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Respondents for Nearly Three Decades: How do loyal sample members differ from others?

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This paper aims to understand panel attrition by exploring response behaviour in longitudinal social surveys using a latent class framework and incorporating measures to account for unknown eligibility. From this, the characteristics of loyal sample members are identified and how they differ from others in the panel are highlighted. *Understanding Society* is a household panel survey that began in 2009, following its predecessor, the British Household Panel Study (BHPS). *The Understanding Society* harmonised BHPS project facilitates this research as it combines both studies such that there are 26 waves of data available. The existing literature on panel attrition is extensive but focuses on attritors that leave the panel completely, despite most panel studies allowing sample members to intermittently respond. Latent class analysis allows the study of atypical patterns of response by classifying respondents into groups based on similar response patterns. The key characteristics for loyal respondents are being older respondents (particularly pensioners), educated, and those from smaller household sizes, and lower reported household moves which is consistent with current attrition research.

Keywords: response patterns; attrition; latent class analysis; panel surveys; unknown eligibility

1 Introduction

Panel surveys are important for longitudinal research as the same individuals are studied over time, meaning that changes can be measured between and within them (Lynn, 2009). However, these surveys suffer from panel attrition; the loss of sample members due to factors such as refusals, moving out of the scope of the survey and death (Fitzgerald et al., 1998; Lugtig, 2014; Thomas et al., 2001; Uhrig, 2008). This is firstly an issue because it reduces the survey sample size, increasing uncertainties around survey estimates. Second, if some population sub-groups attrite more than others, survey estimates can deviate from the study population values (nonresponse biases), which can cause inferences about the population to be invalid.

Given these issues, panel attrition has been extensively researched, both to understand its causes and to attempt to reduce its impact on survey datasets. One aspect of this has been to quantify the correlates of attrition, with the aim of identifying sub-groups to target with intervention strategies to minimise attrition or so post-data collection adjustments can be made (Lynn, n.d., 2017; Uhrig, 2008). However, this research has primarily focused on scenarios in which survey members either respond to a wave or attrite completely (monotone attrition). In actuality, response behaviour in panel surveys is more complex than this, taking place over multiple survey waves, so that intermittent, non-monotone, response patterns are possible. Such patterns are potentially an additional source of information that could be used to identify likely attriting subjects so survey improvements can be attempted, but this cannot be studied using simple correlation or regression methods and have otherwise so far received limited attention.

Observed patterns of response over panel survey waves though, will also depend on factors other than subject interactions with the survey. First, how the survey organisation reacts to subjects not responding is important: some may try to get responses from all panel members at each wave irrespective of their previous behaviour, whereas, to reduce costs, others may stop trying to interview those thought unlikely to respond (for example, those not responding to more than one previous wave). Second, as mentioned in the first paragraph, subjects may also move out of the scope of the survey or die. While in many cases the organisation may be informed about these events (by other household members, for instance), in others they may not, which means it appears that the subject has permanently attritted. Hence, any proper consideration of subject response patterns in a panel survey must also account for survey design and the possibility that

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some attritors may instead have actually become ineligible for the survey.

This paper investigates sample members' patterns of response over survey waves in the British Household Panel Study (BHPS) sample of *Understanding Society:* the UK Household Longitudinal Study (UKHLS), a large longitudinal survey of UK population members (University of Essex & Institute for Social and Economic Research, 2019). The following research questions are addressed:

1. What are the patterns of response for the BHPS sample?
2. What are the characteristics of those that follow these patterns?
3. Specifically, how do loyal sample members differ from those who follow other response patterns?

By answering the above research questions, this paper will contribute further knowledge about attrition in the BHPS and UKHLS surveys (see also Uhrig, 2008), in efforts to maximise survey dataset quality by minimising (under-represented sub-group) panel attrition. Latent class analysis (LCA) is an analysis method used to quantify response patterns for individuals in the sample and therefore, can be used to highlight the way in which individuals participate in a longitudinal survey. By using LCA, this study will be able to distinguish between non-monotone and monotone attritors in the hopes that we can learn more about the causes behind these behaviours. In addition, given limited previous work and the fact that the BHPS sample has been studied for more than 25 waves, providing a dataset of rare quality, this paper will contribute to knowledge about (non-monotone) panel survey attrition and its remedies more generally. This study will also incorporate measures to account for unknown eligibility to ensure attrition estimates are as accurate as possible (H. E. S. A. Sadig, 2015; Watson, 2016). The findings could also contribute to global efforts to understand and reduce panel attrition as it could help to determine further subgroups that could benefit from targeted response inducement strategies that otherwise would not have been identified from focusing on monotone attrition (Lynn, n.d.). This paper will first review the relevant literature and outline the methodology for analysis. It will then identify the key patterns of attrition for the sample, use multinomial regression to examine the characteristics of those that follow those patterns and finally summarise the findings.

2 Literature Review

2.1 Correlates of Attrition in Longitudinal Surveys

There has been a considerable amount of research investigating nonresponse and attrition in panel surveys. Some studies examine attrition overall, and others adopt the framework that it can be divided into three processes, each stage conditional on the previous. Sample members have to be located, contacted and finally, be willing to cooperate and each of these processes have different propensities and covariates that affect them (Lepkowski et al., 2002). Findings suggest that demographic predictors, such as those who are male, young, single or students are less likely to respond, while being married or educated increases the likelihood to respond (Behr et al., 2005; Lemay, 2009; Lynn, 2020; Lynn et al., 2012; Meekins & Sangster, 2004; Rothenbühler & Voorpostel, 2016; Uhrig, 2008). Household factors such as living in an urban area, a rented property, or a flat decrease the probability of response (Branden et al., 1995; Lagorio, 2016; Lemay, 2009; Lynn et al., 2012; Meekins & Sangster, 2004; Uhrig, 2008; Watson & Wooden, 2009). Moreover, the presence of children in the household increases the likelihood of response and more specifically, the more children in the household there are, the more likely the respondent is to respond (Branden et al., 1995).

From a substantive point of view, studies show that factors indicating stability (such as, those who are older, married, homeowners, higher income, live in an accommodation with its own entrance) increase the likelihood of contact as these individuals may be less likely to move (Lagorio, 2016; Lemay, 2009; Uhrig, 2008; Watson & Wooden, 2009). Moreover, factors indicating availability (being retired) or the lack thereof (being employed, children in the household) can be related to whether a sample member is contacted and cooperates, depending on whether they are at home when the interviewer calls and whether they have the free time to participate (Behr et al., 2005; Lynn, 2020; Uhrig, 2008; Watson & Wooden, 2009). Factors suggesting vulnerability (low levels of education and income, unemployed, in poor health, divorced, elderly) decrease the likelihood of location and contact because they are more likely to move. They also may be less likely to respond, especially those who experience a combination of these factors or where the survey questions are related to these factors so are considered intrusive (Fitzgerald et al., 1998; Rothenbühler & Voorpostel, 2016; Uhrig, 2008; Voorpostel & Lipps, 2011). These predictors are used in the multinomial analysis (see Methods section).

While these correlates are generally accepted as universal, the variability across studies, countries and over time should be considered. Cross-country studies have shown that patterns and determinants of attrition vary, which is the case for different studies in different countries and different studies in the same countries (Behr et al., 2005; Lipps, 2009). Interestingly, Lipps (2009) noted the importance of modal effects between the three surveys due to similarities in the attrition patterns between BHPS and the German SOEP, which both are face-to-face, and differences in the Swiss Household Panel (SHP), which uses telephone. Relatedly, correlates of attrition at the start of the panel may differ from those at later waves (Behr et al., 2005; Olson & Witt, 2011). This change over time is important to acknowledge as it could influence the effectiveness of targeted interventions and weighting strategies and is further evidence to why methods that account for atypical patterns of response are necessary.

2.2 Latent Class Analysis (LCA)

Traditional panel attrition studies perceive attrition as a monotonic process and tend to treat the first instance of nonresponse as an indication of panel attrition, emphasising the importance of the first instance. While this is important, it also disregards intermittent response, adopting the reductive assumption that it is relatively indistinguishable from completing dropping out of the survey. It may be easier to encourage those who intermittently respond to return to the panel and these returners can report on the missing information from previous waves (Voorpostel & Lipps, 2011). This concern can be addressed by LCA, an analysis method that identifies and categorises similar response patterns. Lugtig (2014) successfully adopted LCA using 48 waves of the Longitudinal Internet Studies for Social Sciences (LISS), a Dutch monthly web panel. He fitted a set of nested LCA models, each with a different number of classes. From the evaluation criteria, he determined the model with nine classes was preferred, consisting of classes demonstrating loyalty to the survey, monotone attrition, and atypical patterns of attrition. The model also showed that certain classes did not follow a linear process, which would not have been known if the study only focused on the first instance of nonresponse. The "loyal stayers" were the largest group in the sample, had high response probabilities over the 48 waves and were used as a reference category in the subsequent multinomial regression to predict covariates on class membership. The coefficients highlighted that gender was not a significant predictor for most classes and younger people and those with lower education were less likely to be in the "loyal stayers" class. Identifying these non-monotone patterns provides more detailed information about the complex panel response behaviour, which in turn would lead a higher accuracy in determining correlates of attrition for targeted intervention and weighting strategies.

Moreover, Gerry and Papadopoulos (2015) analyse attrition over 10 waves of the Russian Longitudinal Monitoring Survey (RLMS). Similar to Lugtig (2014), they account for non-monotone attrition but use the sequence analysis method instead. 40% of the sample responded at every wave; 43% attrited in a monotone fashion and this was divided into nine groups with the largest group being those who participated in the first wave only then attrited (10%) and 17% followed a non-monotone pattern. Their findings suggest those in the "always in" category are more likely to be married or in the bottom three income quintiles, those that absolutely attrite are more likely to be aged 60+, least educated or unhealthy. Temporary attritors are more likely to be younger, single, divorced, unemployed, unskilled or in poverty.

2.3 Loyalty in Panels

The concept of loyalty has been extensively examined in marketing literature, typically focused on brand or consumer loyalty, where loyalty is considered a psychological predisposition (Rundle-Thiele, 2005). While the context differs, the definition can be applied to loyalty in panel surveys, where loyalty is defined by the survey outcome and refers to the commitment to participate in a panel. Loyalty is important to the longevity of the panel; with each additional wave of participation, a sample member's data becomes more valuable for longitudinal analyses. For the purpose of this research, loyal respondents will refer to those who have participated in every eligible wave in the panel, similar to "loyal stayers" in Lugtig (2014) and the "always in" category in Gerry and Papadopoulos (2015).

Some studies that have examined this concept by examining the demographic characteristics of three response groups; "always in", those who participated at least once ("ever out") and those who did not participate in the last three waves ("lost"). From this, it was found that those in the "always in" category were more likely to be women, older, highly educated and married compared to the other two groups (Voorpostel, 2010). Changes in housing arrangement satisfaction and political interest had an effect on temporary attrition and changes with marital status, employment status, financial satisfaction and pollical interest had an effect on permanent attrition (Voorpostel & Lipps, 2011). While these studies presented interesting findings, it is important to consider that the data was collected from the SHP, a telephone panel survey, so the conclusions could be specific to the mode.

2.4 Unknown Eligibility in Household Panel Surveys

The sample selected for household panel surveys should accurately reflect the population of interest. As such, survey organisations set eligibility criteria to manage the sample, which involves sample members moving in and out of the survey. This can be due to births, deaths or migration (Lynn, 2011). Those who die or move out of the scope of the sample become ineligible so identifying these sample members is important to accurately analyse attrition, calculate response rates and nonresponse weights. Without accounting for eligibility, one can overestimate the levels of attrition in a panel. Determining who is ineligible is not as straightforward as it seems; referring back to Lepkowski et al. (2002)'s nonresponse framework, Watson and Wooden (2009) contend that it is empirically difficult to distinguish between location and contact because it is not until the sample member has been contacted that one can establish with certainty that the address is the correct location. The same can be said for determining eligibility as one would not be able to ascertain a non-contact's eligibility status, in other words, ineligible (such as death, moved out of scope) or eligible (such as not available at time of call or moved but remains in scope).

Therefore, it is necessary to determine the proportion of non-contacts that are actually ineligible and identify the impact of unknown eligibility on the sample. In the context of panel attrition, ignoring unknown eligibility would bias the survey estimates, leading to misidentification of attrition patterns and correlates of attrition. Despite this, there seems to be a limited amount of research into unknown eligibility in household panel surveys. The research that is available examines methods used to account for unknown eligibility by focusing on death. This focus is intentional, firstly because mortality data tends to be recorded and is often accessible for researchers at the population level. Secondly, death is an absorbing state due to its permanent nature, which makes it more straightforward to examine than moving out-of-scope, as moving out-of-scope can be a fluid process. Finally, death also occurs more often than moving-out-of-scope, so accounts for a larger sample size (H. E. S. A. Sadig, 2015; Watson, 2016). H. E. S. A. Sadig (2015) accounts for unknown eligibility by calculating the survival rates using the statistics about the number of deaths and number of residents from the Office for National Statistics (ONS) and other official government statistics providers. By comparing these survival rates to those calculated from the sample, H. E. S. A. Sadig (2015) found that the sample survival rates were larger than those estimated from the population statistics, indicating that some of the unknown eligibility cases may not be eligible. Despite this, the differences were relatively small and mostly concerned those who were aged 60 and above in wave one. This information was then used to create longitudinal nonresponse weights.

Similar to H. E. S. A. Sadig (2015), Watson (2016) concentrated on the death aspect of unknown eligibility by reviewing four methods to account for it using the Household, Income and Labour Dynamics in Australia (HILDA) Survey, as there does not seem to be a preferred approach. These methods include national death registry matching, using life-expectancy tables, calculating survival curve models based on the observed sample and nonresponse weights that implicitly model death. Watson (2016) determined that the first method, national death registry matching, would be the best method if the match rate was high, but this method is financially and time expensive and the data is not always available for researchers. Using method one as a baseline, Watson (2016) compared the other methods, analysing how well each method measures the number and timings of death and the sociodemographic characteristics of those who die. From this, it was recommended that the fourth method, calculating nonresponse weights, would perform best if method one is not possible.

Overall, this literature has shown the way in which latent class analysis can be used to investigated response patterns to learn more about attrition. While Lugtig's 2014 latent class analysis using the LISS panel drew some interesting conclusions, it is important to see whether the same conclusions can be drawn using another sample. The present paper will contribute to this literature by using the BHPS sample of *Understanding Society*, where the mode used is primarily face-to-face. As mentioned previously, Behr et al. (2005) and Lipps (2009) contend that patterns and determinants of attrition may vary depending on the countries and modes. Moreover, the present study's sample spans over 26 waves whereas Lugtig's 2014 LCA was monthly spanning over a period of four years. As such, the concept of unknown eligibility plays a more important role and is therefore one of the focuses of the present study.

3 Methods

3.1 Data

BHPS was an annual face-to-face panel survey that followed select households over time to depict life in Great Britain. In Wave 1 (1991), there were 10,751 eligible individuals located in 5,505 households. The study achieved 18 waves and ended in 2008. Its successor study, *Understanding Society* started with a fresh sample of 40,000 UK households in 2009 and in the second wave, the individuals that were still active in the final wave of BHPS (Wave 18) were invited to join the sample (Lynn, 2006; UK Household Loungitudinal Study, 2019). The data for this study are collected from the *Understanding Society* harmonised BHPS project, which started in 2016 and aimed to facilitate the use of the combined data from the two surveys (Fumagalli et al., 2017; University of Essex & Institute for Social and Economic Research, 2019).

The sample for this study contains 9,912 individuals who completed a full individual interview in the first wave of BHPS. In the study, proxy individual interviews are conducted by another member of the household on the behalf of the respondent and are shorter than the standard individual interview. Therefore, proxy interviews have not been treated as full individual interviews and the sample excludes those with proxy interviews at Wave 1. I use data from Wave 1 of BHPS until Wave 9 of *Understanding Society*. This amounts to 26 waves because these individuals were not eligible to participate at Wave 1 of *Understanding Society*.

3.2 Repeated Measures Latent Class Analysis

Latent class analyses (LCA) are models comprised of observed categorical variables which measure unobserved latent categorical variables. The main assumption for these models is local independence, that is, the observed variables are independent, conditional on the latent variable. In other words, the latent variable explains the relationship between the observed variables (Collins & Lanza, 2009). The models are typically used to determine meaningful classes of observations based on similar patterns across multiple variables. Repeated measures LCA (RMLCA) is one approach where the observed categorical variables are the same, measured at different timepoints, which makes it valuable for studying survey response patterns (Collins & Lanza, 2009). This is especially true for atypical patterns of response that otherwise cannot be observed in studies that use the first instance of nonresponse as indication of attrition. In this study, each observed variable is measured dichotomously to denote whether the individual had a full interview or not, so there are no missing values.

There is a degree of subjectivity in the LCA process as a set of models containing different numbers of classes are tested and the models are compared based on various evaluation criteria. However, the researcher can use a priori assumptions to justify what models to run and this is done by setting a known class, whereby a class reflects an observed variable of the user's choice. In this study, there is a focus on loyal respondents, those who complete a full interview in every eligible wave as well as those who responded at every wave up until becoming ineligible. A binary variable was generated using Stata 15 to indicate whether an individual had participated in all 26 waves or not and this was incorporated when modelling the latent class structure in Latent GOLD 5.1 (StataCorp, 2017; Statistical Innovations, 2016). Therefore, all latent models produced had the first class restricted to only contain the 3,357 "loyal" respondents.

The dataset contained 9,912 individuals with 26 binary indicators of wave response and there were 1,010 distinct response patterns. Therefore, the data were very sparse, but this only affected what evaluation criteria to select. There are a range of tests, which in combination, are considered to be good indicators to evaluate LCA models. Ultimately, the aim is to find the most parsimonious model with a clear interpretation and high separation amongst classes. In a similar study, Lugtig (2014) assesses the models using the deviance, Bayesian information criterion (BIC), Lo-Mendell-Rubin test (LMRT) and entropy. The assessment criteria in this study have been selected based on the software capabilities and whether they are appropriate for the data. Typically, the likelihood ratio chi-square p-value is used to test the fit of LCA models. However, it is not reliable with large sample sizes and sparse data and as such as not been reported (Collins & Flaherty, 2009; McCutcheon, 2009). The deviance is a statistic that can be used to interpret the model fit of nested models. While one cannot directly interpret the deviance value, the statistic is used as a comparison between two nested models, where lower values indicate better fitting models (Singer et al., 2003). Similarly, lower values indicate better fitting models according to the BIC. Entropy demonstrates how well classes can be separated and values above 0.8 are preferred as it indicates that individuals can be accurately assigned to one class (Lugtig, 2014). The bootstrapped likelihood ratio test (BLRT) is similar to the LMRT and both are used to test nested models and determine whether the model improves the fit compared to the previous one (Kim, 2014; Lugtig, 2014).

3.3 Multinomial Regression Analysis

The three-step method was adopted to analyse the covariates. This stepwise approach was preferred over the alternative, one-step method. Researchers have discussed the advantages, disadvantages, and differences between the two methods but for the purposes of this research, the one-step method is not ideal (Bakk et al., 2013; Vermunt, 2010). The main reason why the three-step method was preferred is that the present study's research questions intend to identify the patterns of response and then estimate how the response patterns are related to covariates as separate steps, whereas the one-step method executes these steps simultaneously and as such, the covariates contribute to the response patterns classification. The three-step method is comprised of (1) estimating the latent class model, (2) classifying the observations into latent classes using their posterior class membership probabilities, then (3) estimating a multinomial logistic regression with the assigned class as the dependent variable. Once the LCA model has been estimated, each observation is given a posterior probability of belonging into each class. Each observation can only belong to one class and there are various rules that can be applied to determine which class is best (Bakk et al., 2013). As a result, a classification error is introduced as observations cannot be placed into classes with complete certainty. This classification error is also related to entropy (the class separation indicator) as lower levels of entropy would lead to higher levels of classification error. However, the modified Bolck-Croon-Hagenaars (BCH) approach accounts for this and was used in this study. This involves expanding the dataset such that each individual has C records, where C is the total number of classes from the LCA model. Then, the posterior probabilities generated from the LCA are used as a weight in the multinomial regression analysis (Bakk et al., 2013; Vermunt, 2010).

The present study primarily focused on loyalty in panels and unknown eligibility. Therefore, the covariates modelled were selected based on existing literature and availability in the data (Gerry & Papadopoulos, 2015; Lugtig, 2014; Uhrig, 2008). The sociodemographic covariates included in the model were gender, age, ethnicity, having a partner, highest education qualification, employment status and self-rated general health. The covariates included in the model related to the household were monthly household net income, number of own children and pensioners in the household, dwelling type, tenure, household size and number of reported moves. Moreover, there were covariates included related to political support and political interest.

Age was measured using the Wave 1 variable and number of reported moves was measured by combining the variables from BHPS Wave 1 to UKHLS Wave 9. All other covariates are derived from the individual's last wave that they responded. Therefore, the majority of these covariates were not be missing as all individuals in the sample responded at Wave 1. Moreover, monthly household net income was adjusted using the modified OECD equivalence scale, which allows comparison between households of different sizes and compositions. This is a standard adjustment made to income variables and therefore, provided in the UKHLS data (Canberra Group, 2011; Fisher et al., 2019). As it is derived from the last known monthly household net income, it has also been adjusted by the retail price index so it can be accurately compared across time (Canberra Group, 2011; Fisher et al., 2019; Office for National Statistics, 2020d). In addition to this, the total number of reported moves was divided by the total number of responding waves to allow comparison between individuals who have remained in the panel for different lengths of time. The data management and multinomial models were estimated in Stata 15 (StataCorp, 2017).

3.4 Unknown Eligibility

General population surveys aim to represent a target population. With long-term longitudinal surveys, over time it can become unclear whether non-responding sample members remain eligible to participate, especially when they cannot be contacted. In many cases, survey organisations can identify who is ineligible (i.e., those who have died or moved out of the scope of the survey) and therefore not in the population of interest through survey reporting or linking to administrative data. However, often this cannot be determined, and this is what is referred to as unknown eligibility. When analysing data with the aim of making inferences about the target population, it is necessary to adjust data analyses to exclude ineligible cases to avoid biases in the estimates, which would otherwise assume those who have not responded to the survey remain eligible. Sample members can become a non-contact by chance (after being issued to field) or by design (not issued to field), such as removing the sample member from the sample after not responding for two waves. In these analyses, non-contacts by chance or design will be treated the same as for both cases eligibility is unknown and as such estimated in the same way. Ideally, the eligibility status would be estimated for all sample members with unknown eligibility, however, for the purpose of this study, the focus will be on accounting for death as a source of ineligibility. Firstly, death accounts for the largest proportion of ineligibility and is a permanent state. Secondly, the external data required to adjust the analysis is widely available for deaths but not for the other circumstances that lead to ineligibility. There are various methods used to account for unknown eligibility, which have been examined by H. Sadig (2014) and H. E. S. A. Sadig (2015) and Watson (2016). One method is the life tables approach which uses population estimates and death registrations separated by age and sex to calculate the survival rate for the study population. This information, combined with the survey information on known ineligibles, is used to estimate the eligibility rate amongst the unknown eligibility cases (Watson, 2016). This approach is used here to calculate the estimated probability of being alive, as explained below. These estimated probabilities were then applied as weights in both the latent class and multinomial regression analyses.

The BHPS Wave 1 sample contained individuals aged 16+ living in Great Britain in 1991 so the national life tables for England, Scotland and Wales were collected (Office for National Statistics, 2020a, 2020b, 2020c) for all years from 1991 to 2018. The national life tables provide mortality rates ($q_{t,x,y}$) between age x and age ($x+1$) for persons aged x in year t (top coded at age 90), where sex = y. These rates are based on population estimates and registered births and deaths over a period of three years. Thus, survival rates ($1 - q_{t,x,y}$) were used to estimate the probability of survival until each wave at which an individual's eligibility was unknown as follows (dropping for clarity all subscripts y):

$$(1 - q_{t,x}) \cdot (1 - q_{(t+1),(x+1)} \cdot \ldots \cdot (1 - q_{26,(x+26-t)}) \quad ,$$

where x is the age at last wave known to be alive, and t is the last wave at which the individual was known to be eligible (alive).

In the analyses, sample members with a known eligible status had a weight of 1.0. Those with a known ineligible status had a weight of 1.0 while they were eligible and a weight of 0.0 in the wave they are confirmed to be ineligible and subsequent waves. Those with unknown eligibility status had multiple entries each corresponding to a possible mortality scenario and each with a weight equal to the probability of that scenario applying. For example, someone known to be eligible for 25 waves, but with unknown eligibility at wave 26 would have two records. The first would indicate that they were eligible at all 26 waves and the weight would be the probability (estimated as shown above) of them having survived from wave 25 to wave 26, while the second would indicate that there were eligible for 25 waves but ineligible at the 26$^{\text{th}}$, with a weight equal to the probability of them not surviving from wave 25 to 26. Thus, for each individual the sum of the weights across possible eligibility scenarios equalled 1.0. The latent class and multinomial analyses are first performed without this adjustment for unknown eligibility and then performed with the adjustment to demonstrate the difference the adjustment makes, and this is presented in the Results section. For the multinomial analyses, both models are performed with the aforementioned BCH adjustment to appropriately account for classification error.

4 Results

As noted in the Methods section, this section only contains the weighted analyses. These weighted analyses account for the estimated probability of the sample member being alive and as such, more accurately reflect the true population because the unweighted (see Appendix) assumes everyone in the sample is still eligible to participate. Therefore, the weighted LCA models are very different from the unweighted as respondents are also classified based on the assumption of being eligible, which changes the class sizes and evaluation statistics, resulting in a model with different response patterns being preferred. Despite this, the coefficients in the multinomial regression remain fairly similar but it should be noted that the interpretation is correlates of attrition rather than correlates of attrition and death in the unweighted model.

4.1 Patterns of Response

A set of RMLCA nested models were estimated, where each model included an additional class when compared to the previous. Table 1 shows the six best fitting models according to the model evaluation criteria and accounts for unknown eligibility using the life tables method. As the number of classes in the model increases, the deviance and BIC decrease, which suggests that the models with more classes have better fits. In comparison to the unweighted models (shown in Table A1), the deviance and BIC statistics in Table 1 are generally lower. The entropy values are fairly similar in the unweighted and weighted models (ranging from 0.941 too 0.965), but generally, the unweighted models are slightly higher than in Table 1, but all models still have good entropy, indicating that the majority of individuals are highly classified into only one class. The bootstrapped likelihood ratio test (BLRT) is another test used for nested models and determines whether the model improves the fit compared to the previous one (Kim, 2014). The BLRTs for these five nested models indicate that the inclusion of an additional class in the model is a significant improvement on the previous model.

These tests may indicate what model is best fitting and parsimonious, however, it is also necessary to investigate the interpretability of the models. This is done by looking at the parameters to see whether classes have meaningful distinct patterns, and this highlighted a noteworthy finding. As shown in Figure 1, the response probabilities for Class 6 start off very high but rapidly decline from Wave 8 to 0.06 by Wave 18. At UKHLS Wave 2 (depicted as Wave 19), there is a large increase to 0.83 and then the decline recommences from Wave 21, but the response probabilities remain above 0.41. As active respondents in BHPS Wave 18 were invited to join UKHLS at Wave 2, this large increase could be indication that those in Class 6 are susceptible to encouragement techniques, such as targeted intervention strategies. This class will therefore be referred to as the "abruptly nudged" class, to reflect this behaviour and a similar class was found in the unweighted model (see Figure B1). The response pattern for this class is unique to UKHLS, due to the transition from the predecessor survey, BHPS.

Moreover, the response probabilities for Class 7 alternates between decreasing and increasing patterns but overall is on a declining trajectory until Wave 8 (0.33). From Wave 9 (0.29), it continues the alternating decrease and increase with an overall increasing trajectory until Wave 26 (0.77). This response pattern seems to imply that something (in Wave 5 and/or Wave 8) encouraged those in this class to continue responding, similar to the nudged class identified in the unweighted model. However, the difference here is that it seemed to have a more gradual effect, gradually increasing in the final 18 waves and therefore, this class will be referred to as the "gradually nudged" class. Ideally, we want the most parsimonious model so although lower values of deviance and BIC indicate better fitting models, the more classes there are, the harder it will be to interpret the model and distinguish the classes from each other. For these reasons, Model 3 is preferred and will be the focus for further in-depth analysis as it has an entropy value higher than 0.8 and each class can be interpreted well in relation to the data.

The summary statistics for the weighted Model 3 are presented in Table 2 and the depiction of the classes and response patterns over the 26 waves are presented in Figure 1. The summary statistics were calculated based on the posterior probabilities generated by the LCA and account for classification error by adopting the BCH method. In the sample of 9,912 respondents, 54% of respondents are female, 4% are ethnic minorities and the mean age is 44. Classes 1 to 6 have a similar percentage of female respondents, ranging from 50% to 59%, however Class 7 is an outlier with 42% indicating that there are more male respondents in this class. The mean age ranges from 39 to 49, which is very similar to the unweighted model (see Table A2). The percentage of ethnic minority respondents in Classes 1 to 3, 4, 5 and 6 are between 2% and 5%. In contrast, Classes 2 and 7 are outliers with 6 and 12%, representing 21% and 1% of the sample respectively. As mentioned, the models were estimated with a known class set. Class 1 is comprised of these "loyal" respondents and accounts for 34% of the sample and therefore, is the same in both the unweighted and weighted models.

As shown in Table 2, Classes 2, 3 and 5 account for 21%, 17% and 12% of the sample respectively. These classes represent monotone attrition, which seems to occur every six to eight waves and therefore have been termed "attrition by W8, W16 and W22". However, these classes do not have parallel decreasing patterns suggesting that the response probabilities do not decrease at similar rates. Class 4, 12% of the sample, reflects Class 4 in the unweighted model and resembled what Lugtig (2014) refers to as "stayers". Both classes had high

Table 1

Model fit information and statistics for the six best fitting models (weighted)

						Class Size of sample (in %)		
Model	Classes	Deviance[c]	df	BIC[a](LL)	Entropy	Min.	Max.	BLRT[b]
1	5	91,418	9778	92,651	0.962	13	34	0.000
2	6	88,265	9751	89,747	0.957	7	34	0.000
3[d]	7	88,692	9724	90,422	0.955	1	34	0.000
4	8	86,858	9697	88,836	0.950	1	34	0.000
5	9	85,058	9670	87,285	0.948	1	34	0.000
6	10	82,211	9643	84,686	0.941	2	34	0.000

$N = 9,912$. Lower values of the BIC indicate better fitting models (Nylund et al., 2007). Entropy demonstrates how well classes can be separated, where values closer to 1 indicate better separation (Lugtig, 2014). The BLRT p value is used for nested models and shows whether the model (k) is a significant improvement when compared with the previous model ($k - 1$) (Kim, 2014; Lugtig, 2014). [a] Bayesian Information Criterion [b] Bootstrapped Likelihood Ratio Test [c] Deviance = $-2 \cdot$ Log Likelihood [d] Selected as final model

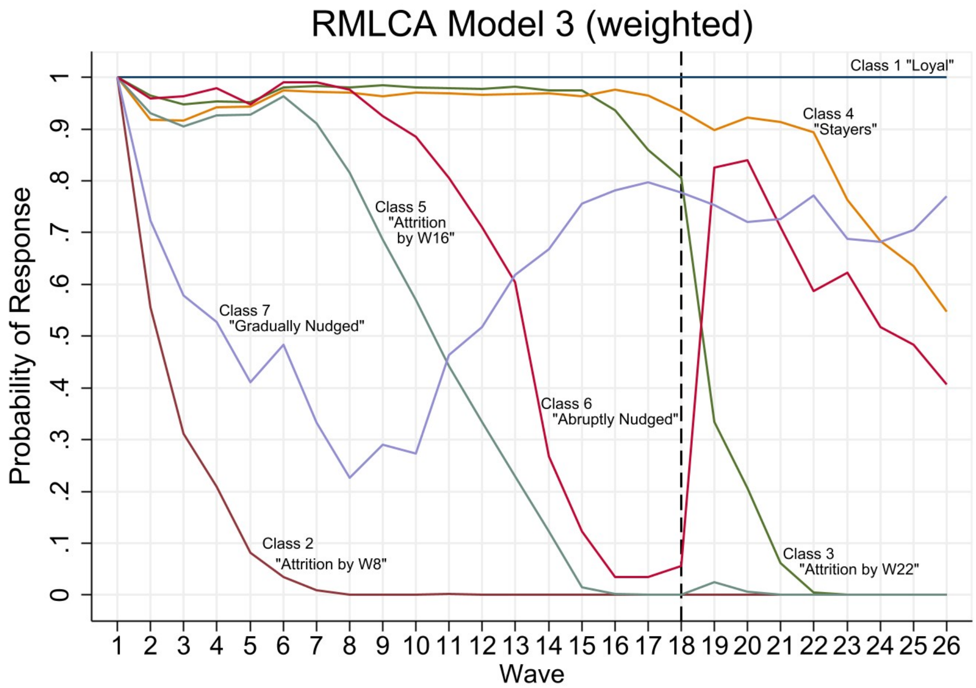

Figure 1

Response probabilities for the weighted Model 3 (7 Classes). Note: Dashed line indicates the end of BHPS (Wave 18) and transition to UKHLS. UKHLS Waves 2–9 are referred to as Waves 19–26 for readability.

Table 2

Summary statistics for the weighted Model 3

Class	Class size	%	Females %	Mean Age	Ethnic Minor. %
1	3,366	34	54	49	2
2	2,094	21	50	44	6
3	1,720	17	56	42	3
4	1,227	12	56	39	4
5	1,226	12	53	41	5
6	164	2	59	44	4
7	115	1	42	40	12
Total	9,912	100	54	44	4

response probabilities throughout BHPS but starts to decline after the transition to UKHLS, and this could be an early indication of future attrition. Interestingly, the weighted model has two "nudged" classes (as discussed previously) and the first, Class 6, represents 2% of the sample and is similar to Class 7 in the unweighted model. The second Class 7 follows a more gradual increasing pattern in comparison to Class 6 and represents 1% of the sample.

4.2 Characteristics of Respondents

Table 3 and Table 4 show the multinomial regression model that depicts the characteristics of respondents in Class 2–7 compared to Class 1 ("loyal" respondents) in the weighted model. The logit coefficients are reported to allow comparison of the predictive power of the covariates (Lugtig, 2014). The model has been separated into two tables for readability; Table 3 depicts coefficients from Classes 2, 3 and 5, the classes that attrited at some point and Table 4 depicts coefficients from the remaining classes that are still present in the sample. As with the RMLCA analysis, this model includes a classification weight multiplied by an eligibility weight to account for classification error and unknown eligibility.

The results from Table 3 show that female respondents are more likely to be "loyal" respondents, when compared to W8 attritors. The findings suggest a somewhat positive relationship between age and attrition for the attriting classes where those aged 35+, 55–64 and 45+ are more likely to be W8, W22 and W16 attritors respectively. Moreover, ethnic minorities are more likely to be in the attriting classes than the "loyal" class. Those with a partner are more likely to be in the "loyal" class than W8 attritors and W22 attritors. In terms of educational qualifications, those with qualifications are more likely to be in the "loyal" class than those with no qualifications. The key findings for job status imply that being retired strongly predicts the likelihood of being in the "loyal" class and being unemployed predicts the likelihood of being W8 attritors. Interestingly, in terms of self-rated general health, those in the attriting classes are more likely that report high levels of health compared to the "loyal" class. Overall, the coefficients suggest that those who are interested in politics or support a political party are more likely to be in the "loyal" class than the attriting classes.

For household composition variables, as the monthly household net income and number of pensioners in the household increase, the likelihood of being in the "loyal" class increases when compared to W8 and W16 attritors. Those in the "loyal" class are also more likely to own their home and live in a dwelling with its own entrance. As the household size increases, the likelihood of being in the attritors classes increase. However, there is an opposing effect for the number of pensioners, as this increases, the likelihood of being in the "loyal" class increases. There are also large significant differences which overall suggest that those in the "loyal" class move house less than the other classes.

The results from Table 4 show that there is no significant difference for being female when comparing the "abruptly nudged" and "stayers" to the "loyal" class. However, female respondents are more likely to be in the "loyal" class than in the "gradually nudged" classes. The findings for age suggest a somewhat positive relationship between age and loyalty; older respondents (25+) are more likely to be in the "loyal" class when compared to the "stayers" and "gradually nudged" classes. For the ethnicity binary indicator, the findings suggest that ethnic minority respondents are more likely to be in the "stayers" and "gradually nudged" classes than the "loyal" class. This is concerning because the "stayers" class resembled the "loyal" class until the BHPS to UKHLS survey transition. Notably, ethnic minority respondents are very likely to be in the "gradually nudged" class, compared to the "loyal" class, which suggests a growing interest in the survey (depicted by the gradual increase in response probability) from BHPS Wave 10. Moreover, those with the highest educational qualifications (degree) are more likely to be in the "loyal" class when compared to those with no educational qualifications for the two "nudged" classes. Unlike the attriting classes (shown in Table 3), there are no significant differences for the classes that still remain in the sample, when compared to "loyal" class for those who are retired. This suggests that retired sample members tend to stay in the sample until they become ineligible (through death, incapacitation or moving out of scope). Those with higher levels of self-rated general health are more likely to be in the "loyal" class than in the "stayers" class. In general, as the household size and number of reported moves increase, the likelihood of being in the "loyal" class decreases.

Overall, while the unweighted and weighted LCA models differ slightly, the multinomial regression weighted coefficients resemble the unweighted coefficients. Older respondents were more likely to be in the attriting classes than the “loyal” but were also more likely to be in the “loyal” class than the remaining classes. This suggests that while older respondents do experience monotone attrition as expected, they are also more likely to participate at every wave rather than respond intermittently. Moreover, ethnic minorities were more likely to be in attriting classes and very likely to be in the “gradually nudged” class. However, there is no significant difference for the “abruptly nudged” class. This shows that while ethnic minority respondents may be susceptible to encouragement techniques, it may take a longer period of time to observe the effects.

Table A5 models class membership on reasons for nonresponse and shows that Classes 2–6 are more likely to be noncontacts than refusals when compared to Class 7 (“gradually nudged”). However, older respondents in these classes (aged 45+) are more likely to be refusals than noncontacts, which suggests that younger respondents who refuse can be encouraged to participate again whereas for older respondents it is those who previously couldn’t be contacted. The “gradually nudged” class is also more likely to have another reason for nonresponse besides noncontact and refusal (e.g., being ineligible).

5 Discussion and Conclusion

This paper aimed to address the use of LCA to understand response behaviour in longitudinal social surveys and to identify loyal respondents while accounting for atypical patterns of response. In regard to the first research question, “What are the patterns of response for the BHPS sample?”, the RMLCA framework highlighted that the weighted model with seven classes had interesting response patterns and was a good fitting model according to the evaluation criteria. The weighted model showed that 34% of the sample participated at every eligible wave and this group was categorised as the “loyal” class. Moreover, 50% of the sample followed a pattern of monotone attrition and 15% followed an atypical pattern. Two interesting classes were highlighted, the “abruptly nudged” class, which followed a similar pattern to the “nudged” class in the unweighted model and the “gradually nudged” class. Both of these classes had declining response probabilities at first then began to increase, and this increase was sharp in the “abruptly nudged” class and gradual in the “gradually nudged” class. The weighted model was very different from the unweighted model as it accounted for the estimated probability of the respondent being alive and therefore, did not include death as part of the nonresponse.

Research questions 2 and 3 aimed to address the characteristics of the individuals following these response patterns and specifically, how the “loyal” sample members differ from the other respondents. For the unweighted model and in line with current attrition research, this study finds that white, older, and educated sample members are more “loyal”. The “loyal” also are more likely to have fewer people in the household and less reported house moves(Uhrig, 2008). More broadly, the results suggest that those in classes that remained in the sample, (i.e., “stayers” and “nudged”) have more similarities with the “loyal” class than the other classes. Despite this, it is clear that the distinction between monotone attrition and atypical patterns of attrition was necessary. Unknown eligibility was an issue that had to be considered because the data spans over a long period. The results from the weighted model suggested that similar conclusions can be drawn.

There was a strong association between being an ethnic minority and being in the “nudged” class. This class had the interesting spike in response between wave 18 of BHPS and wave 2 of UKHLS. This implies that this group could be more susceptible to targeted intervention than other groups. However, the response pattern declines again which suggests that the interest in the survey was not maintained. In the weighted model, ethnic minorities were more likely to be in the “gradually nudged” class which had declining response probabilities until wave 10 and then gradually increased until wave 26. One recommendation for future research would be to test targeted intervention techniques using the classes identified with LCA. From this, one would be able to identify the types of techniques (such as, incentives or reminders) that groups with a particular response history would benefit from (Lynn, 2017).

Notably, the combination of age, being retired and the number of pensioners in the survey highlights that pensioners are more likely to be loyal to the survey, which is likely due to having more free time. Older respondents are more likely to be in the attriting classes than the loyal class but are more likely to be in the loyal class compared to the classes that are still present in the sample. This along with the results modelling class membership on reasons for attrition show that older respondents are more likely to be loyal to the survey than their younger counterparts, while they are still eligible to do so. In addition to this, the results show that the loyal class have lower levels of general health compared to the attriting classes, which is consistent with Uhrig (2008). While this may seem counterintuitive, this corresponds with pensioners. In general, pensioners are more likely to have lower levels of health, so these findings imply that pensioners are loyal to the survey while they are physically able to be and are more likely to exit the panel through death instead of non-response. Therefore, another recommendation for future research is to separate response into contact and cooperation (Lepkowski et al., 2002). This would allow investigation into whether response patterns differ based on non-contact and refusals, and whether different covariates give further insight on the characteristics.

Overall, this paper has contributed to the global effort of understanding attrition in social surveys by identifying loyal

Table 3

Multinomial regression coefficients of covariates on class membership (weighted)

	Class 2 Attrition by W8		Class 3 Attrition by W22		Class 5 Attrition by W16	
	Coef.	SE	Coef.	SE	Coef.	SE
Female	−0.16***	0.06	0.09	0.06	0.01	0.07
Age (ref: 16-19)						
20-24	−0.17	0.17	−0.21	0.17	−0.37**	0.17
25-34	0.04	0.15	−0.02	0.15	−0.19	0.15
35-44	0.56***	0.16	0.15	0.16	0.25	0.17
45-54	1.65***	0.18	0.25	0.17	0.70***	0.19
55-64	2.44***	0.21	0.56***	0.18	0.94***	0.20
65+	2.84***	0.21	−0.08	0.19	1.05***	0.21
Ethnic Minority	0.63***	0.17	0.30*	0.18	0.52***	0.19
Has Partner	−0.49***	0.08	0.14*	0.07	−0.07	0.08
Highest Qualification (ref: No qualification)						
Degree	−1.82***	0.14	−0.73***	0.12	−1.05***	0.14
Other higher degree	−0.95***	0.13	−0.36***	0.12	−0.79***	0.14
A-Level etc.	−0.83***	0.10	−0.13	0.09	−0.66***	0.11
GCSE etc.	−0.66***	0.09	−0.18**	0.09	−0.38***	0.10
Other qualification	−0.51***	0.11	0.04	0.10	−0.28**	0.12
Job (ref: Employed, in education or training)						
Unemployed	0.58***	0.19	−0.26	0.23	0.16	0.21
Retired	−2.63***	0.12	−0.60***	0.11	−1.42***	0.13
Other	−0.69***	0.12	−0.50***	0.12	−0.65***	0.13
Self-rated General Health (ref: Very poor)						
Excellent	2.28***	0.17	0.58***	0.14	1.04***	0.15
Good	1.62***	0.15	0.38***	0.11	0.58***	0.14
Fair	0.76***	0.15	0.04	0.11	0.21	0.14
Poor	0.31*	0.17	−0.01	0.12	0.07	0.14
Level of interest in politics (ref: Not at all int)						
Very interested	−0.08	0.13	−0.55***	0.12	−0.32**	0.14
Fairly int	−0.03	0.09	−0.35***	0.09	−0.25**	0.10
Not very int	−0.08	0.09	−0.32***	0.08	−0.19**	0.09
Supports a political party	−0.30***	0.07	−0.21***	0.06	−0.26***	0.07
Monthly Household Net Income (£000s)	−0.69***	0.10	−0.02	0.05	−0.12*	0.06
No. of Own Children in the Household	−0.00	0.06	−0.11*	0.06	0.04	0.07
No. of Pensioners in the Household	−0.43***	0.06	−0.02	0.05	−0.37***	0.07
Dwelling type (ref: Own entrance)						
Flats and other multi-storey units	0.50***	0.09	−0.13	0.10	0.33***	0.10
Bedsits/institutions/other structures	−0.16	0.17	−0.08	0.14	−0.02	0.16
Own Home	−0.21***	0.08	0.01	0.07	−0.09	0.08
Household Size	0.57***	0.04	0.39***	0.04	0.36***	0.04
No. of Reported Moves	1.03***	0.39	1.25***	0.26	2.07***	0.28
Constant	−1.38***	0.26	−1.11***	0.22	−1.02***	0.25
N			348,133			
Weighted N			9,912			
Pseudo R^2			0.11			

See table 4 for classes 4, 6 and 7. The reference group is Class 1 (loyal)
* $p < .05$ ** $p < .01$ *** $p < .001$

Table 4

Multinomial regression coefficients of covariates on class membership (weighted)

	Class 4 Stayers		Class 6 Abruptly Nudged		Class 7 Gradually Nudged	
	Coef.	SE	Coef.	SE	Coef.	SE
Female	0.10	0.07	0.16	0.14	-0.57^{***}	0.18
Age (ref: 16-19)						
20-24	-0.09	0.17	0.28	0.45	-0.58	0.38
25-34	-0.29^{*}	0.16	0.36	0.38	-0.96^{***}	0.34
35-44	-0.76^{***}	0.17	0.28	0.39	-0.92^{**}	0.36
45-54	-0.86^{***}	0.19	0.04	0.43	-1.19^{***}	0.41
55-64	-0.88^{***}	0.21	-0.23	0.46	-0.92^{**}	0.44
65+	-2.00^{***}	0.22	-0.17	0.44	-1.60^{***}	0.42
Ethnic Minority	0.32^{*}	0.18	0.33	0.42	1.44^{***}	0.32
Has Partner	-0.45^{***}	0.08	-0.21	0.17	-0.13	0.22
Highest Qualification (ref: No qualification)						
Degree	0.03	0.13	-0.81^{***}	0.28	-0.73^{*}	0.38
Other higher degree	0.04	0.13	-0.35	0.27	-0.01	0.36
A-Level etc.	0.19^{*}	0.11	-0.23	0.23	-0.38	0.29
GCSE etc.	0.16	0.11	-0.38^{*}	0.22	0.24	0.26
Other qualification	0.00	0.13	0.03	0.23	0.25	0.30
Job (ref: Employed, in education or training)						
Unemployed	-0.39	0.25	0.33	0.48	0.34	0.44
Retired	0.09	0.13	0.11	0.28	-0.52	0.32
Other	-0.52^{***}	0.14	-0.31	0.29	0.40	0.26
Self-rated General Health (ref: Very poor)						
Excellent	-0.57^{***}	0.15	-0.50	0.35	-0.25	0.37
Good	-0.71^{***}	0.12	-0.19	0.25	-0.19	0.27
Fair	-0.40^{***}	0.12	-0.32	0.25	-0.39	0.28
Poor	-0.20^{*}	0.12	-0.28	0.26	0.04	0.29
Level of interest in politics (ref: Not at all int)						
Very interested	-0.19	0.14	-0.09	0.27	0.12	0.33
Fairly int	-0.25^{**}	0.10	-0.15	0.21	-0.25	0.25
Not very int	-0.15	0.10	-0.08	0.20	-0.04	0.24
Supports a political party	-0.01	0.07	-0.26^{*}	0.15	-0.03	0.19
Monthly Household Net Income (£000s)	0.08	0.05	-0.04	0.10	-0.49^{*}	0.26
No. of Own Children in the Household	-0.13^{*}	0.07	-0.20	0.15	0.03	0.15
No. of Pensioners in the Household	0.30^{***}	0.06	0.04	0.13	0.27^{*}	0.14
Dwelling type (ref: Own entrance)						
Flats and other multi-storey units	-0.20^{*}	0.11	-0.17	0.23	0.34	0.27
Bedsits/institutions/other structures	-0.03	0.18	0.52^{*}	0.31	0.20	0.41
Own Home	-0.03	0.09	0.40^{**}	0.17	0.36	0.23
Household Size	0.29^{***}	0.05	0.34^{***}	0.08	0.19^{*}	0.11
No. of Reported Moves	1.12^{***}	0.27	1.19^{***}	0.46	1.00	0.61
Constant	-0.41^{*}	0.24	-3.43^{***}	0.49	-2.23^{***}	0.55
N			348,133			
Weighted N			9,912			
Pseudo R^2			0.11			

See table 3 for classes 1–3. The reference group is Class 1 (loyal).
* $p < .05$ ** $p < .01$ *** $p < .001$

sample members and it shown how they differ from others in the sample. The results show that there are atypical patterns of response, which would not have been observed if we used the traditional attrition analysis methods. The findings highlight that the classes have different characteristics, which suggests that survey estimates could suffer from bias if they are not properly accounted for in research. Recommendations for future research have been suggested, which could be not only be beneficial for further insight into panel attrition but also increasing participation in panel surveys.

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Appendix A
Tables

Table A1

Model fit information and statistics for the six best fitting models (unweighted)

Model	Classes	Deviance[c]	df	BIC[a](LL)	Entropy	Class Size of sample (in %) Min.	Max.	BLRT[b]
1	5	91, 710	9778	92, 943	0.965	13%	34%	0.000
2	6	88, 592	9751	90, 074	0.958	7%	34%	0.000
3[d]	7	88, 774	9724	88, 504	0.954	2%	34%	0.000
4	8	84, 929	9697	86, 907	0.952	2%	34%	0.000
5	9	83, 323	9670	85, 550	0.945	2%	34%	0.000
6	10	83, 318	9643	85, 794	0.946	1%	34%	0.000

$N = 9,912$. Lower values of the BIC indicate better fitting models (Nylund et al., 2007). Entropy demonstrates how well classes can be separated, where values closer to 1 indicate better separation (Lugtig, 2014). The BLRT p value is used for nested models and shows whether the model (k) is a significant improvement when compared with the previous model ($k - 1$) (Kim, 2014; Lugtig, 2014). [a] Bayesian Information Criterion [b] Bootstrapped Likelihood Ratio Test [c] Deviance = $-2 \cdot$ Log Likelihood [d] Selected as final model

Table A2

Summary statistics for the unweighted Model 3

Class	Class Size	% of Sample	% of Female Respondents	Mean Age	% of Ethnic Minority Respondents
1	3,357	34	54	49	2
2	2,041	21	50	44	6
3	1,535	15	56	42	3
4	1,212	12	56	39	4
5	860	9	54	42	5
6	708	7	54	42	4
7	201	2	49	39	10
Total	9,912	100	54	44	4

Table A3

Multinomial regression coefficients of covariates on class membership (unweighted)

	Attrition by W8 (Class 2)		Attrition by W23 (Class 3)		Attrition by W14 (Class 5)		Attrition by W22 (Class 6)	
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
Female	-0.15^{**}	0.07	0.09	0.07	0.04	0.08	−0.02	0.09
Age (ref: 16-19)								
20-24	−0.16	0.18	−0.14	0.18	-0.43^{**}	0.19	−0.30	0.21
25-34	0.05	0.16	0.02	0.16	−0.26	0.17	−0.04	0.18
35-44	0.58^{***}	0.17	0.17	0.17	0.38^{**}	0.18	0.07	0.20
45-54	1.68^{***}	0.19	0.29	0.18	0.68^{***}	0.22	0.52^{**}	0.23
55-64	2.50^{***}	0.23	0.56^{***}	0.20	1.11^{***}	0.24	0.76^{***}	0.25
65+	2.92^{***}	0.22	−0.14	0.21	1.33^{***}	0.24	0.89^{***}	0.26
Ethnic Minority	0.62^{***}	0.18	0.25	0.19	0.55^{***}	0.21	0.38	0.23
Has Partner	-0.49^{***}	0.08	0.13^{*}	0.08	−0.15	0.10	0.07	0.10
Highest Qualification (ref: No qualification)								
Degree	-1.84^{***}	0.16	-0.73^{***}	0.13	-1.16^{***}	0.17	-0.85^{***}	0.18
Other higher degree	-0.96^{***}	0.15	-0.34^{**}	0.13	-0.89^{***}	0.18	-0.43^{**}	0.18
A-Level etc.	-0.81^{***}	0.11	−0.10	0.10	-0.72^{***}	0.14	-0.40^{***}	0.15
GCSE etc.	-0.66^{***}	0.11	-0.17^{*}	0.10	-0.42^{***}	0.13	-0.24^{*}	0.14
Other qualification	-0.52^{***}	0.12	0.07	0.11	-0.27^{*}	0.14	−0.08	0.15
Job (ref: Employed, in education or training)								
Unemployed	0.59^{***}	0.20	−0.19	0.24	0.22	0.23	−0.21	0.29
Retired	-2.66^{***}	0.14	-0.55^{***}	0.12	-1.60^{***}	0.16	-0.89^{***}	0.16
Other	-0.70^{***}	0.13	-0.50^{***}	0.13	-0.68^{***}	0.15	-0.52^{***}	0.16
Self-rated General Health (ref: Very poor)								
Excellent	2.30^{***}	0.19	0.50^{***}	0.15	1.01^{***}	0.19	1.00^{***}	0.20
Good	1.63^{***}	0.17	0.28^{**}	0.12	0.64^{***}	0.17	0.61^{***}	0.18
Fair	0.76^{***}	0.17	−0.04	0.12	0.19	0.17	0.33^{*}	0.18
Poor	0.30	0.19	−0.05	0.13	0.04	0.18	0.16	0.19

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	Attrition by W8 (Class 2)		Attrition by W23 (Class 3)		Attrition by W14 (Class 5)		Attrition by W22 (Class 6)	
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
Level of interest in politics (ref: Not at all int.)								
Very int.	−0.04	0.15	-0.63^{***}	0.14	-0.30^{*}	0.17	-0.29^{*}	0.18
Fairly int.	−0.02	0.10	-0.38^{***}	0.10	−0.17	0.12	-0.30^{**}	0.13
Not very int.	−0.08	0.10	-0.32^{***}	0.09	−0.14	0.11	-0.25^{**}	0.12
Supports a political party	-0.32^{***}	0.07	-0.16^{**}	0.07	−0.12	0.09	-0.54^{***}	0.09
Monthly Household Net Income (£000s)	-0.70^{***}	0.11	−0.03	0.05	−0.10	0.08	−0.04	0.06
No. of Own Children in the Household	−0.01	0.07	-0.14^{**}	0.07	0.05	0.07	0.04	0.08
No. of Pensioners in the Household	-0.42^{***}	0.07	0.00	0.06	-0.45^{***}	0.09	-0.28^{***}	0.09
Dwelling type (ref: Own entrance)								
Flats and other multi-storey units	0.50^{***}	0.10	−0.10	0.11	0.42^{***}	0.12	−0.00	0.14
Bedsits/institutions/other structures	−0.17	0.20	−0.02	0.18	−0.14	0.21	0.09	0.21
Own Home	-0.21^{**}	0.08	0.04	0.08	-0.18^{*}	0.10	0.02	0.11
Household Size	0.58^{***}	0.04	0.40^{***}	0.04	0.36^{***}	0.05	0.36^{***}	0.05
No. of Reported Moves	0.92^{**}	0.42	1.16^{***}	0.27	2.23^{***}	0.31	1.82^{***}	0.30
Constant	-1.44^{***}	0.28	-1.23^{***}	0.23	-1.37^{***}	0.30	−1.92	0.30

Note. The reference group is Class 1 (loyal). This multinomial model has been separated into two tables for readability purposes and therefore only shows Classes 2, 3, 5 and 6. The coefficients are rounded to 2 decimal places.

* $p < .05$; ** $p < .01$; *** $p < .001$

$N = 9,464$ Pseudo $R2 = .11$

Table A4

Multinomial regression coefficients of covariates on class membership (unweighted)

	Stayers (Class 4)		Nudged (Class 7)	
	Coef.	SE	Coef.	SE
Female	0.11	0.07	−0.21	0.14
Age (ref: 16-19)				
20-24	−0.10	0.17	−0.39	0.30
25-34	-0.31^{**}	0.16	-0.51^{*}	0.27
35-44	-0.78^{***}	0.17	$-0.49{*}$	0.29
45-54	-0.89^{***}	0.19	-0.86^{**}	0.34
55-64	-0.91^{***}	0.21	-0.95^{**}	0.38
65+	-2.11^{***}	0.22	-2.06^{***}	0.38
Ethnic Minority	0.35^{*}	0.19	1.16^{***}	0.28
Has Partner	-0.46^{***}	0.08	-0.37^{**}	0.16
Highest Qualification (ref: No qualification)				
Degree	0.02	0.13	-0.55^{**}	0.26
Other higher degree	0.04	0.14	−0.27	0.28
A-Level etc.	0.19	0.11	−0.36	0.23
GCSE etc.	0.17	0.11	−0.10	0.21
Other qualification	0.00	0.13	−0.10	0.25
Job (ref: Employed, in education or training)				
Unemployed	−0.36	0.25	0.34	0.36
Retired	0.09	0.13	−0.33	0.25
Other	-0.51^{***}	0.14	0.00	0.23
Self-rated General Health (ref: Very poor)				
Excellent	-0.61^{***}	0.16	−0.33	0.32
Good	-0.74^{***}	0.12	−0.19	0.25
Fair	-0.43^{***}	0.12	−0.39	0.25
Poor	-0.23^{*}	0.12	0.02	0.26
Level of interest in politics (ref: Not at all int)				
Very interested	−0.18	0.14	0.00	0.25
Fairly int	-0.24^{**}	0.11	-0.37^{*}	0.20
Not very int	−0.15	0.10	−0.21	0.19
Supports a political party	−0.01	0.07	0.03	0.15
Monthly Household Net Income (£000s)	0.08	0.05	-0.30^{**}	0.15
No. of Own Children in the Household	-0.13^{*}	0.07	−0.09	0.12
No. of Pensioners in the Household	0.31^{***}	0.06	0.31^{***}	0.11
Dwelling type (ref: Own entrance)				
Flats and other multi-storey units	-0.21^{*}	0.12	0.16	0.22
Bedsits/institutions/other structures	−0.02	0.19	0.30	0.37
Own Home	−0.01	0.09	0.34^{*}	0.18
Household Size	0.29^{***}	0.05	0.27^{***}	0.08
No. of Reported Moves	1.10^{***}	0.27	1.23^{**}	0.48
Constant	−0.40	0.24	-1.93^{***}	0.44

Note. The reference group is Class 1 (loyal). This multinomial model has been separated into two tables for readability purposes and therefore only shows Classes 4 and 7. The coefficients are rounded to 2 decimal places.
* $p < .05$; ** $p < .01$; *** $p < .001$
$N = 9{,}464$. Pseudo $R2 = .11$

Table A5

Multinomial regression coefficients of class membership, covariates, and interactions on reasons for nonresponse (weighted)

	Non-Contact		Other	
	Coef.	SE	Coef.	SE
Class (ref: C7: Gradually Nudged)				
C2: Attrition by W8	2.97***	0.77	−3.41***	0.96
C3: Attrition by W22	3.15***	0.78	−2.26**	0.94
C4: Stayers	2.48***	0.85	−1.62*	0.97
C5: Attrition by W16	3.34***	0.78	−2.70***	0.95
C6: Abruptly Nudged	2.45*	1.33	−2.39**	1.16
Age (ref: 16-19)				
20-24	0.44	1.30	0.39	1.51
25-34	0.99	1.01	−1.56	1.07
35-44	0.71	0.95	−1.17	1.15
45-54	1.74*	0.91	0.25	1.10
55-64	2.94***	0.95	−0.46	1.03
65+	2.61***	0.83	0.41	0.92
Ethnic Minority	0.30**	0.14	0.05	0.17
Self-rated General Health (ref: Very poor)				
Excellent	−0.78***	0.16	−1.56***	0.14
Good	−0.84***	0.15	−1.49***	0.12
Fair	−0.47***	0.15	−1.27***	0.12
Poor	−0.26	0.17	−0.56***	0.13
No. of Pensioners in the Household	−0.38***	0.08	−0.52***	0.08

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	Non-Contact		Other	
	Coef.	SE	Coef.	SE
Class (ref: C7: Gradually Nudged) × Age (ref: 16-19)				
C2: Attrition by W8 × 20-24	−0.19	11.32	−0.73	11.57
C2: Attrition by W8 × 25-34	−1.00	11.03	0.80	11.14
C2: Attrition by W8 × 35-44	−1.49	0.97	0.86	11.21
C2: Attrition by W8 × 45-54	-3.32^{***}	0.94	−0.24	11.16
C2: Attrition by W8 × 55-64	-5.05^{***}	0.98	0.78	11.09
C2: Attrition by W8 × 65+	-4.56^{***}	0.84	2.02^{**}	0.97
C3: Attrition by W22 × 20-24	−1.11	11.33	−0.95	11.54
C3: Attrition by W22 × 25-34	-2.11^{**}	11.04	0.39	11.11
C3: Attrition by W22 × 35-44	-2.10^{**}	0.99	0.01	11.19
C3: Attrition by W22 × 45-54	-3.34^{***}	0.96	−0.60	11.15
C3: Attrition by W22 × 55-64	-3.73^{***}	0.98	1.10	11.07
C3: Attrition by W22 × 65+	-2.95^{***}	0.85	1.10	0.96
C4: Stayers × 20-24	−0.18	11.38	−0.38	11.56
C4: Stayers × 25-34	−0.87	11.10	1.14	11.14
C4: Stayers × 35-44	−1.12	11.07	1.16	11.22
C4: Stayers × 45-54	-2.79^{***}	11.07	0.17	11.17
C4: Stayers × 55-64	-3.17^{***}	11.06	1.49	11.10
C4: Stayers × 65+	−1.26	0.97	2.31^{**}	11.02
C5: Attrition by W16 × 20-24	−0.75	11.32	−0.88	11.56
C5: Attrition by W16 × 25-34	−1.66	11.04	1.01	11.13
C5: Attrition by W16 × 35-44	-1.84^{*}	0.98	0.56	11.21
C5: Attrition by W16 × 45-54	-2.91^{***}	0.95	−0.30	11.16
C5: Attrition by W16 × 55-64	-3.93^{***}	0.99	1.92^{*}	11.08
C5: Attrition by W16 × 65+	-3.78^{***}	0.86	2.79^{***}	0.97
C6: Abruptly Nudged × 20-24	−0.54	12.00	1.10	11.81
C6: Abruptly Nudged × 25-34	−0.78	11.56	2.13	11.36
C6: Abruptly Nudged × 35-44	−0.56	11.53	1.55	11.44
C6: Abruptly Nudged × 45-54	−1.48	11.52	0.59	11.39
C6: Abruptly Nudged × 55-64	-3.13^{*}	11.63	2.13	11.33
C6: Abruptly Nudged × 65+	-2.72^{*}	11.45	2.87^{**}	11.20
Constant	-2.67^{***}	0.77	2.61^{***}	0.91

Note. The reference group is Refusal, and the model only contains nonrespondents. This multinomial model has been separated into two tables for readability purposes. The coefficients are rounded to 2 decimal places.
* $p < .05$; ** $p < .01$; *** $p < .001$
$N = 382,999$. Pseudo $R2 = .17$

Appendix B
Figure

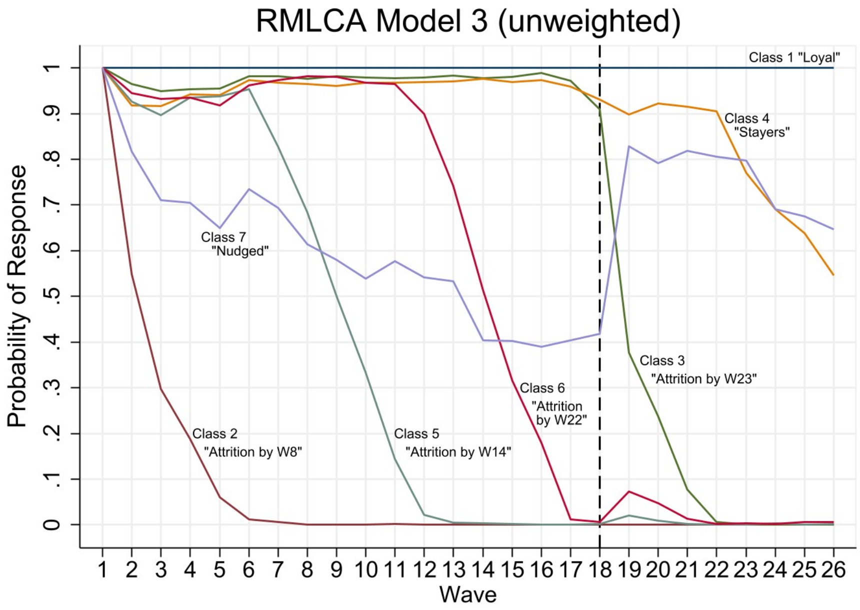

Figure B1

Response probabilities for the unweighted Model 3 (7 Classes). Note: Dashed line indicates the end of BHPS (Wave 18) and transition to UKHLS. UKHLS Waves 2-9 are referred to as Waves 19-26 for readability.