*690*
Both	45.4	47.4	66.7	67.5	*435*

Type of incentive					
10.0	41.8	46.9	63.6	66.4	*968*
5+5	43.8	44.6	68.5	65.6	*971*
Mailing design					
Normal	43.7	46.0	68.0	65.9	*968*
Inkpact	41.8	45.6	64.1	66.1	*971*

Note: * p_value<0.05; **p_value<0.01.
Ho: Attrition rate is the same for treatment and control group
Test: Test of proportions
a. For age there are 11 individuals eligible who did not have a valid age value
b. Variable length of debt just applies to those that said that missed some payment.

Table 7 shows that in general the attrition rate does not differ between the treatment and control group. The attrition rates only significantly differ for the F2F subgroup (sample source) in wave 3 and for the South East region. This implies that the proportion of people from the F2F sample source and from South East that attrite in wave 3 is not equal for the treatment and control group. Therefore, at wave 3 the proportion of people in the control group recruited F2F is higher than for those in the experimental. Further analyses have to be conducted (below) to understand if this can affect the comparability of control and experiment groups.

3.5.2. The effect of being in the treatment or the control group on attrition

To control for the confounding effect of third variables, logistic regression models of attrition at waves 2 and 3 were fitted, each conditional on participation at wave 1. Hence, this is the same model applied in table 4 but including those respondents that left the panel because unwillingness to share contact details. The same demographic and substantive variables used in Table 4 are used as independent variables. Besides, the agreement to being re-contacted by telephone has been included to control the unbalanced probability of inclusion in the treatment group (the probability depended only on this variable, so this fully controls for differences in the allocation to treatment). The dependent variable is a dichotomous indicator of nonresponse (1=Nonresponse, 0= response). With this logistic regression model we assess whether being in the control or the treatment group increases or decreases the probability of leaving the panel, which would indicate that the treatment is not only affecting the outcomes of interest but also the risk to attrite. Besides, there is the interest of seeing which variables are related to leaving the panel when including the unwilling respondents, and how this change from the results without the unwilling ones.

Table 8. Determinants of attrition in waves 2 and 3

	Wave 2	**Wave 3**
Treatment	1.09	1.09
Re-contact phone	1.03	1.40*

Mode		
F2F	-	-
Online omnibus	.31**	.21**
Online ad-hoc	.31**	.23**
Male	1.14	1.27
Age	.96**	.97**
Work status		
Working full-time	-	-
Working part-time	.79	.98
Not working	.79	.87
Region		
North East	-	-
North West	.53	.44
Yorkshire	1.29	.66
East Midlands	.44	.36*
West Midlands	.90	.53
East of England	1.06	.78
London	1.00	1.08
South East	.95	.58
South West	1.05	.83
Wales	.67	.74
Scotland	.93	.98
Children	.77	.82
Level debt		
No debt	-	-
Up to 2500	.85	.71
+2500	1.13	.63
Length of debt		
Up to one year	-	-
More than one year	.82	.91
Type of debt		
High burden	-	-
Missing payments	-	-
Both	1.19	1.40*
Type of incentive		
5+5	.94	1.12
Mailing design		
Inkpact	.97	.83
Constant	11.66**	30.18**
Negelkerke R2	.14	.17
N	981	981

Notes: cell entries are odds ratios from two separate logistic regression models. Thus, for example the entry of 0.96 for 'age at wave 2 indicates that the log-odds of being a wave 2 nonrespondent reduce by a factor of 0.96 for each additional year of age, after controlling for all other independent variables in the model; * p_value<0.05; **p_value<0.01

Table 8 shows that the effect of being in the treatment group on the risk of leaving the panel is not significant in waves 2 and 3. Hence, being in the treatment group does not significantly increase the probability of leaving the panel. The variables that seem to affect this risk are the mode of data collection, with both online modes reducing the probability to attrite compared to Face to Face. Besides, age significantly reduces the probability to attrite in both waves. In addition, living in East Midlands (instead than in North West) also reduce the probability to attrite in wave 3. Moreover, if we compare these results with table 4, we can appreciate that small changes can be appreciated when including the unwilling respondents. The significant variables remain the same, and the coefficients are overall similar. Hence, since the relationship between key participant's characteristics and nonresponse is similar with and without unwilling respondents, it seems that our assumption that willing and unwilling respondents are overall similar holds

3.5.3. Determinants of attrition for control and treatment groups

Next, we explore whether being in the treatment or the control group has different implications for sample composition at waves 2 or 3. Thus, we first focus on exploring whether differences exist between treatment and control groups in how respondents' characteristics affect the risk of leaving the panel. For each group, separate logistic regression models of attrition (cumulative) at waves 2 and 3 are fitted, each conditional on participation at wave 1. These models are the same in structure as for table 8, but run for control and treatment groups separately (thus, no group variable is included in the model). Several demographic and substantive variables were included in the models, all observed at wave 1. Results are presented in Odds ratios.

Table 9. Determinants of attrition from the panel in waves 2 and 3

	Wave 2		**Wave 3**	
	Control	**Treatment**	**Control**	**Treatment**
Re-contact phone	1.17	.95	1.33	1.07
Mode				
F2F	-	-	-	-
Online omnibus	.26**	.39**	.13**	.25**
Online ad-hoc	.26**	.41**	.17**	.30**
Male	1.28	.98	1.22	1.18
Age	.96**	.95**	.96**	.95**
Work status				
Working full-time	-	-	-	-
Working part-time	1.02	.73	1.27	.67
Not working	1.03	.75	1.06	.62

Income				
<£10,000				
£10,000-£19,999	1.55	.98	1.46	.71
£20,000-£29,999	1.08	1.04	.65	.70
£30,000-£39,999	2.16	.82	1.22	.53
£40,000-£49,999	1.69	.89	.94	.82
£50,000-£59,999	8.76**	1.23	4.52	.59
>£60,000	2.83	.85	3.44	.59
Region				
North East	-	-	-	-
North West	1.64	.18**	.50	.29
Yorkshire	4.34*	.49	1.44	.39
East Midlands	1.22	.22*	.45	.30
West Midlands	3.32	.38	1.08	.32
East of England	3.25	.47	1.28	.51
London	4.46*	.34	2.14	.53
South East	1.93	.72	.61	.77
South West	3.02	.49	1.43	.64
Wales	2.10	.35	.82	.51
Scotland	2.33	.50	1.38	.67
Children	.84	.66	.90	.66
Level of debt				
No debt	-	-	-	-
Up to 2500	.62	1.14	.50	.70
+2500	.61	1.37	.63	.58
Length of debt				
Up to one year	-	-	-	-
More than one year	.77	.92	.84	.87
Type of debt				
High burden	-	-	-	-
Missing payments	-	-	-	-
Both	1.17	1.30	.94	1.92*
Type of incentive				
5+5	1.15	.69	1.44	.71
Mailing design				
Inkpact	.93	.98	.81	.1.11
Constant	3.02	43.02**	25.03**	188.98**
Negelkerke R2	.21	.17	.27	.22
N	461	485	407	424

Notes: cell entries are odds ratios from four separate logistic regression models; * p_value<0.05; **p_value<0.01

As we can see, the mode of data collection has a significant impact on the attrition in waves 2 and 3, with both online modes reducing the probability to attrite compared to Face to Face. Besides, age significantly reduces the probability to attrite in both waves. In addition, some differences between treatment and control group can be found for wave 2, in terms of region and income, and for wave 3 in terms of type of debt. This implies that, for some reason, the variables related to attrition for control and treatment groups differ, which depending on the extent of the effect could indicate the introduction of some bias. We test in the next section whether this is the case.

3.5.4. Sample composition for treatment and control groups

To understand if attrition is affecting the composition of the treatment and the control group in a way that makes these significantly different, table 10 presents the marginal distribution for each group and a chi-square test of differences between the groups. If attrition does not affect differently treatment and control groups, this will be reflected in the fact that subgroup distributions are not significantly different between control and treatment groups in all the waves. However, if control and treatment groups significantly differ for some characteristics in waves 2 and 3, it will imply that because of attrition control and treatment groups are no longer comparable in anything related to these characteristics. For instance, if for wave 2 there are more people in debt in the treatment group than in control group, and for wave 2 we find that the proportion of people taking up debt advice is higher, this might not be entirely attributed to the treatment (being contacted). This is because taking debt advice might be related to being in debt; therefore, the difference might be produced by the treatment but also by the differential sample distribution.

Several demographic and substantive variables are compared, all observed at wave 1. The analysis is carried out separately for the wave 1 (reference), wave 2 and wave 3 responding samples.

Table 10. Tests of differences in sample distributions of treatment and control groups at waves 1, 2 and 3.

Percentage	**Wave 1**		**Wave 2**		**Wave 3**	
	Control	**Treatment**	**Control**	**Treatment**	**Control**	**Treatment**
Mode (W1 $\chi 2(2) = .15$; p= .928. W2 $\chi 2(2) = .26$; p= .878. W3 $\chi 2(2) = 4.93$; p= .085)						
F2F	24.2	24.9	16.0	17.0	5.4	10.1
Online omnibus	24.0	24.1	28.0	28.1	34.1	32.3
Online ad-hoc	51.8	51.0	56.1	54.9	60.4	57.6
Gender (W1 $\chi 2(1) = .17$; p= .680. W2 $\chi 2(1) = .19$; p= .667. W3 $\chi 2(1) = 2.11$;p= .15)						
Male	36.3	35.5	34.8	33.5	36.6	31.2
Age[a] (W1 $\chi 2(6) = 4.49$; p= .611. W2 $\chi 2(5) = 1.81$; p= 0.875. W3 $\chi 2(5) = 4.35$; p= .50)						
16-17	0.1	0.5	0.2	0.2	0.0	0.3
18-24	9.5	8.3	5.2	4.0	3.3	3.4
25-34	24.1	24.1	20.7	20.5	21.8	19.3
35-44	23.2	24.4	27.5	28.4	25.4	30.1
45-54	24.3	25.2	27.5	29.0	31.1	31.3
55-64	12.7	11.9	12.6	11.9	11.2	11.0
65+	6.2	5.6	6.5	6.0	7.3	4.6

Working Status (W1 χ2(2)= 1.44; p= .487. W2 χ2(2)= .97; p= .615. W3 χ2(2)= 1.40; p= .50)						
Working full-time	40.4	37.9	38.0	36.0	43.2	38.7
Working part-time	18.2	19.5	18.8	21.0	19.3	21.3
Not working	41.4	42.6	43.2	43.0	37.5	39.9
Income (W1 χ2(6) = 7.17; p= .305. W2 χ2(6) = 4.27; p= 0.641. W3 χ2(6) = 4.49; p= .61)						
<10,000	23.7	28.3	22.9	26.3	19.5	23.0
10,000-19,999	33.1	30.5	33.5	31.4	31.1	33.2
20,000-29,999	21.1	19.1	23.1	19.7	26.4	21.1
30,000-39,999	9.4	10.0	8.5	9.5	10.4	9.9
40,000-49,999	6.0	5.5	6.7	6.6	7.6	6.1
50,000-59,999	3.2	2.6	2.5	2.7	2.5	2.9
>60,000	3.4	4.0	2.7	3.9	2.5	3.8
Region (W1 χ2(10) = 9.92; p= .448. W2 χ2(10) = 9.70; p= .467. W3 χ2(10) = 9.72 ;p= .470)						
North East	4.6	3.9	5.4	3.4	3.6	3.7
North West	12.8	10.1	13.6	11.9	15.4	12.2
Yorkshire	8.1	7.7	7.5	6.9	6.3	7.9
East Midlands	6.9	8.1	8.1	10.1	8.5	10.1
West Midlands	9.1	9.0	7.7	8.4	9.4	10.1
East of England	8.8	11.7	9.1	11.3	9.4	11.3
London	13.2	13.2	11.1	13.2	8.8	12.2
South East	12.8	12.3	13.4	11.1	16.3	10.1
South West	9.4	9.7	10.0	9.7	9.7	9.8
Wales	4.7	5.6	4.5	5.9	5.1	5.5
Scotland	9.4	8.7	9.5	8.0	7.6	7.3
Children in household (W1 χ2(1) = .15; p= 0.702. W2 χ2(1) = .28; p= 0.597. W3 χ2(1) = .94; p= 0.333)						
Yes	42.9	42.0	40.9	42.5	39.9	43.6
Level of debt (W1 χ2(2) = 1.55; p= .460. W2 χ2(2) = 1.23; p= .540. W3 χ2(2) = .19 ;p= .907)						
No debt	23.2	20.8	21.1	18.8	15.8	14.6
Up to 2500	35.8	37.3	35.6	38.4	36.1	37.1
+2500	41.1	42.0	43.4	42.8	48.1	48.3
Length of debt[b] (W1 χ2(1) = .27; p= .605. W2 χ2(1) = .07; p= .795. W3 χ2(1) = .43 ; p= .512)						
Up to one year	75.8	74.5	74.5	73.5	75.7	72.7
More than one year	24.2	25.6	25.5	26.5	24.3	27.3

Type of debt (W1 χ2(2) = 3.26; p= .196. W2 χ2(2) = 2.20;p= .332. W3 χ2(2) = 1.34;p= .512)						
High burden	43.9	40.0	47.5	43.2	45.3	40.9
Missing payments	34.9	36.3	32.3	33.8	33.8	36.6
Both	21.2	23.7	20.3	22.9	20.9	22.6
Type of incentive (W1 χ2(1) = .00; p= .946. W2 χ2(1) = .34; p= .561. W3 χ2(1) = 1.10 ;p= .294)						
10 conditional	49.9	50.0	50.7	49.0	53.5	49.4
5+5	50.2	50.0	49.3	51.1	46.5	50.6
Mailing (W1 χ2(1) = .00; p= .982. W2 χ2(1) = .04; p= .841. W3 χ2(1) = .54; p= .461)						
Normal	50.0	49.9	49.1	49.7	47.1	50.0
Inkpact	50.1	50.1	50.9	50.3	52.9	50.0
n	975	964	558	523	331	328

a. For age there are 11 individuals eligible that, for some unknown reason, did not have a valid age value
b. Variable length of debt just applies to those that said that missed some payment.

No variable presents a significant difference in distribution between the treatment and control groups for any of the waves. Hence, for each wave treatment and control groups are comparable in terms of the key demographic and substantive variables analysed. Besides, attrition does not unbalance the comparability of both groups. This finding is rather reassuring, implying that treatment and control groups can be confidently compared at subsequent waves and that any differences found in outcomes can be ascribed to the treatment rather than being an artefact of differential attrition.

3.6. Sample proportions

In this section we present sample proportions of different debt-related experiences and behaviours. Most of these experiences and behaviours were asked in waves 2 and 3, thus, there is no data for wave 1. Contrary to other analyses, data is from each wave. Therefore, differences should not be interpreted as changes in the original composition but on people's attitudes and behaviours. The prime purpose of this analysis is to allow estimation of subgroup sizes likely to be available for analysis in the main study. For example, if a main study is designed to provide 2,000 respondents at wave 3, then we can estimate that around 774 of them will have high burden debt at that stage (2000 x 0.3869).

Table 11 shows that for wave 2 and 3 there is a significantly lower proportion of individuals considering that it is a high burden to keep paying the bills and missing payments than for wave 1. In addition, waves 2 and 3 present significantly higher proportion of individuals considering that their financial and economic situation is better now than 6 months before. Similarly, a significantly lower proportion of individuals reports experiencing some sort of financial difficulty (electricity cut, etc.) for waves 3 and 2 than for wave 1. However, the proportion of individuals owing more than £2,500 is significantly higher. In addition, a lower proportion in waves 3 considers that debt advice is for people like them.

In terms of variables only included in waves 2 and 3, we can see how in wave 3 a higher proportion of participants consider that they have their finances under control and have confidence with companies to which he/she own money. Contrary to what should be expected, a lower proportion of individuals reports having ever sought debt advice of any type and particularly fromfree agencies such as those funded by MAS (now MaPS).

Table 11. Sample proportions of debt-related experiences and behaviours

	Wave 1	Wave 2	Wave 3
High burden	64.98	**37.99**	**38.69**
Missing payments	58.75	**33.49**	**36.54**
+2500 pounds debts	41.50	**48.29**	**47.04**
Better financial situation	16.62	**27.66***	**32.63**
Agree that debt services for me	29.24	29.32*	**23.67**
Financial difficulties	66.37	**43.57**	**39.91**
Financial stress	-	37.93	33.33
Contact creditor	-	58.71	57.98
Contact other	-	4.15	6.16
Control finance	-	35.34**	44.16
Confident finance companies	-	23.22**	37.69
Sought debt advice ever	-	58.28**	39.45
Sought debt advice free agency	-	28.95**	13.20
Worried fees	-	5.83	4.25
Don´t know where to start	-	7.77	6.22
No suitable adviser	-	1.02	.61
Check MAS website	-	5.37	8.35
N	1939	1081	659

Note: * p_value<0.05; **p_value<0.01 in wave 2 column indicates significant differences between waves 2 and 3; **Bold** indicates significant difference <0.05 between wave 1 and wave 2 or 3.

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Appendices

Appendix A. Definition of variables used in the analysis

	Values	Question(S) W1	Question(s) W2/3	Comments
Mode	1=Face to Face 2= Online omnibus 3=Online adhoc	ModeW1		
Gender	0=Female 1=Male	0 if Gender==2 1 if Gender==1	0 if GenderW2==2 1 if GenderW2==1	
Age	1= 16-17 2= 18-24 3= 25-34 4= 35-44 5= 45-54 6= 55-64 7= 65+	Create a discrete variable using the variable Age	Create a discrete variable using the variable AgeW2	
Working	**Wave 1** 1= Working full-time 2= Working part-time 3= Not working / **Wave 2** 1= Working full-time 2= Working part-time 3= Self-employee 4= Not working	1 if Work_online==1 1 if Work_f2f== 1 2 if Work_online==2 2 if Work_f2f==2 3 if Work_online==3 3 if Work_f2f==3 3 if Work_f2f==4 3 if Work_f2f==5 3 if Work_f2f==6 3 if Work_f2f==7 3 if Work_f2f==8	1 if WorkstatW2==1 2 if WorkstatW2== 2 3 if WorkstatW2==3 4 if WorkstatW2==4 4 if WorkstatW2==5 4 if WorkstatW2==6 4 if WorkstatW2==7 4 if WorkstatW2==8 4 if WorkstatW2==9 4 if WorkstatW2==10 4 if WorkstatW2==11	The not working category comprises people not working and looking for job, not working and not looking for job, retired and still studying full-time.
Income	1= <10,000 2= 10,000-19,999 3= 20,000-29,999 4= 30,000-39,999 5= 40,000-49,999 6= 50,000-59,999 7= >60,000	1 if Q12==1 1 if Q12==2 2 if Q12==3 2 if Q12==4 3 if Q12==5 3 if Q12==6 4 if Q12==7 4 if Q12==8 5 if Q12==9 5 if Q12==10 6 if Q12==11 7 if Q12==12 7 if Q12==13 7 if Q12==14 7 if Q12==15		

Region	1= North East 2= North West 3= Yorkshire 4= East Midlands 5= West Midlands 6= East of England 7= London 8= South East 9= South West 10= Wales 11= Scotland	GOR		
Children in household	0= No children in household 1= Children in household	0 if Child==0 0 if Child==2 1 if Child==1 0 if kids_online==1 1 if kids_online>1 & kids_online!=.	ChildrenW2	
Level of debt	0=No debt 1= Up to 2500 2= +2500	0 if Q9==13 0 if Q9==14 1 if Q9==12 2 if Q9==1 2 if Q9==2 2 if Q9==3 3 if Q9> 3 & Q9<12	0 if Size_debtsW2==1 1 if Size_debtsW2==2 1 if Size_debtsW2==3 1 if Size_debtsW2==4 2 if Size_debtsW2> 4 & Size_debtsW2!=.	Amount of loans, overdrafts and credit agreements in their own name
Length of debt	1= Up to one year 2= More than one year	1 if Q3>= 1 & Q3<3 2 if Q3> 2 & Q3<7		Time missing these payment regularly
Type of debt	**Wave 1** 1= High burden 2= Missing payments 3= Both / **Wave 2** 0= No longer in debt 1= High burden 2= Missing payments 3= Both	1 if Q1==3 & Q2!=1 2 if Q1!=3 & Q2==1 3 if Q1==3 & Q2==1	1 if Burden_nowW2==3 & Arrears_6W2!=1 2 if Burden_nowW2!=3 & Arrears_6W2==1 3 if Burden_nowW2==3 & Arrears_6W2==1 0 if Burden_nowW2==1 & Arrears_6W2==2 0 if Burden_nowW2==2 & Arrears_6W2==2 0 if Burden_nowW2==4 & Arrears_6W2==2 0 if Burden_nowW2==1 & Arrears_6W2==3 0 if Burden_nowW2==2 & Arrears_6W2==3	Type of debt: if keeping with bills and credit commitments is a high burden, if they are missing payments and if these both conditions apply.
Type of incentive	1=10 conditional 2= 5+5	IncentiveExp		
Mail experiment	1= Normal 2= Inkpact	MailingExp		

Re-contact phone	0= Do not agree for their contact details to be passed to a financial advice organization 1= Agree	Q25		
Better financial situation	0= Not better financial situation now 1=Better financial situation now		0 if Finsat_nowW2==3 0 if Finsat_nowW2==4 0 if Finsat_nowW2==5 1 if Finsat_nowW2==1 1 if Finsat_nowW2==2	
Agree that debt services for me	0= Do not agree or strongly agree that debt advice is for me 1= Agree or strongly agree that debt advice is for me		0 if Q20_6 ==3 0 if Q20_6 ==4 0 if Q20_6 ==5 1 if Q20_6 ==1 1 if Q20_6 ==2	
Financial difficulties	0= Haven't experienced financial difficulties the last 6 months 1= Have experienced		0 if Fin_stressW2= 1 0 if Fin_stressW2= 2 0 if Fin_stressW2= 3 1 if Fin_stressW2= 4 1 if Fin_stressW2= 5	
Financial stress	0= Not finding difficult or very difficult to manage their finances 1= Finding it difficult or very difficult		0 if Fin_stressW2= 1 0 if Fin_stressW2= 2 0 if Fin_stressW2= 3 1 if Fin_stressW2= 4 1 if Fin_stressW2= 5	
Contact creditor	0= Not contacted the people or organization they owe money 1= Contacted		Creditors_contactW2_01	
Contact other	0= Not contacted debt advice agencies 1= Contacted		Creditors_contactW2_02	
Control finance	0= Does not feel more in control of their finance than past xx months 1= Feels more in control than 6 months ago		0 if ControlW2==2 0 if ControlW2==3 1 if ControlW2==1	

Confident finance companies	0= Does not feel more confident dealing with finance companies 1= Feels more confident than 6 months ago		0 if ControlW2con==2 0 if ControlW2con==3 0 if ControlW2con==4 1 if ControlW2con==1	
Sought advice ever	0= I have never sought advice 1= I have sought advice (any source)		1 if Debtadvice_everW2_1==1 (…) 1 if Debtadvice_everW2_10==1	
Sought advice free agency	0= I haven't sought advice from a free agency in the last 6 months 1= I have sought advice from a free agency in the last 6 months		Debtadvice_everW2_01	
Worried fees	0= Not worried 1= I do not seek advice because I am worried about the fees of the advice		Barriers_adviceW2_07	
Don´t know where to start	0= Not because I do not know where to start 1= I do not seek advice because I don't know where to start		Barriers_adviceW2_08	
No suitable adviser	0= Not because I couldn't find a suitable adviser 1= I do not seek advice because I couldn't find a suitable adviser		Barriers_adviceW2_11	
Check MAS website	0= During the last 6 months I haven't visited the MAS website 1= I have visited it		OnlinehelpW2_01	

Appendix B. Differences between Respondents Willing and Unwilling to Share Contact Details with a Different Survey Agency

	Willing	Unwilling
Mode		
F2F	11.37	29.87
Online omnibus	30.65	21.14
Online Adhoc	57.98	48.99
Age[a]		
18-24	4.34	4.71
25-34	20.05	17.17
35-44	27.33	27.95
45-54	31.16	22.22
55-64	10.98	18.86
65+	6.13	9.09
Children in household		
Yes	44.44	36.58
Level of debt		
No debt	20.69	32.21
Up to 2500	27.59	28.52
+2500	51.72	39.26
N	783	298

As we can see, willing individuals come in a lower proportion from F2F and in a higher from the online options. Hence, F2F respondents were significantly more unwilling to share contact details. In terms of age, unwilling respondents are older, presenting a significantly higher proportion of individuals from +55 years old than for the willing group. In addition, the unwilling group presents a significantly lower proportion of respondents having a child in the household. Finally, those unwilling to share contact details have lower debt problems, presenting a significantly higher proportion of participants with no debt at all.